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DIGITAL COLLATERAL

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ABSTRACT

A new form of secured lending using "digital collateral" has recently emerged, most prominently in low- and middle-income countries. Digital collateral relies on lockout technology, which allows the lender to temporarily disable the flow value of the collateral to the borrower without physically repossessing it. We explore this new form of credit both in a model and in a field experiment using school-fee loans digitally secured with a solar home system. Securing a loan with digital collateral drastically reduces default rates (by 19 pp) and increases the lender's rate of return (by 38 pp). Employing a variant of the Karlan and Zinman (2009) methodology, we decompose the total effect on repayment and find that roughly one-third is attributable to adverse selection, and two-thirds is attributable to moral hazard. In addition, access to digitally secured school-fee loans significantly increases school enrollment and school-related expenditures without detrimental effects to households' balance sheet.

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1 Introduction

Using collateral to secure debt helps overcome economic frictions, thereby expanding the supply of credit and reducing the cost of providing credit. Indeed, more than 80% of total household debt in the US is secured by a physical asset.[1] Yet, secured debt is much less prevalent in low- and middle-income countries (LMICs).[2] Why? On the supply side, property rights are difficult to establish and enforce in economies with weak legal institutions, which translates to a high cost of repossessing collateral for creditors. This is especially true for lenders servicing households in remote areas, where the costs associated with locating, repossessing, and redeploying collateral can be prohibitive. On the demand side, the primary source of income for many households in LMICs is self-employment, which is subject to more frequent shocks than formal sector wages. These households, which lack savings, are more likely to default for nonstrategic reasons and may choose to avoid the risk of having assets repossessed.

Recent technological innovations have facilitated new financial contracts that use "digital collateral." An emerging example is pay-as-you-go (PAYGO) financing. The typical PAYGO contract requires a nominal down payment to take possession of an asset, followed by frequent, small payments made via a mobile payment system. PAYGO lenders rely on an embedded lockout technology, enabling them to remotely disable the flow of services from the asset. In other words, the lender can *digitally repossess* the asset without the need to physically repossess it. Digital collateral has two distinct technological features. First, disabling the flow of services is cheap and easily reversible. Second, borrowers unable to make a payment do not lose the asset, rather they are simply unable to consume the flow of services from the asset until they start paying again. These features allow for a richer space of financial contracts involving flexible repayment schedules (e.g., pay per usage) and temporary repossession for non-payment.[3]

In this paper, we argue that digital repossession can serve a useful role in credit markets,

[1]Source: "Quarterly Report on Household Debt and Credit," Federal Reserve of the Bank of New York (2020), https://www.newyorkfed.org/medialibrary/interactives/householdcredit/data/pdf/HHDC_2020Q2.pdf.

[2]In our baseline survey, we find that only 30% of money borrowed by households is secured by a physical asset (house, land, livestock, or vehicle). The Transparent Pricing Initiative, which covers standardized pricing data from 23 institutions operating in Uganda, shows that only 16% of loan products during 2011-2014 explicitly mention the usage of collateral (Transparent Pricing Initiative, 2014). In a survey, Elum and Kanu (2018) find that 47% of the farmers in Nigeria agreed that collateral requirement was a problem in accessing formal credit.

[3]These features are in contrast to the typical secured loan that involves a fixed repayment schedule and permanent repossession in default.

especially in settings where physical repossession is impractical. We develop a theoretical model to understand the implications of digital repossession in lending markets and how it contrasts with physical repossession. The model also provides a framework for interpreting the results of our experiment. In the experiment, we quantify the extent to which digitally secured loans have better repayment than "unsecured" loans for which the lockout feature is disabled.[4] We explore the mechanism for the increase in repayment and ask whether digitally secured credit is a feasible equilibrium contract. We then examine how access to this form of credit affects households.

Traditional collateral serves two roles: (i) the lender recovers something of value, thereby insuring them against default, and (ii) the household loses something of value, thereby providing them an incentive to repay the loan or decline the loan if they expect to default. Digital collateral serves the latter role, but not the former. Still, much like with traditional collateral, securing loans with digital collateral reduces the lender's cost of providing financing via two channels relative to unsecured credit. First, it provides households with an incentive to repay the loan when they can afford to do so, thereby mitigating the moral hazard problem of strategic default (which is also often referred to as limited enforcement). Second, when combined with a down payment, digital collateral serves as a screening mechanism to mitigate adverse selection. That is, a household that is more likely to default will have less incentive to accept a digitally secured loan. By reducing moral hazard and adverse selection, digital collateral enables lenders to offer more financing to credit-worthy borrowers at terms they find acceptable.

Despite reducing agency costs, a more effective lockout technology—which enables collateral to be digitized—does not necessarily increase welfare. More effective lockout destroys more surplus (i.e., household utility) when it is utilized, which can offset the welfare gains of the credit expansion, even if it is utilized less frequently. As a result, an intermediate degree of lockout following non-repayment can be welfare maximizing. This finding is consistent with the temporary and relatively lenient nature in which lockout is deployed in PAYGO contracts compared to traditional secured lending.

Our field experiment was designed to identify the impact of digital collateral on credit market frictions and household outcomes. We partnered with Fenix International, the largest solar-home system (SHS) provider in Uganda. An SHS provides a household with access to a modest amount of

[4] While we refer to the latter type of loans as unsecured, technically all of the loans in our experiment are secured in the same way as most other secured debt in LMICs, i.e., with a low probability of physical repossession conditional on default.

electricity without being connected to the grid. Fenix offers PAYGO financing for their SHS. They also offer follow-up loans for good payers, where the SHS is re-used as digital collateral to secure the loan. Our study examined the effects of digital collateral with Fenix's most popular follow-up product: a cash loan offered to customers near the beginning of each school term when school fees are due.

We randomized a sample of Fenix customers into three treatment groups and a control group. In the first treatment, the customer was offered a loan secured with digital collateral. In the second treatment, the customer was offered an unsecured loan. In the third treatment, a customer was offered a secured loan, but if accepted, the customer was (positively) "surprised" and received an unsecured loan. The "surprise unsecured" group is used to disentangle adverse selection from moral hazard a la Karlan and Zinman (2009). Other than the collateral terms, all other terms of the offered loan contracts were identical across treatment groups.

Our experiment yielded four main results. First, consistent with our hypothesis that digital collateral reduces adverse selection, the take-up rate was about 7 percentage points (pp) lower for customers offered a (digitally) secured loan than those offered an unsecured loan (44% vs 51%). The differential in take-up rates is statistically significant ($p = 0.007$).

Second, securing a loan with digital collateral significantly increased loan repayment and profitability. Securing the loan with digital collateral increased average repayment by 11 pp over the unsecured repayment rate of 62%. Furthermore, the fraction of households that fully repaid the secured loan was 19 pp higher than for unsecured loans. About two-thirds of the total increase in repayment can be attributed to a reduction in moral hazard, while one-third was due to a reduction in adverse selection. Consistent with our model's predictions, the reduction in moral hazard was concentrated among higher-risk borrowers, whereas the reduction in adverse selection was concentrated among lower-risk borrowers.

Unsecured loans were highly unprofitable. By securing loans with digital collateral, the annualized internal rate of return (IRR) of lending increased by 38 pp. Yet, securing loans with digital collateral was not sufficient to ensure profitability. The top two terciles of households with secured loans had positive IRRs, but the third tercile had a negative IRR. It is likely that the secured loans had lower profitability in our experiment because the lender relaxed eligibility requirements and offered larger loans for the purposes of powering the experiment. Digitally secured loans under the lender's normal lending practices were profitable across all terciles (see Figure 2). Overall, these findings suggest that firms should be unwilling to offer unsecured credit. Since the market for traditional secured loans is largely non-existent, loans secured with digital collateral appear to be a feasible contract design that can facilitate households' access to credit. However, screening remains a necessary component of sustainable lending.

Third, the school-fee loan offer increased enrollment, attendance, and school-related expenditures (i.e., school fees, uniforms, supplies, transport, and meals). Children in households that were offered a school-fee loan (secured or unsecured) were significantly more likely to be enrolled at school compared to children in the control group. To get a sense of the magnitudes, consider a (median) household with three school-aged children. The loan offer increased the likelihood that each child was enrolled by 3 pp (from 88% to 91%, $p = 0.02$), implying that households that took up the loans saw the share of unenrolled children fall by 50%. Furthermore, the loan offer increased investment in school-related expenditures by 26% ($p = 0.005$) per child.

Fourth, the loan treatment did not have significant effects on household balance sheets in any of the treatment groups. Asset purchases and sales remained largely unchanged. Total household borrowing increased by about 30% of the school-fee loan, commensurate with the increase in school expenditures, but the magnitude is not statistically significant.

Altogether, our results suggest that digital collateral increases the share of households to whom a lender can profitably offer loans. Moreover, the loan treatments significantly increased school enrollment and expenditures, suggesting that some customers did not have sufficient access to other sources of financing to pay for school fees. Indeed, 15% of households in our sample report having been denied for a loan in the last 12 months.

While these findings suggest a welfare improvement, securing loans with digital collateral is not without cost. First, there are costs to produce and integrate the lockout technology. Second, locking the device creates an (ex-post) inefficiency. The median household with a secured loan was locked for 50 of the first 200 days from loan origination. On the one hand, this is a feature of the PAYGO contract; households need not make payments on days in which they do not require electricity, whereas borrowers face permanent repossession if they fail to repay a traditional secured loan. On the other hand, it suggests that there is potential room for improvement in the contract design. We provide a more detailed discussion of the welfare implications in Section 7.3.

Our study helps to explain why digital collateral is being employed in a range of applications.

For example, PayJoy, a FinTech firm based in San Francisco, developed a lockout technology for smartphones and has been offering digitally secured credit for the purchase of smartphones since 2016. Similar to Fenix's school-fee loan product, they now offer secured cash loans to customers who have completed the payments on the primary loan by recollateralizing the smart phone. PayJoy has large scale operations in Mexico, and a growing customer base in a number of other countries. In India, digitally secured lending for smartphones is widespread, especially among two of the largest consumer lenders, Bajaj Finserv and TVS Credit (Fiorin et al., 2023).[5] With the proliferation of smart devices, secured lending via digital collateral could easily be extended to a wide range of other devices such as laptops and televisions. Importantly, the capacity to reuse collateral for future loans, as demonstrated by Fenix and PayJoy, expands the potential impact of the innovation as a vehicle for affordable access to credit.

Electric, telecommunication, and water companies have been using similar contracts to finance last mile connection costs (Devoto et al., 2012; van den Berg and Danilenko, 2014; Coville et al., forthcoming). In addition, some utilities use their flow of services as digital collateral to provide financing for other asset purchases. For example, TELMEX, a Mexican telecom, provides secured loans to customers for the purchase of computer equipment using the customers' access to internet service as digital collateral.[6]

Even in rich countries, there is potential to expand access to credit through digitally secured loans, especially to borrowers with limited or damaged credit histories. Indeed, a similar technology has already been deployed in the United States for subprime auto loans. Starter interrupt devices, which allow the lender to remotely disable the ability to start the car if the borrower is not in good standing on the loan, have been installed in more than two million vehicles.[7] Recently, Ford Motor Company filed for a patent on a technology that can remotely disable features (e.g., air conditioning, stereo, cruise control) for borrowers who are delinquent on auto loan payments.[8]

[5] See also https://restofworld.org/2021/loans-that-hijack-your-phone-are-coming-to-india/ (Date Accessed: June 2, 2023).

[6] See https://telmex.com/web/hogar/credito-telmex.

[7] See https://dealbook.nytimes.com/2014/09/24/miss-a-payment-good-luck-moving-that-car.

[8] See https://www.msn.com/en-us/money/other/miss-a-car-payment-and-ford-s-patent-could-shut-off-your-ac/ar-AA189iNK

2 Related Literature

Our paper relates to several different literatures, including the use of collateral in credit markets and education in developing countries.

Collateral in Credit Markets There is a large theoretical literature explaining the use of collateral in credit markets. Our contribution to this literature is to explicitly model the repossession technology and to understand how its characteristics impact economic outcomes. Most relevant to our work are the numerous papers that have illustrated how collateral can be useful to mitigate inefficiencies associated with moral hazard, adverse selection, and limited enforcement. Bester (1985) shows that the credit rationing in Stiglitz and Weiss (1981) can be (partially) overcome through the use of collateral as a screening device: better credit risks post more collateral and receive a lower interest rate, thereby eliminating the need for rationing.[9] Another explanation for the use of collateral is to alleviate moral hazard problems: posting collateral makes it more costly for a borrower to risk shift, shirk, or strategically default (Bester, 1987; Chan and Thakor, 1987; Tirole, 2006).[10]

An extensive empirical literature explores the role of collateral in credit markets. Consistent with our experimental findings, a number of papers have found observational evidence consistent with moral hazard (Berger and Udell, 1990, 1995; Jimenez et al., 2006).

There is also evidence that a more efficient repossession technology facilitates an expansion of credit. One source of inefficiency is liquidation costs after repossession. Assunção et al. (2013) show that loan spreads dropped and credit expanded, but default rates increased after a Brazilian reform that simplified the sale of repossessed cars. Benmelech and Bergman (2009) find that debts secured by more redeployable collateral exhibit lower credit spreads, higher credit ratings, and higher loan-to-value ratios. Another source of inefficiency are the costs associated with repossessing collateral after default due to weak creditor rights. In countries with stronger creditor rights protection, thus lower costs of repossession, credit markets are more developed, which may contribute to economic growth (e.g., La Porta et al., 1998; Qian and Strahan, 2007; Djankov et al., 2007). The potential

[9] Similar findings obtain in Chan and Kanatas (1985); Bester (1987); Besanko and Thakor (1987a,b).

[10] The theoretical literature also illustrates other roles for the use of collateral (or control rights), including incomplete contracts (Aghion and Bolton, 1992; Hart and Moore, 1994), monitoring incentives (Rajan and Winton, 1995), priority (Ayotte and Bolton, 2011), limited enforcement (Rampini and Viswanathan, 2013), exclusivity (Donaldson et al., 2019), and as a commitment device (DeMarzo, 2019).

economic benefits of digital collateral are, therefore, more significant in less developed countries and countries with weaker creditor rights (Liberti and Mian, 2010; Benmelech et al., 2020).

Existing literature has shown that there are trade-offs associated with secured borrowing. Exhausting pledgeable assets may mean losing financial flexibility and giving up profitable future investment opportunities (e.g., Acharya et al., 2007; Rampini and Viswanathan, 2010, 2013; Li et al., 2016; Donaldson et al., 2019). By pledging collateral, a firm limits its flexibility to sell or redeploy assets to craft a better business operation. Indeed, Benmelech et al. (2020) document a significant decline in the fraction of secured debt among US firms over the twentieth century, attributed in part to these reasons.

While secured lending is uncommon in LMICs, one recent study uses a field experiment to study the potential for asset collateralization to expand access to credit in rural Kenya. Jack et al. (2023) find that a reduction in the down payment on a water tank from 25% to 4% led to a significant increase in take-up with only a modest increase in default rates, which they attribute almost entirely to adverse selection rather than moral hazard. This is in contrast with our findings that securing loans increases repayment primarily by a reduction in moral hazard. This difference is likely attributable to the contrast between digital and traditional collateral and to differences in study design. In Jack et al. (2023), borrowers in default faced physical repossession regardless of the treatment group. Whereas, in our study, borrowers faced digital repossession when they were delinquent and not just in default, but only if they were assigned to the secured treatment group.

Education in Developing Countries In most African countries, families struggle to the out-of-pocket costs for education, including school fees, books, uniforms, meals, and transport (Williams et al., 2015). A number of recent observational studies find that reducing or eliminating those costs improve enrollment and educational attainment (İşcan et al., 2015; Moussa and Omoeva, 2020; Ajayi and Ross, 2020; Adu Boahen and Yamauchi, 2017; Masuda and Yamauchi, 2018; Chicoine, 2019, 2020; Delesalle, 2019; Valente, 2019; Moshoeshoe et al., 2019). In a randomized controlled trial in Ghana, Duflo et al. (2019) show that scholarships for financially-constrained students, who had already passed the entrance exam, increased both secondary and tertiary attainment as well as long-run labor market outcomes.

To our knowledge, our study is the first to demonstrate that access to credit is an effective mechanism for increasing K-12 enrollment and school-related expenditures in LMICs. However, loans are common for tertiary education, and have been studied in middle income countries such as Chile, South Africa, and China (Solis, 2017; Gurgand et al., 2011). While loans have been effective in improving college enrollment, several studies have found evidence of adverse effects on students graduating with debt (Cai et al., 2019; Dearden, 2019). In contrast, we do not find an adverse impact of K-12 loans on households' balance sheets.

3 Model

In this section, we propose a stylized model of collateralized lending. The purpose of the model is twofold. First, to understand the basic implications of securing loans with digital collateral and how it contrasts with more traditional secured lending. Second, to provide a framework for interpreting our experimental results. We start by considering a setting where households finance the purchase of a durable good. We then map the model to our experimental setting in Section 3.4.

The model has two dates (0 and 1) and two types of agents (households and firms). Households would like to purchase a durable good produced by firms but have limited wealth. Firms produce the good and can also provide financing for it. However, due to incomplete markets (i.e., moral hazard, adverse selection), firms require collateral in order to underwrite household debt.

Households. There is a unit mass of households, indexed by $i \in [0,1]$. Household i derives utility from consuming the good at date 1, denoted by $\tilde{v}_i$, which is distributed according to F on support $[\underline{v},\bar{v}] \in \mathbb{R}$. Household i privately observes $\tilde{v}_i$ at the beginning of date 1.[11]

Each household has date-1 income denoted by $\tilde{y}_i$. Households are heterogeneous with respect to income risk. With probability q_i, household i experiences an income shock and $\tilde{y}_i = 0$. With the complementary probability, household i has sufficient income, $\tilde{y}_i = y > \bar{v}$, but may still choose to strategically default. Thus, higher q_i correspond to riskier households. Without loss of generality, order the households so that q_i is increasing in i. Households know their risk type. Let G and g denote the distribution and density of risk types in the population, which has support $[0,1]$. For simplicity, we assume that all households have the same date-0 wealth, $w_i = w$ for all i, and that

[11] A higher realization of $\tilde{v}_i$ can be interpreted either as a shock leading to a particularly high value for consuming the good or from a positive income shock and thus a lower marginal utility from consumption of other goods.

households are risk-neutral utility maximizers with a discount factor normalized to 1.[12]

Firms. There are $N \geq 1$ identical firms. Each firm has the technology to produce the good at marginal cost c. Firms can also provide financing to their customers. More specifically, firms can offer a contract, which is a pair (d,p), where d is the downpayment required at date 0 to take possession of the good and p is the price of consuming the good at date 1. If a household takes possession at date 0, but does not make the payment at date 1, then the firm "repossesses" the good.[13]

Repossession. Repossession has two implications. First, the lender *recovers* something of value. Second, the household loses something of value, which provides *incentives* to repay the loan conditional on acceptance or decline the loan offer.

In most models of collateralized lending, these two roles, recovery and incentives, are inseparable and characterized by a single parameter (e.g., Kiyotaki and Moore, 1997). The lockout technology decouples the two roles by providing incentives without the costs and benefits associated with physical repossession. To separate the two roles, we parameterize firms' repossession technology by the pair (κ,λ), where κ denotes the effectiveness of recovery—it is the fraction of the production cost that the firm recovers from repossession, and λ denotes the effectiveness of repossession on incentives—the borrower enjoys only a fraction $1-\lambda$ of her value for good when it is repossessed.[14]

As discussed earlier, physical repossession is costly in economies with high transaction costs, weak creditor rights, and limited enforcement. In such environments, a traditional secured loan, where the asset is physically repossessed in default, is characterized by relatively low κ. A loan secured with digital collateral may involve little recovery in default (i.e., $\kappa = 0$), but still provide strong incentives for borrowers (i.e., $\lambda \approx 1$). Our primary interest will be to explore how an increase in λ (i.e., a more effective lockout technology) affects equilibrium quantities.

We make the following parametric assumptions.

[12]Risk-neutrality simplifies the space of relevant contracts since there is no demand for intra- nor inter-temporal consumption smoothing. However, fixing the contract space, our main results can be extended to a setting with risk-averse households.

[13]We take the form of contract as given because it is representative of what is used in practice by PAYGO lenders and in our experiment. If households are identical ex-ante (e.g., $q_i = q$ for all i) then this contract is optimal within a more general class of mechanisms in which the date-1 transfer and repossession are contingent on the household's reported value.

[14]One can interpret λ as the probability with which the good is successfully repossessed from the borrower and $\kappa c/\lambda$ as the firm's salvage value for the good conditional on successfully repossessing it.

Assumption 1 (Trade is efficient ex-ante). $\mathrm{E}(\tilde{v}_i) > c$.

Assumption 2 (Repossession is inefficient ex-post). $\lambda v > \kappa c$ *for all* $v \in [\underline{v}, \bar{v}]$.

Given these assumptions, the first-best outcome is for all households to purchase the good and for firms to never repossess the good. This outcome can be sustained as an equilibrium if households have sufficient wealth. Assumption 3 rules out this possibility.

Assumption 3 (Households are financially constrained). $w < c - \underline{v}$, *but households that do not experience a shock have sufficient wealth and income to afford the good:* $w + y > c$.

Finally, we impose the Myerson (1981) regularity assumption on the distribution of values.

Assumption 4 (Monotone virtual surplus). $v - \frac{1-F(v)}{f(v)}$ *is monotonically increasing in* v.[15]

3.1 Household Behavior

We begin by considering the behavior of households taking the contract as given. Suppose that household i purchases the good at date 0. The household will repay at date 1 provided that (i) it does not experience an income shock, and (ii) that its utility for consuming the good is sufficiently high, i.e., $\lambda \tilde{v}_i \geq p$. Our first observation is that a more effective lockout technology leads to a higher probability of repayment.

Proposition 1 (Lockout Reduces Moral Hazard). *Fixing a contract, a more effective lockout technology (i.e., higher* λ*) decreases the probability that household* i *strategically defaults.*

Next, consider the purchase decision of households. The expected date-1 surplus to household i is given by

$$S_i(p) \equiv (1-q_i)\left[\int_{\underline{v}}^{\bar{v}} \max\{v-p, (1-\lambda)v\} dF(v)\right] + q_i(1-\lambda)\mathrm{E}(\tilde{v}_i).$$

Household i will purchase the good if they can afford to do so and the surplus from purchasing is non-negative. More concisely, household i will purchase the good if

$$d \leq \min\{w, S_i(p)\}. \tag{1}$$

[15]This assumption holds for many commonly used distributions (e.g., uniform, normal, exponential) and is implied by the monotone likelihood ratio property (MLRP).

Let $U_i(d,p) = S_i(p) - d$ denote household i's expected utility from purchasing the good. Noting that $S_i(p)$ is decreasing in both q_i and λ, we have the following result.

Proposition 2 (Lockout Reduces Adverse Selection)**.** *Fix a contract (d,p) such that $S_1(p) < d \leq w < S_0(p)$. Then, there exists $q^\lambda \in (0,1)$ such that only households with income risk $q_i \leq q^\lambda$ accept the contract. Moreover, q^λ is decreasing in λ.*

This results shows that in combination with a downpayment, lockout leads to *positive selection*. Higher risk households choose not to accept the contract because they anticipate a higher chance of being locked. It is worth noting that Proposition 2 is only a partial equilibrium result. In equilibrium, the firm will respond to a change in λ by adjusting the contract. The first statement of the proposition continues to hold in equilibrium (Corollary 1). However, the comparative static on q^λ is ambiguous.

3.2 Firm Profits

The highest utility type that strategically defaults when the price is p is

$$v(p) = \begin{cases} \underline{v} & p \leq \lambda \underline{v} \\ p/\lambda & p \in (\lambda \underline{v}, \lambda \bar{v}) \\ \bar{v} & p \geq \lambda \bar{v}. \end{cases} \tag{2}$$

For any p, the probability that household i repays is $(1-q_i)[1-F(v(p))]$ and a firm's expected revenue at date-1 from selling to household i is

$$R_i(p) = \kappa c + (1-q_i)[1-F(v(p))](p - \kappa c).$$

Date-1 revenue is increasing in both κ and λ and decreasing in q_i. The profit from selling to household i is

$$\pi_i(d,p) = \begin{cases} d + R_i(p) - c & \text{if } d \leq \min\{w, S_i(p)\} \\ 0 & \text{otherwise.} \end{cases} \tag{3}$$

3.3 Equilibrium

The equilibrium will naturally depend both on the degree of competition among firms and whether household income risk is observable. Here, we consider the monopolistic equilibrium with observable household risk. In Appendix B, we demonstrate our results hold with perfectly competitive firms and discuss the model with unobservable risk.

When the firm is a monopolist, the contract offered to household i solves

$$(d_i, p_i) \in \operatorname*{argmax}_{d,p} \pi_i(d,p)$$

We decompose the problem into two steps. First, maximize profit conditional on selling to household i. Then, decide whether to sell to household i. Clearly, the firm's profit is increasing in d, so it will be optimal to set $d_i = \min\{w, S_i(p)\}$. Thus, the firm's problem can be written as

$$\max_p (\min\{w, S_i(p)\} + R_i(p) - c)$$

Consider the problem of maximizing date-1 revenue with respect to the highest type that strategically defaults, $v = p/\lambda$. The marginal revenue from increasing v is

$$(1-q_i)[(1-F(v))\lambda - f(v)(\lambda v - \kappa c)].$$

and the first order condition is

$$v^* - \frac{1-F(v^*)}{f(v^*)} = \frac{\kappa c}{\lambda}, \tag{4}$$

which has a unique solution by Assumption 4. Equation (4) is intimately linked to the monopoly price. In particular, when households are sufficiently constrained, the monopoly price is $p^* \equiv \lambda v^*$.

Lemma 1 (Monopoly Prices)**.** *Conditional on selling to household i, the solution to the monopolist problem involves $d_i = w$ and*

$$p_i = \begin{cases} p^* & \text{if } w \leq S_i(p^*) \\ S_i^{-1}(w) & \text{otherwise} \end{cases}$$

When household wealth is small, the monopolist prioritizes date-1 revenue by charging $p_i = p^*$. When $w > S_i(p^*)$, the firm charges less than p^* at date 1 in order to extract a larger downpayment.

Focusing on the first case, notice from (4) that v^* is independent of q_i, and increases with κ, but decreases with λ. Both higher κ or higher λ correspond to a "better" repossession technology, but they have different effects on the marginal household type who strategically defaults. Thus, we have the following contrast between the two roles of repossession.

Proposition 3 (Recovery vs Lockout)**.** *When the firm is a monopolist and household wealth is sufficiently small, i.e., $w < S_i(p^*)$:*

(i) More efficient recovery (higher κ) leads to ***more*** *strategic default and repossession.*

(ii) More effective lockout (higher λ) leads to ***less*** *strategic default and repossession.*

Increasing κ gives the firm more incentive to repossess the good and makes strategic default less of a concern, so the firm sets a higher price and households default more frequently. The first part of Proposition 3 is consistent with evidence from Assunção et al. (2013): making it easier for lenders to recover value from collateral leads to an increase in credit supply, but also higher default rates. While increasing λ also expands credit supply, it has the *opposite* effect on default rates. It makes strategic default more costly to the firm because it increases the wedge between the firm's payoff conditional on repayment and the payoff conditional on default.

If the implied profit from the contract in Lemma 1 is positive, then the firm will sell to household i. Otherwise, the household will reject any offer that the firm is willing to make.

Proposition 4 (Monopoly Quantities)**.** *The firm will sell to household i if and only if either*

(i) $w + R_i(p^*) \geq c$ *when* $S_i(p^*) \geq w$*, or*

(ii) $w + R_i(S_i^{-1}(w)) \geq c$ *when* $S_i(p^*) < w$*.*

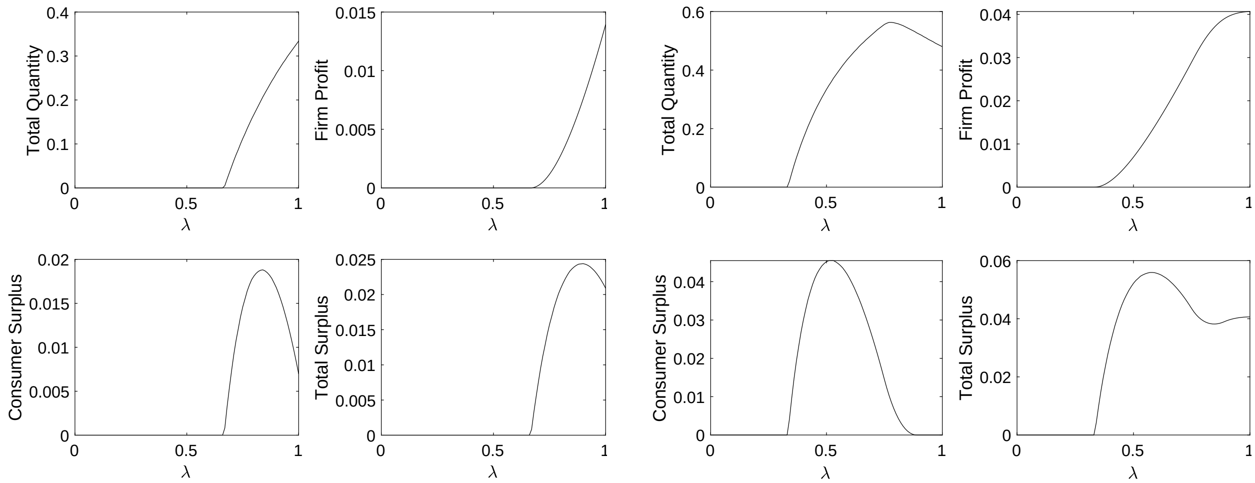
Noting that both R_i and S_i are decreasing in q_i, we can conclude that positive selection also emerges as an equilibrium outcome.

Corollary 1. *For any $\lambda > 0$, there exists q^* such that only households with $q_i < q^*$ will purchase the good.*

Since the downpayment is simply a transfer, we can ignore it when computing total surplus, which is given by

$$TS = \int_0^{q^*} (R_i(p_i) + S_i(p_i) - c) dG(q_i).$$

Firm profit and consumer surplus are given by $\Pi = \int_0^{q^*} \pi_i(d_i,p_i)dG(q_i)$ and $CS = \int_0^{q^*} U_i(d_i,p_i)dG(q_i)$.



(a) Low household wealth, $w = \frac{1}{12}$.

(b) High household wealth, $w = \frac{1}{6}$.

Figure 1: The effect of lockout on equilibrium quantities. In this example F and G are uniform distributions on [0,1], $\kappa = 0$, and $c = \frac{1}{4}$.

Figure 1 illustrates quantities of interest for a parametric example and two levels of household wealth. Quantity and profit is initially increasing in λ as more households get access to credit. Household welfare increases with λ on the extensive margin ($q_i = q^*$) as more households get served. However, households that were already purchasing the good ($q_i < q^*$) face higher date-1 prices. As a result, aggregate household welfare can decrease with λ. This possibility is clearly illustrated in Figure 1b, where both household and total surplus decreases for λ large enough. Intuitively, a stronger lockout technology increases the incentive to repay, but also destroys more value when the household defaults. This effect is most pronounced on households with higher income risk as they are more likely to default for non-strategic reasons.

Consumer surplus and total surplus can also decrease with λ when firms are perfectly competitive (see Figure B.1(b)). This finding is related to Dubey et al. (2005), who show that interior default penalties can be optimal in general equilibrium setting with incomplete markets, and suggest that a more lenient repossession policy may be preferable. For example, the firm could repossess the good only after a certain number of missed payments or only with some probability less than one. Indeed, a key innovation of the PAYGO model is that the punishment for missing a payment is not too severe.

3.4 Mapping the Model to the Experimental Setting

There are two noteworthy differences between the model presented above and our experimental setting. First, households in our experiment have already financed the purchase of an SHS and completed payments on the loan. The product that they are offered in the experiment is a follow-up loan in which the SHS is "re-used" as digital collateral. Second, households in our experiment have incentives to remain in good standing with the lender in order to be eligible for future product offerings and upgrades.[16] In this section, we extend the model to accommodate these features in order to derive additional predictions and further interpret our experimental results.

Extending the Model Each household owns a durable good, which will serve as collateral for a loan. Households have an investment opportunity that requires one unit of capital at date 0 and pays a gross expected return $R>1$ at date 2. The firm offers households a secured loan that provides one unit of capital at date 0 in exchange for a payment of p at date 1.

The expected payoff (net of income) from accepting the loan is

$$\Pi_{i,a}=R+(1-q_i)\mathrm{E}[\max\{\tilde{v}_i+\tilde{w}_i-p,(1-\lambda)\tilde{v}_i\}]+q_i(1-\lambda)\mathrm{E}[\tilde{v}_i],$$

where $\tilde{w}_i$ denotes household i's continuation (or intrinsic) value from successfully repaying the follow-up loan. The continuation value may derive from the expectation of future goods and services from the lender and/or moral satisfaction. We assume that $\tilde{w}_i$ is independent of $(\tilde{y}_i,\tilde{v}_i)$, unknown at date 0, and realized at date 1. Households' outside option is to reject the loan offer, which gives them an expected (net) payoff of $\Pi_{i,r}=\mathrm{E}[\tilde{v}_i]$. It is straightforward to show that Propositions 1 and 2 extend to this setting.[17]

Decomposition In our experiment, we test the impact of digital collateral by comparing households offered a digitally secured loan with households offered an unsecured loan. Households are

[16] Much like the optimal contract in a dynamic setting (Abuquerque and Hopenhayn, 2004), the lender provides dynamic incentives to households by increasing the size of subsequent loans following successful repayment.

[17] First, household i repays the loan if it does not experience a shock and $\tilde{v}_i+\tilde{w}_i-p\geq(1-\lambda)\tilde{v}_i$. Therefore, the probability of strategic default is given by $(1-q_i)\Pr(\lambda\tilde{v}_i+\tilde{w}_i-p\geq 0)$, which is decreasing in λ as in Proposition 1. Second, household i accepts the loan if $\Pi_{i,a}-\Pi_{i,r}\geq 0$. Noting that $\Pi_{i,a}-\Pi_{i,r}$ is decreasing in both q_i and λ, the analogy of Proposition 2 also holds. That is, there exists a $\underline{q}$, which is decreasing in λ, such that only households with $q_i<\underline{q}$ accept the loan.

randomly allocated to treatment groups, and we hold the price and all other terms of the loan fixed. We interpret a digitally secured loan as a loan with $\lambda = 1$ and an unsecured loan as a loan in which $\lambda = 0$. Let $\underline{q}^s$ and $\underline{q}^u$ denote the respective threshold risk types that accept a secured and unsecured loan. Let $h(q) \equiv \mathrm{E}(q_i | q_i \leq q)$ denote the expected income risk of a household conditional on having risk below q.

The probability of repayment in the digitally secured treatment group is $\Pr(\tilde{v}_i + \tilde{w}_i \geq p)(1 - h(\underline{q}^s))$. The probability of repayment in the unsecured treatment group is $\Pr(\tilde{w}_i \geq p)(1 - h(\underline{q}^u))$. We can therefore decompose the total difference in repayment between the secured and unsecured treatment groups as

$$\underbrace{(\Pr(\tilde{v}_i + \tilde{w}_i \geq p) - \Pr(\tilde{w}_i \geq p))(1 - h(\underline{q}^s))}_{\text{moral hazard effect}} + \underbrace{\Pr(\tilde{w}_i \geq p)(h(\underline{q}^u) - h(\underline{q}^s))}_{\text{adverse selection effect}}$$

The moral hazard effect is how much repayment increases from digitally securing the loan, holding fixed the set of households who accept it. The adverse selection effect is how much repayment increases due to the positive selection associated with a digitally secured loan. We next demonstrate two comparative static results that will be useful in interpreting heterogeneous treatment effects (see Section 6.2). First, we consider how the distribution of device values affects measurable quantities of interest.

Proposition 5. *An increase in the distribution of device values (in the sense of first-order stochastic dominance) leads to a decrease in loan take up, and an increase in both the moral hazard and adverse selection effect.*

Intuitively, households' willingness to pledge the collateral is lower when the device value is higher, which leads to lower take up and more positive selection (i.e., $\underline{q}^s$ decreases). Further, the incentive to repay a digitally secured loan is stronger when the device value is higher.

Next, we ask how the distribution of continuation values affects outcomes. To do so, suppose that households either have a high continuation value, $\tilde{w}_i = \bar{w} \geq p$, or zero continuation value. If continuation value is high, the household will repay the loan regardless of $\tilde{v}_i$, provided they do not experience an income shock. Let $\mu = \Pr(\tilde{w}_i = \bar{w})$ denote the fraction of households in the population with a high continuation value.

Proposition 6. *An increase in μ leads to a decrease in the moral hazard effect and an ambiguous change in the adverse selection effect.*

Higher μ means there are fewer households that entertain strategic default, which renders the incentive effect of collateral on repayment smaller. The reason for the ambiguity in the adverse selection effect is that, although $\Pr(\tilde{w}_i \geq p) = \Pr(\tilde{w}_i = \bar{w}) = \mu$ is clearly increasing in μ, an increase in μ also makes households more eager to accept a secured loan, which causes $h(\underline{q}^u) - h(\underline{q}^s)$ to decrease.

4 Intervention

We tested the effect of digital collateral on a school-fee loan product offered by Fenix International, a technology company operating in Eastern Africa. As of mid-2019, Fenix had more than half a million solar home system (SHS) customers across six countries in Sub-Saharan Africa.[18] When we ran our experiment, Fenix was the largest SHS provider in Uganda.[19] Fenix's most popular system was 10 Watts, capable of powering LED lamps, a radio, and charging cell phones.[20] Fenix's SHSs differ from the solar panels on homes in the US and Western Europe. They produce roughly two orders of magnitude less electricity and they are standalone systems, meaning they are not connected to a grid.

Like most SHS providers, Fenix sold most of its units through a PAYGO model.[21] Customers make a small down payment (3-6% of the cash price or \$5-10 for the 10W system) to take possession of the SHS. Subsequently, customers make small payments using mobile money until they have paid off the loan. If a customer does not make a payment on time, the SHS will lock (i.e., the battery will not discharge electricity) until the next payment is made.

Fenix also used remote mobile payment and locking technologies to offer product upgrades and secondary loans. Their most popular follow-up product was a 100,000 Ugandan Shilling (UGX, \$27) school-fee loan.[22] These were cash loans offered to the better-paying customers three times

[18]See https://www.fenixintl.com/blog/ (Date accessed: October 29, 2020).

[19]See Table 8 of the Global Off-Grid Solar Market Report: Semi-Annual Sales and Impact Data, 2018. Available at https://www.gogla.org/publications. Fenix has since been acquired by the French energy conglomerate Engie.

[20]Fenix's biggest SHS was 34 Watts and could support a variety of small electrical appliances, including a fan, speakers, and an 18.5-inch television. Information about Fenix's system can be found at https://www.fenixintl.com/product/ (Date accessed: October 29, 2020).

[21]Over 85% of SHSs sales in the second half of 2018 were PAYGO financed (see Global Off-Grid Solar Market Report: Semi-Annual Sales and Impact Data, 2018. Available at https://www.gogla.org/publications).

[22]All conversions from UGX to USD in this paper are at the 2019 average of 3,704 UGX to 1 USD. Source: https://data.worldbank.org/indicator/PA.NUS.FCRF?locations=UG.

a year at the beginning of school terms.

Our study focused on a 300,000 Ugandan Shilling (UGX, \$81) school-fee loan. The loan amount corresponds to roughly 6% of average annual household income and 25% of average household borrowing. Obtaining the loan required customers to make a deposit of 50,000 UGX (\$13).[23] To maximize sample size, our study made the school-fee loan available to all customers who had paid off the original SHS loan. Fenix's usual business practice was to only make the 300,000 UGX loans available to customers who had repaid the original SHS loan in a timely manner and who had already repaid smaller school-fee loans of 100,000 and 200,000 UGX.

Several days after customers made their deposits, funds were disbursed to them via mobile money. Customers received seven free days of light after which they were responsible for making daily payments of 3,000 UGX (less than \$1) for 100 days. Many customers chose to pay for several days or a week of light at a time rather than make daily payments. Fenix considered the loan repaid if the customer made nominal payments totaling \$81 (not including the deposit) within 145 days of the loan issue date. This arrangement implied that customers who took longer to repay faced a lower effective interest rate. For instance, a customer who made a payment every day paid an annual percentage rate (APR) of 119%, whereas a customer who made a payment only every other day paid an APR of 64%. (Of course, the latter APR does not reflect the cost of being locked.) The median household in our sample faced an APR of 92%, which is high, but consistent with interest rates on microfinance loans in Uganda.[24]

Customers who did not pay off the loan within 45 days of the target repayment date faced interest charges of 2% per month on any remaining principal. After 180 days of no payments, the loan was considered to be in default and Fenix reserved the right to repossess the SHS system. In practice, only a very small fraction of defaults (less than 5%) resulted in physical repossession, which is consistent with our hypothesis that the traditional repossession technology is expensive and ineffective in this setting.[25] In addition, failure to repay the loan in a timely manner rendered

[23]While down payments on collateralized loans are standard, a deposit in advance of a cash loan is an uncommon practice. We explore the implications of this practice in Gertler et al. (2023).

[24]Data from 2011-2014 provided by Transparent Pricing Initiative (https://www.mftransparency.org/microfinance-pricing/uganda/), which covers standardized pricing data from 23 institutions operating in Uganda representing an estimated 85% of Uganda's microloan borrowers, suggest that the average APR is 73.1% (SD = 28.0%) for loans of less than \$200, similar to the loan size in our experiment.

[25] In our sample, physical repossession was costly relative to the outstanding value of the loan as most customers lived in rural areas that were difficult to access. Once the lender reached a delinquent customer, found them at

customers ineligible for future loan offers.[26]

4.1 Background: Education and School Fees in Uganda

Formal schooling in Uganda starts at age 5. Primary school extends for seven years, through age 12. Secondary school is for children aged 13-20. Primary and secondary-aged children in Uganda have access to both public and private schools. In 2016, the most recent year for which data are available, 80% of primary-aged students attended public schools and 20% attended private schools. At the secondary level, over 50% of children attend private schools.[27] The government has offered a universal primary education program since 1997, although in practice not all students have access to subsidized primary education, and even those that do incur expenses for uniforms, books, other supplies and school lunches.

School fees and school related expenditures constitute a non-trivial portion of household expenses in Uganda. Conditional on enrollment, the median household spends 14% of income on primary education and 21% of income on secondary education based on data from the 2019 nationally representative World Bank Living Standards Measurement Study (LSMS). School fees for both government and public schools are typically due three times per year. Two of the three due dates are not proximate to harvest season, and hence are periods of low income across rural Uganda. In one study, 53% of families reported having their children sent home because they were unable to pay school fees (Intermedia, 2016).

5 Experimental Design

Our universe of eligible loan recipients consisted of Fenix customers that fully repaid the primary loan on their SHS and did not have an outstanding school-fee loan. In May 2019, we sent an SMS message to the 27,081 eligible customers inviting them to reply if they were interested in a school-fee

home, and still in possession of the SHS, the SHS may have been inoperable. Even for units that were repossessed in good working condition, Fenix did not have a ready use for many of its older components.

[26]Notably, Fenix did not use risk-based pricing, either by loan size or customer attributes. Many lenders in LMICs lack clear measures of risk, like credit scores. Also, because it leaves less discretion to local agents, standardized pricing may reduce collusion between sales agents customers.

[27]Statistics from the Uganda Ministry of Education and Sports at http://www.education.go.ug/wp-content/uploads/2019/07/FACT-SHEET-2016.pdf.

loan. 3,300 customers (12%) responded affirmatively. The Appendix (Table A.1, columns 2 and 3) uses administrative data to compare our sample of Fenix customers to population-wide statistics from rural Uganda based on the LSMS (column 1). Fenix customers are more likely to be male, married, and have more children than the average rural Ugandan head of household. They also are more likely to be employed outside the agricultural sector and more likely to come from the (relatively more wealthy) central region.

5.1 Randomization

Figure 3 illustrates our experimental design. We randomly allocated the interested customers into four groups - a control group, a treatment group that was required to post their SHS as digital collateral to get the loan ("Secured"), a treatment group that did not have to post digital collateral ("Unsecured"), and a treatment group that was offered the same terms as the Secured treatment group, but households were later (positively) "surprised" that they would not have to post the digital collateral after accepting the loan offer ("Surprise Unsecured"). Customers in each treatment group were offered the school-fee loan described in the previous section: 300,000 UGX, requiring a 50,000 UGX deposit and 100 daily payments of 3,000 UGX after a seven-day grace period. Appendix C.1 describes how power calculations guided the sample sizes for our experimental groups. Our experimental groups are balanced on observable characteristics at baseline and endline, as documented in Tables A.2 to A.5.[28]

Following Karlan and Zinman (2009), the Surprise Unsecured group allows us to separately identify moral hazard and adverse selection. More specifically, we identify the moral hazard effect by comparing repayment of the Secured group to that of the Surprise Unsecured group—both received and accepted the secured loan offer, but only the Secured group faced digital repossession for non-repayment. We identify the adverse selection effect by comparing the Unsecured group to the Surprise Unsecured group—neither group was ultimately required to post collateral, but the latter group accepted the loan expecting that they would have to post collateral and thereby were positively selected compared to the former. Since customers are only eligible for school-fee loans

[28]Six of the 96 p-values in Table A.3 are below 0.05, and the p-value associated with Pillai's trace in a MANOVA is 0.22. Similarly, four of the 96 p-values in Table A.5 are below 0.05, and the p-value associated with Pillai's trace in a MANOVA is 0.27. The small number of statistically significant differences is consistent with sampling variation as opposed to being unbalanced.

once they have successfully paid off their SHS loan, our sample likely understates the importance of adverse selection in the market for new loans.

Because Fenix included a provision for physical repossession if the borrower was sufficiently delinquent (more than 180 days), our experimental treatment identifies the effect of digital collateral over and above the threat of physical repossession. In practice, however, the lender rarely attempted to physically repossess collateral from delinquent borrowers.

5.2 Implementation

We made the loan offers through phone calls. Our call center attempted to reach the households in the treatment groups using the phone number to which we had sent the SMS messages. The call center reached over 80% of households in the treatment groups. Call center operators explained that the customer was eligible for a loan and asked if they were interested in proceeding. The Secured and Surprise Unsecured treatment groups were informed they would have to post their SHS as digital collateral to obtain the loan, whereas the Unsecured treatment group was informed they would not have to post their SHS as digital collateral. Control households were not contacted by our call center but could apply for a loan if they initiated it on their own. Before the experiment began, we agreed to compensate Fenix for losses they incurred on unsecured loans relative to the average secured loan in the sample.

Field teams administered a baseline survey to the set of customers that were offered a loan and the control group. In some cases, the field team reached households in the Surprise Unsecured treatment group and revealed the surprise before the household had made the deposit to finalize the loan. Thus, we observed a multi-stage decision process, in which households first verbally accepted the loan terms, but then only about half of those customers made the deposit. Given that some of the households in the Surprise Unsecured group knew they would not have to post collateral before they made the second decision (to pay the deposit), we separately considered only households that paid the deposit prior to interaction with the field team as a robustness check. We also conducted an endline survey six months after the loans had been disbursed. Appendix C.2 provides more detail on both our administrative and survey data.

All households who received a loan were sent regular SMS payment reminders: three days before and one day before the payment due date, on the payment due date, if they were two days late, and again if they were one week late in making a payment. This was standard practice for Fenix and helps us rule out alternative hypothesis as we discuss in Section 7.

6 Results

We describe four categories of experimental results: (i) take-up rates, (ii) repayment and profitability, (iii) educational outcomes, and (iv) balance sheet outcomes and resilience to shocks. Specifications that analyze repayment rates and profitability only include households that received a loan, while the educational and balance sheet results compare the treatment groups to the control group.

6.1 Take-up Rates

The bottom row of Figure 3 indicates the share of households in each group that took the loan as a share of households that the call center was able to reach. Take-up rates were above 40% in all treatment groups.[29] Consistent with our model, we see clear evidence that digital collateral serves as a screening device: 44% of households in the Secured treatment group took the loan compared to 51% in the Unsecured group. The take-up differential is statistically different from zero ($p=0.007$).[30] Importantly, the take-up differential would likely be smaller in a non-experimental setting since the price for a secured loan would be lower. By comparison, 9% of the surveyed households in the control group obtained a school-fee loan over the same time period.

Table A.6 in the Appendix explores whether there are significant differences in the baseline characteristics of the households that took up the loan across treatment groups. Most baseline characteristics are individually and jointly statistically indistinguishable across the two groups, suggesting that digital collateral is screening on characteristics that are not captured by variables in administrative or survey data.

Our take-up results are broadly consistent with other studies examining the role of physical collateral in LMICs. In a joint-liability lending setting in Tanzania, Flatnes and Carter (2019) find

[29] The analyses of microfinance summarized by Banerjee et al. (2015) find average take-up rates of 40%.

[30] We focus on the take-up differential between the Secured and Unsecured treatment groups because some of the Surprise Unsecured households were notified of the surprise before making a deposit (see the discussion at the end of Section 6.2). That said, the take-up rate of the Surprised Unsecured group (46%) was similar to that of the Secured treatment group (44%). The take-up rate of both groups combined is 45%, which remains statistically different from the Unsecured treatment group ($p=0.004$).

that a 20% collateral requirement reduces take-up by 7 pp, similar to the reduction we find from requiring digital collateral. Jack et al. (2023) find that a 21% increase in the collateral requirement reduces the take-up rate by 17 pp. Unlike in our setting, both studies find minimal impacts on repayment, presumably because borrowers' ex post incentives are unchanged.

6.2 Repayment and Profitability

Repayment We measure repayment as the household's cumulative payments towards the principal divided by the total loan principal (i.e., the fraction of principal repaid). Figure 4(a) plots the fraction of principal repaid over time for customers in the three treatment groups. Figure 4(b) plots the differences between the three groups. Consistent with our model's predictions, repayment in the Secured group was consistently higher than repayment in either unsecured group. As discussed in Section 5, the moral hazard effect is derived by comparing repayment in the Secured group to repayment in the Surprise Unsecured group. The effect on adverse selection is derived by comparing repayment in the Surprise Unsecured group to repayment in the Unsecured group.

Table 1, Panel A presents results from regression specifications of the following form:

$$r_{it} = \alpha_t + \beta_t Treatment\ group_i + \epsilon_{it}, \tag{5}$$

where r_{it} is the repayment rate for household i, t days after loan origination. The treatment effect is β_t, α_t is a constant, and ϵ_{it} is an error term. The results in Table 1 reflect Local Average Treatment Effects (LATE) estimates, accounting for imperfect compliance; i.e., the fact that some customers were initially given the wrong contract. In virtually all cases, Fenix quickly corrected the mistaken noncomplying loans to the assigned status so that noncompliance was partial and did not cover the full repayment period. Altogether, 16% of loans started in noncompliance, which lasted 17 days on average. Overall, only 6% of loan days were out of compliance. Table A.7 shows that non-compliance was uncorrelated with treatment group assignment and orthogonal to a large number of baseline socio-economic characteristics.[31]

[31] There were two general types of imperfect compliance: (1) administrative errors at the beginning of the experiment, and (2) unsecured customers who upgraded their SHS systems and were sometimes switched to the secured contract. Of the 1031 loans given, 169 (16%) started in noncompliance. On average, these noncomplying loans were quickly brought back into compliance, and the loans were out of compliance for 6% of the days in the loan contract. The other source of noncompliance was when the customer purchased a physical upgrade to

The column labeled "Secured Treatment" in Table 1 captures the total effect of securing loans with digital collateral. The specification in this column includes households in the Secured and Unsecured groups, where $Treatment\ group_i$ is equal to one for households in the Secured group. The specification in the column labeled "Adverse Selection" includes households in the Surprise Unsecured and Unsecured groups, where $Treatment\ group_i$ is equal to one for households in the Surprise Unsecured group. The specification in the column labeled "Moral Hazard" include households in the Secured and Surprise Unsecured groups, where $Treatment\ group_i$ is equal to one for households in the Secured group. The rows report the results at $t = 100$, 150 and 200 days from loan origination. The standard errors indicate that the secured treatment effect is significant at the 1% level, the moral hazard effect significant at the 5% level while the adverse selection effect is not statistically significant. We cannot reject that the moral hazard effect is equal to the adverse selection effect.

Overall, digital collateral increased repayment by 13 pp at both 100 days (from 46% to 59%) and 150 days (from 57% to 70%). Moral hazard accounts for the bulk of the overall effect: 9 pp at both 100 and 150 days. Adverse selection accounts for 4-5 pp of the overall increase in repayment.

As an alternative measure of repayment, we consider the fraction of loans that have completed payments in Table 1, Panel B. A loan is recorded as completed when the repayment rate equals one. Our results convey a similar message under this alternative measure. Digitally securing the loan led to a 19 pp increase (from 47% to 66%) in the completion rate after 200 days, with moral hazard accounting for slightly more than two thirds of the total effect and adverse selection accounting for slightly less than one third of the total effect.

Profitability To understand how customer repayment translates to firm profitability, we calculate the monthly internal rate of return (IRR).[32] For each treatment group, we sorted households into terciles based on the IRR of individual loans and then calculated portfolio-level IRRs. Figure 2 plots the monthly IRRs by tercile for each treatment group. Secured loans yielded higher IRRs than Unsecured loans in each tercile, although by more for the two lower terciles (21 pp and 5 pp, respectively) than in the highest tercile (1 pp). Across all consumers, using digital collateral

the SHS system. At that point, they were issued a new secured loan contract for the remaining amount of the school-fee loan plus the new amount for the upgrade. This happened in 20 cases. See Tables A.8-A.10 for more details and for the Intent to Treat (ITT) estimates.

[32]The internal rate of return is the discount rate such that the net present value of cash flows on the portfolio is equal to zero.

increased the monthly IRR by 3.2 pp (38 pp annualized). When we restrict attention to loans with perfect compliance, the increase in monthly profitability for secured loans was even larger (4.5 pp, 54 pp annualized). Figure 5 plots the cumulative distribution of individual loan IRRs. Securing loans with digital collateral reduced the left tail of the distribution by 5-7%.

Fenix's average returns for both the secured and unsecured loans in our experiment were negative: the monthly IRR was -3.7% for secured loans and -6.9% for unsecured loans. Figure 2 shows that loans in the top two terciles were profitable, but the bottom tercile drags down overall profitability. As described in Section 4, we relaxed Fenix's eligibility criterion to include higher risk customers and offered a larger loan size than Fenix's usual business practice.

For more perspective on profitability, we calculated IRRs for school-fee loans that Fenix had offered in prior school terms (in 2018) under their usual business practices, again broken into terciles. As illustrated by the black line in Figure 2, the prior school-fee loans were considerably more profitable. The overall monthly IRR was 5.1%. Overall, our findings suggest that securing a loan with digital collateral increases, but does not ensure, profitability. Screening and dynamic incentives (as used under Fenix's usual business practice) remain important components of a sustainable lending business.

Heterogeneity across households Table 2 analyzes the treatment impact on repayment rates and loan completion for households interacted with repayment history on the primary/original SHS loan. Worse primary-loan repayers were also worse repayers on the follow-up loan: at 150 days, repayment on the secured loan was 15 pp lower for borrowers that were above median risk (i.e., below median repayment on the primary loan). More interestingly, we find that virtually all of the effect on repayment for above median risk customers was due to moral hazard and not selection, whereas the opposite was true for lower risk households. We can reject that the moral hazard effect is equal to the adverse selection effect for above median-risk consumers ($p = 0.02$).

We can interpret these findings within the context of the model in Section 3.4. Table 2 shows that the moral hazard effect was significantly bigger for households with below median repayment on the primary loan. Bad repayers on the primary loan are more likely to have a low continuation value for remaining in good standing with the lender (i.e., μ is lower among the worse primary-loan repayers). Proposition 6 predicts that we should see a bigger moral hazard effect in this subset of households. Table 2 also shows that the adverse selection effect was significantly larger among households with above median repayment on the primary loan. Better repayers on the primary loan are more likely to have higher device values. Proposition 5 predicts that we should see a larger adverse selection effect in this subset of households because households with a high value for SHS services are less willing to risk being locked and therefore less willing to accept a secured loan unless they are confident they can repay it.

Incorporating survey data on willingness to pay (WTP) for electricity provides additional evidence on the role of device values. Recall from Proposition 5 that households with higher device values should be less willing to accept a secured loan compared to households with lower device values. Figure 6 analyzes loan take-up by respondent's stated WTP for an extra day of access to their SHS.[33] We group the responses into three categories (low, medium, and high). Indeed, households with the highest WTP were significantly less likely to accept a secured loan compared to an unsecured loan, while households in the low and medium groups were equally likely to accept them. Also consistent with Proposition 5, we find the effect on repayment was larger for households with above median WTP (see Table A.11). For instance, the effect of digital collateral was 10 pp higher at 150 days for households with above (vs below) median willingness to pay, with 7 pp attributed to an increase in the adverse selection effect and 3 pp attributed to an increase in the moral hazard effect.

We also test robustness of our main estimates by exploring heterogeneity with respect to how quickly households accepted the loan. As mentioned in Section 5, after accepting the loan, some of the households in the Surprise Unsecured group were notified by our field staff that they would not be required to post collateral before completing the paperwork and making the deposit. While take-up rates were not meaningfully different across the two groups (46% for the Surprise Unsecured treatment group and 44% for the Secured treatment group, see Figure 3), it is nonetheless possible that the households who made the deposit after they were notified were different than the households in the Secured treatment group.[34] To understand by how much this potential selection affects our decomposition, we re-estimated versions of the specifications in Table 1 using only those households that completed the deposit before they were visited by our field staff. These results

[33]We elicit willingness to pay by asking households whether they would hypothetically be willing to pay 1,000 UGX (about $0.30) to unlock their device and then increasing the amount in the question by 1,000 until they answer, "No." Until recently, Fenix's systems did not record the number of hours of use by households, so we could not use that as a revealed preference measure of value, although even average hours of usage would be an imperfect measure.

[34]Note that this potential selection does not impact the estimate of the overall effect.

are reported in Table A.12. Interestingly, the overall effect of digital collateral on repayment was 1.5-2 times larger among early adopters, pointing to considerable heterogeneity on this dimension. Nevertheless, the overall conclusion that moral hazard explains the bulk of the effect remains.

6.3 Schooling Outcomes

While the results presented thus far clearly suggest that securing loans with digital collateral increases repayment and firm profitability, we are also interested in the impact of the loans on household-level outcomes. At a high level, access to credit may facilitate welfare-enhancing investments in human capital. As discussed in Section 4, the loans we study were offered in May 2019, just before school fees were due for Term 2. The product was marketed as a school-fee loan, though Fenix offered them to all eligible customers, regardless of whether they had school-aged children. Nevertheless, almost 90% of our sample households had school-aged children and 92% who accepted a school-fee loan reported using it for education-related expenditures.

To understand whether the loans had an impact on schooling outcomes, we estimate the following regression equation:

$$y_i = \alpha + \beta Loan\ Offer_i + \gamma SAC_i + \delta SAC_i \times Loan\ Offer_i + \epsilon_i, \tag{6}$$

where y_i is an outcome variable for household i and SAC_i is the number of school-aged children (individuals aged 5 to 20) within the household, which was measured at endline. We include SAC_i interacted with treatment to adjust for the fact that the loan is the same size for all households, which translates into less money per child for households with more school-aged children. Hence, we would expect the effect of the loan to be smaller in such households. In this subsection, we will quantify the effect sizes for a household with the median number of school-aged children (three).

Table 3 reports results from estimates of equation (6) for several schooling-related outcomes. We report the ITT estimate separately for each treatment group and for the pooled sample of all households offered credit (i.e., any treatment). Columns 1 and 2 report impacts on the share of 5 to 20-year-old children within a household who were enrolled in school. The sample is restricted to households with at least one school-aged child. In the pooled sample (column (1)), the loan treatment increased school enrollment by 3 pp per child ($=0.09-0.02\times 3$, $p=0.02$).[35] Given that 88 percent of children in the control group are enrolled, access to the loan reduced the share of children who are not enrolled by roughly 25%.[36] Only about half of the households took up the offered loans, so the (LATE) effect size for households who took loans is 6 pp, suggesting that the loans decreased the share of unenrolled children by 50% for households that took up the loan offer.

One potential concern with the pooled estimates described above is that the treatment effect may be driven by households in the Unsecured treatment group. Because Unsecured loans are clearly unprofitable, they are unlikely to to be offered outside of the experiment. Therefore, we also evaluated whether the treatment effect varied by treatment group (column (2)). Reassuringly, the point estimates are close for all three treatments and are not statistically different from one another.[37]

Columns 3 and 4 of Table 3 analyze the impact on monthly absences from school. The coefficients suggest that a loan offer reduces absences by 0.7 days per child per month ($-1.83+3\times 0.38$, $p=0.05$) in the pooled treatment.[38] Again, the impacts on days absent are close to one another across the three treatments and are not statistically different.

Columns 5 and 6 show that expenditures for school-related items (including school fees, uniforms, supplies, transport and meals) increased by 26% per child ($p=0.002$) in the pooled treatment.[39] The increase in school-related expenditures corresponds to roughly 25% of the loan amount (net of the deposit) or $20 per child. The increase in expenditures was largest in the Secured treatment group, but again not statistically different from the Unsecured treatment group. For columns 7 and 8, we combine the schooling-related outcomes to form an index. Following Anderson (2008) and Casey et al. (2012), we standardize each of the three education outcomes with respect to the control group, and weight the outcomes by the inverse of the covariance matrix. The coefficient estimates suggest

[35] The p-values are computed using the delta method.

[36] Enrollment rates among households in our sample appear roughly comparable to enrollment rates for the population. According to the LSMS, nationwide 91% of primary school-aged children and 68% of secondary school-aged children are enrolled at school.

[37] The probability of having school-aged children does not vary by group (see Table A.13). In Table A.14 we report specifications including households without children, coding zero for enrollment, thirty for days absent (thirty is the maximum in the data set) and zero for log school expenditures. Results are slightly noisier but the coefficient estimates are similar to those in Table 3.

[38] In unreported specifications, we conditioned on enrollment and found that this effect is primarily driven by the extensive margin. Conditional on enrollment, the estimated treatment effects are statistically indistinguishable from zero.

[39] The percentage increase in expenditures for households with three school-aged children who were offered a loan is $e^{0.37-3\times.05}-1=25\%$.

that the pooled treatment effect is about one-seventh of a standard deviation per child ($p = 0.002$).

Table 4 presents the ITT results on enrollment and expenditures by child, separating outcomes for males and females. The unit of observation is now the child and not the household. We therefore cluster standard errors at the household level for statistical inference. This table indicates that enrollment and attendance increased more for female children, who have a higher base rate enrollment (control mean) and fewer days absent. The loan was associated with a significant increase in school expenditures for males (34% for males) and slightly smaller and insignificant increase for females (20% for females). Overall, however, effects for male and female children are similar in magnitude and statistically indistinguishable.

In summary, Fenix's loans had an economically meaningful and statistically significant impact on educational outcomes. These findings suggest that households did not have sufficient access to credit for schooling-related expenditures. The LSMS reinforces this interpretation: only 3% of households in the LSMS had a loan with a commercial bank, only 6% had other formal loans, and only 1% had a loan with a microfinance institution.

6.4 Household Balance Sheet Outcomes and Resilience to Shocks

Loans with high interest rates, especially if they are misunderstood by customers, may have detrimental effects on households' balance sheets. Table 5 reports the results of regressing household balance sheet outcomes and borrowing in the six months prior to the endline survey on $\textit{Loan Offer}_i$. For balance sheet outcomes, we measure the purchases and sales of household assets. Angelucci et al. (2015) highlight the importance of asset sales as a measure of financial distress given that secondary markets yield low returns, for example because of the lemons problem. Our measures of borrowing include informal channels, which may be a substitute for Fenix's loans. The estimated effects of the loan on changes in household balance sheets are small and not statistically significant for all three outcome variables. We repeated the analysis using endline stocks of assets, loans, and net differences variables in Table 6. The estimated effect of the loan on household net balance is small and is not statistically different from zero.

The point estimates show that borrowing among the pooled treated groups is $23 higher than in the control group (Table 5), which corresponds to 30% of the loan amount and is commensurate with the estimated increase in school spending discussed in the previous section. We also decomposed borrowing into formal and informal sources and observe that treated households appear to have substituted away from informal channels (Table A.15), although the coefficient estimate is not precisely estimated except for households in the secured group.

For another perspective on the impact on households' financial position, we asked a series of questions about financial shocks that households had experienced in the six months prior to the endline survey and their concern about being able to cope with those shocks.[40] The results are summarized in Table 8. Panel A reports the results for shocks related to not having enough money for basic needs including (i) food and clothing, (ii) living expenses, (iii) education, (iv) medical treatment, and (v) debt owed to others. The dependent variable in columns (1) and (2) is the proportion of these five categories of shocks that households experienced in the last 6 months. For instance, in the control group, the typical household experienced two out of five of these shocks. Notably, we found no effect of having a loan on the propensity to experience these types of shocks. In columns (3) and (4), the dependent variables show how worried the household is about being able to cope with these shocks. Again, there is no impact of the loan on worrying about coping with the shocks and we can rule out increases that would have been one-ninth of the control group standard deviation. Panel B reports the results for shocks related to health, unemployment, accidents, and disasters. Again, we see no systematic or significant differences between households that were offered loans and the control group.[41]

7 Discussion

In this section, we discuss alternative explanations for our findings and other potential channels through which digital collateral may affect credit market outcomes. We conclude with a discussion of the welfare implications.

7.1 Alternative Explanations

We have interpreted digital collateral as providing a repayment incentive for households that reduces both moral hazard and adverse selection. An alternative interpretation is that getting locked simply

[40]Suri et al. (2021) find that the introduction of small-value digital loans reduced the impacts of negative shocks.
[41]Results are similar if we transform the Likert scales used in the survey responses to binary variables.

serves as a reminder or a nudge to repay. Indeed, there is evidence that payment reminders increase on-time repayment (Cadena and Schoar, 2011; Medina, 2020). In our setting, this explanation is less plausible because all of the borrowers received frequent payment reminders. Fenix sent reminders to all customers three days and one day before payment was due, on the day the payment was due, when the customer was two days late, and when the customer was one week late.

The estimated effect of digital collateral on reducing moral hazard is large and significant. Yet, it is possible that our estimate is biased downward for the following reason. Fenix offers school-fee loans three times per year. In order to be eligible, the customer must have completed payments on their prior school-fee loan (i.e., completed the loan within 120 days). Thus, households with a high continuation value for a loan in the next term have a strong incentive to complete payments in a timely manner regardless of whether the loan is digitally secured.[42] As shown in Proposition 6, the moral hazard effect is decreasing in the fraction of households with a high continuation value. It is therefore plausible that our estimate of the moral hazard effect is smaller than the "pure" moral hazard effect one would expect in the absence of dynamic incentives.[43]

To get a sense for the magnitude of the bias, suppose a fraction μ of households have a high continuation value (as in Section 3.4) and complete payments within 120 days regardless of whether or not lockout is applied. Absent this high continuation value, the true moral hazard effect is Δ.[44] If continuation value and willingness to pay are independently distributed, then we would estimate the moral hazard effect on loan completion to be $(1-\mu)\Delta$. Under the assumption of independence, we can provide an upper bound on Δ using the observation that 40% of households in the Surprise Unsecured treatment complete the loan within 120 days. Thus, μ is at most 0.4 and Δ is at most two-thirds larger than the effect size that we estimate. This upper bound is only slightly larger than the magnitude of the moral hazard effect we estimate among below-median repayers on the primary loan (i.e., households with low continuation values, see Section 6.2 and Table 2) suggesting the bound is nearly tight.

Our finding that adverse selection accounts for a smaller portion of the increase in repayment

[42] Consistent with this view, notice that Figure 4(c) exhibits a moderate increase in the rate of loan completion right near the 120 day for all treatment groups.

[43] We are grateful to Antoinette Schoar for pointing out the potential for a downward bias. Bryan et al. (2015) also account for the potential for selection on the propensity to be impacted by "ex post moral hazard." We conjecture that is less prominent in this context since customers have experience paying off the SHS loan.

[44] Within the context of the model in Section 3.4, $\Delta = (1 - F(p))(1 - h(\underline{q}^s))$.

than does moral hazard can partially be attributed to the fact that our sample had already been screened via other measures. First, in order to be eligible for the school-fee loan, customers must have already successfully completed payments on the primary loan. The adverse selection effect is likely to be larger for first-time borrowers. Second, eligible school-fee loan customers were required to put down a 20% deposit before getting the school-fee loan. In an experiment on a different sample of Fenix customers, we investigated the role of the deposit and found evidence consistent with it serving as an effective screening device (Gertler et al., 2023).

7.2 Other Potential Roles for Digital Collateral

In addition to reducing moral hazard and adverse selection, there are other implications of securing loans with digital collateral. First, the digitally secured loan contract effectively functions as a commitment-savings device. Much like a typical fully amortizing mortgage contract, each payment that a customer makes covers both interest and principal. The principal payment is akin to saving. This savings vehicle could be particularly valuable to households who lack self control because there is an added incentive to save (Laibson, 1994) to avoid temporary repossession and the savings are illiquid and cannot be easily or immediately accessed (Laibson, 1997). Second, if lenders lack commitment power to physically repossess collateral, they may face a hold-up problem (Hart and Moore, 1998) from strategic borrowers who know they will be tempted to renegotiate rather then incur repossession costs. By effectively lowering the lender's repossession cost, the lockout technology provides a credible method to avoid the hold-up problem.

Finally, because repossessing digital collateral imposes a cost on the borrower without any reciprocal benefits for the lender, it may raise ethical questions especially if some non-repayment is due to income shocks rather than strategic default. Are there financial contracts that are too punitive for borrowers? Should governments regulate certain contracts on ethical grounds?[45] These are important questions, and our study aims to provide evidence useful to inform answers. However, for the particular product in our experiment, we do not believe they should be of much concern. First, as discussed earlier, digital repossession in our setting is temporary and reversible, so it is significantly less punitive than physical repossession, a practice that is widely accepted.

[45] An economic reason to regulate certain types of financial contracts is if the punishments impose externalities on third-parties (Bond and Newman, 2009; Leong et al., 2021).

Second, the magnitude of the cost imposed on households by digital repossession of their SHS is small compared to those that are usually restricted on moral grounds (e.g., imprisonment or bondage). Finally, the households in our study are familiar with the contractual terms and appear to make informed decisions: households with a higher willingness to pay for the service flow from the SHS were significantly less likely to take up secured loans.

7.3 Welfare Implications

There are several channels through which the introduction of digitally secured loans may affect welfare. This first is an increase in credit supply. Our results suggest that firms should be unwilling to offer unsecured school-fee loans due to their low repayment and negative profitability. Observational evidence is consistent with this finding: unsecured credit for investment in education is not offered by for-profit firms in sub-Saharan Africa. Therefore, the appropriate counterfactual household to investigate the welfare implications of the Secured treatment group is the control group, who were not offered (digitally secured) school-fee loans.

By a revealed preference argument, the ex-ante expected welfare should be higher for households who were offered the opportunity to take a secured school-fee loan compared to the control group. Consistent with this argument, households with the median number of school-aged children in the Secured treatment group exhibit an increase in school enrollment of 5 pp (Table 3, column (2)) and more investment in school-related expenditures by 38% (Table 3, column (6)) suggesting that the access to secured credit leads to a greater accumulation of human capital. In order to make this investment, the Secured treatment group borrows $23 more than the control group (Table 5, column (6)). While this additional debt is not statistically significant and constitutes only a small percentage of household income ($\approx$2%), it suggests that the control group did not have access to close substitutes.

Because this is a long-term investment and we do not find significant treatment effects on household balance sheets (Table 5) or household income (Table A.16), we can infer households likely decreased current consumption moderately in order to make the human capital investment. Although we did not collect household-level consumption data, one category in which we can observe such a reduction is the household's SHS consumption. The median household in the secured treatment group was locked on 1/4 of days during loan repayment, corresponding to a 25% reduction in SHS consumption compared to the control group (Table 7). While the 25%

reduction in SHS consumption likely overstates the loss in utility to households from being locked, the welfare loss due to being locked is not insignificant.[46]

For additional evidence on the welfare effects, our endline survey asked a series of questions about financial shocks and household's ability to cope with them (see Section 6.4). Notably, we found no evidence that the secured treatment group was more likely to experience shocks nor that their ability to cope with them was compromised (see Table 8).

That said, behavioral biases may complicate welfare conclusions. For example, if consumers are present-biased, especially if they are naive about their own biases, they may over-borrow at high-interest rates (Garz et al., 2021). Less access to high-interest-rate loans may increase welfare (Allcott et al., 2022). In our context, sophisticated present-biased consumers may prefer and benefit from a loan that locks them out of a valued service if they do not pay. On the other hand, the welfare implications of commitment devices are complicated by noisy valuations and (potentially incorrect) beliefs (Carrera et al., 2021).

In summary, the evidence suggests that access to digitally secured school-fee loans increased school enrollment and human capital investment at the primary cost of a decrease in SHS consumption (and likely a modest decrease in other forms of consumption). Quantifying the welfare effects would require additional structure on the environment (e.g., household preferences, returns to education, etc.), which is beyond the scope of this paper. However, we believe that a structural estimation to identify the welfare effects of digitally secured loans is an important next step for future research.

8 Conclusion

In this paper, we explore a novel form of financial contracting that uses lockout technology to create digital collateral, which does not rely on physical repossession. Rather, the lender temporarily disables the flow value of the collateral to the borrower when the borrower misses a payment. We show that digitally secured loans exhibit significantly higher repayment and are therefore substantially more profitable to the lender. About one-third of the increase in repayment can be attributed to screening and about two-thirds to reducing moral hazard. Access to these loans had positive

[46] As in the model, it is optimal for the household not to repay on days where their value for the SHS's electricity is below a threshold value.

effects on educational outcomes and did not have negative effects on household balance sheets.

Our finding that moral hazard drives the majority of the repayment increase implies that credit provision is both sustainable and acceptable to a large fraction of households, provided they are given the right incentives. Therefore, the potential for digital collateral to expand access to credit is significant. By contrast, if we had found that adverse selection drove most of the increase in repayment, then digital collateral serves primarily as a screening device and only a select subset of households provide profitable lending opportunities.

Our field experiment also demonstrates the potential for private institutions to offer digitally secured loans to pay for schooling, resulting in increased enrollment and expenditures without a significant impact on the household balance sheet. This result is important as schooling-related costs are large relative to income and must be paid in periods of low income for many households, especially those working in agriculture and other informal jobs.

There are numerous other potential applications in which digital collateral could be used to provide cheaper access to credit, which appear especially promising in economies with an underdeveloped banking and financial system. With the proliferation of smart devices, secured lending via digital collateral could easily be extended to a wide range of investments such as laptops, automobiles, and farming equipment. Importantly, the capacity to reuse collateral for future loans expands the potential impact of the innovation as a vehicle for affordable access to credit. Many utility companies (e.g., electric, telecommunication, and water) are able to remotely disable service and thus are natural candidates for offering credit secured by access to the flow of services they provide. We believe there is significant potential to further scale the use of digital collateral in providing affordable access to credit.

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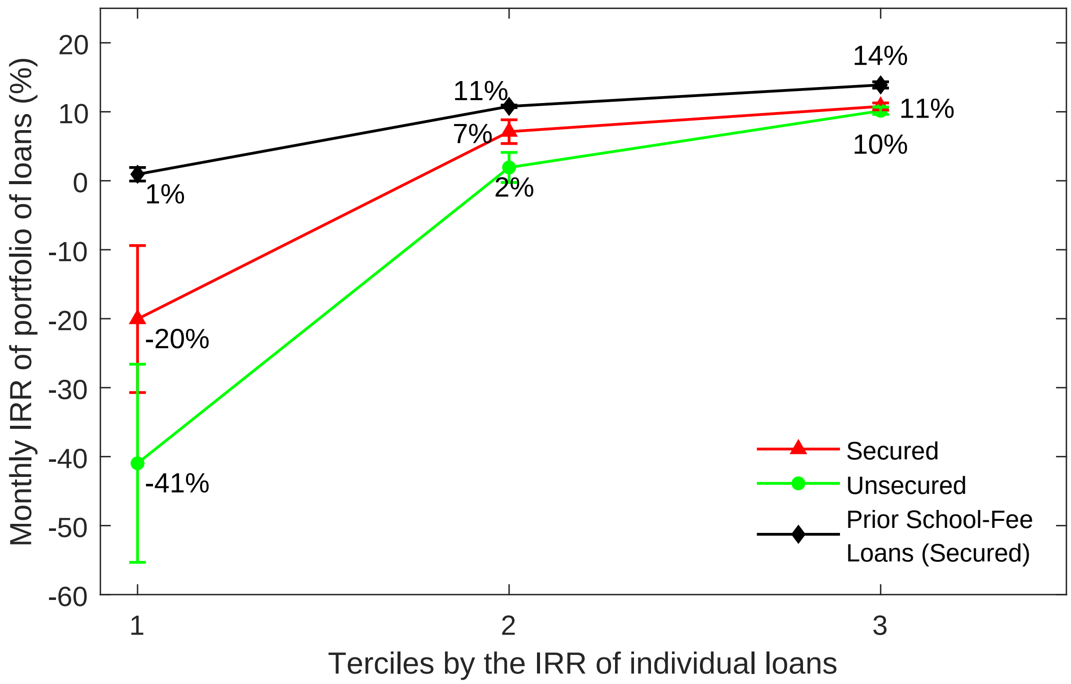
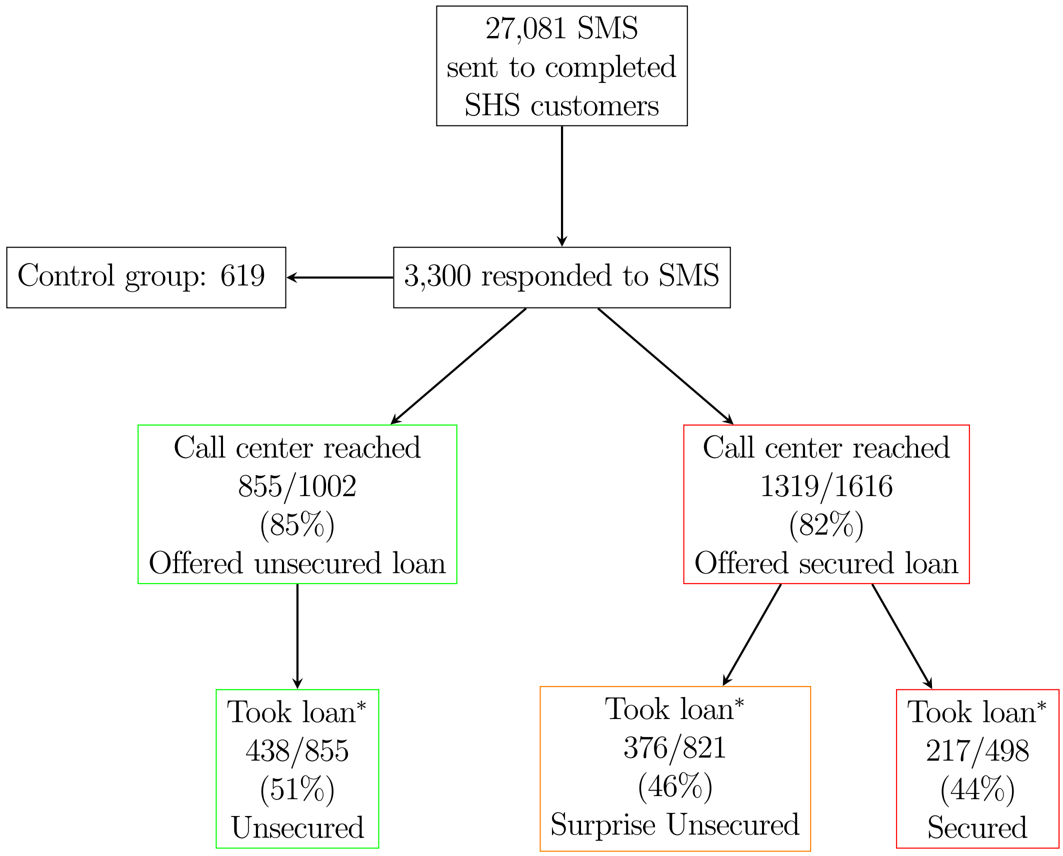
9 Figures and Tables

Figure 2: Monthly IRRs of portfolios by terciles



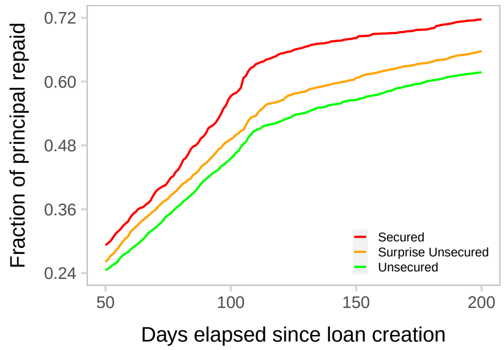
Note: The internal rate of return (IRR) is the discount rate that makes the net present value of cash flows on the loan or the portfolio equal to zero. For a typical 300,000 UGX loan, the initial cash outflow incurred by Fenix is 250,000 UGX. The cash inflows are the periodic repayment made by customers, for which we use the whole repayment history without truncation. We then sort loans within each treatment group into terciles and form portfolios using each tercile. This figure reports the IRRs on these portfolios. The confidence intervals are obtained via bootstrapping. We redraw the sample with replacement 1,000 times and plot the 95% confidence intervals.

Figure 3: Experimental Design

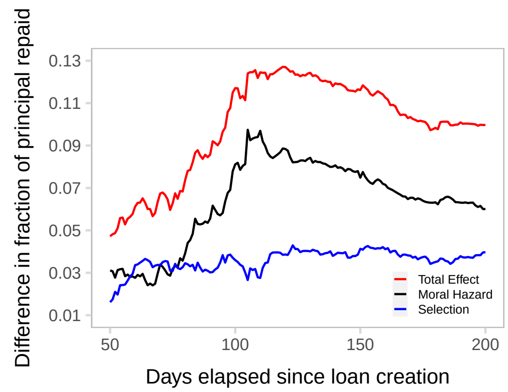


Note: "Took loan*" refers to accepting the loan, completing the necessary paperwork, and paying the deposit. Combining the Surprise Unsecured and Secured groups, 45% of households in the Secured group accepted the loan offer ((376+217)/(821+498) = 0.45).

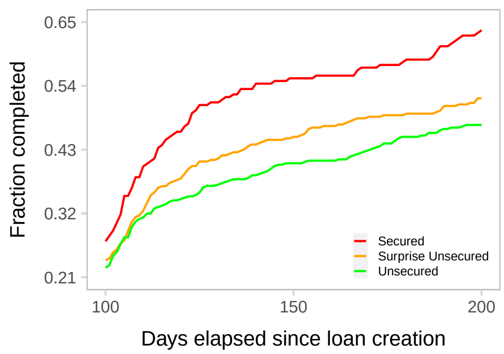
Figure 4: Loan Repayment and Completion



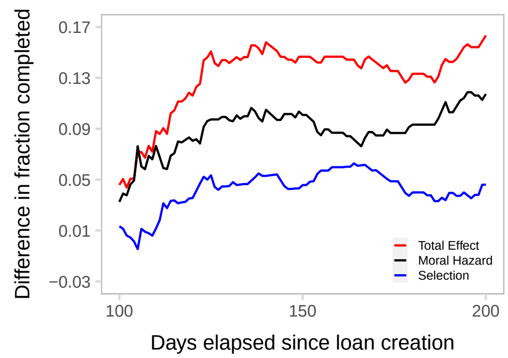
(a) Loan repayment



(b) Differences in repayment



(c) Loan completion



(d) Differences in completion

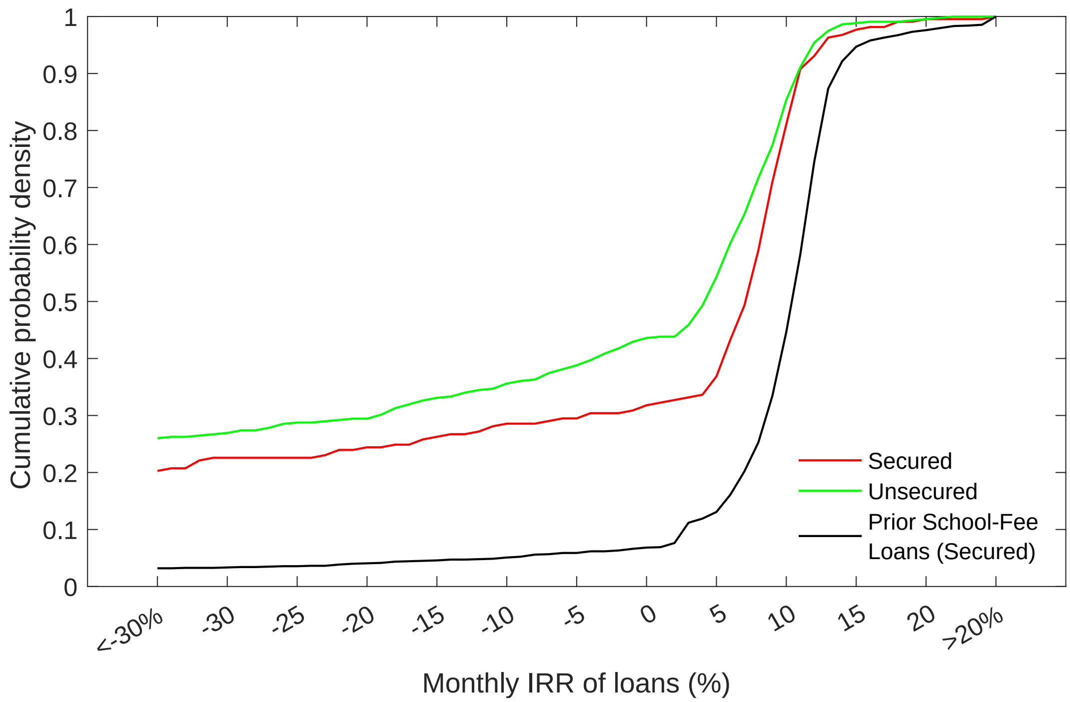
Note: Panel (a) plots the average fraction of the loan principal repaid by days elapsed since loan origination for each treatment group. Panel (b) plots the difference in the average fraction of the loan principal repaid by days elapsed for each treatment group. Panel (c) plots the average fraction of customer loans completed by days elapsed for each treatment group. The difference in average fraction of customer loans completed by days elapsed for each treatment group is in Panel (d). In Panel (b) (Panel (d)), "Total Effect" displays the difference in average fraction of the loan principal repaid (customer loans completed) between the Secured and Unsecured groups, "Moral Hazard" displays the difference in the average fraction of the loan principal repaid (customer loans completed) between the Secured and Surprise Unsecured groups, and "Selection" displays the difference in the average fraction of the loan principal repaid (customer loans completed) between the Surprise Unsecured and Unsecured groups. (Differences in) both the fraction of the loan principal repaid and fraction of customer loans completed are displayed over the sample of 1,031 loans, of which 217 are secured loans, 376 are surprise unsecured loans, and 438 are unsecured loans.

Table 1: Effect of Securing a Loan with Digital Collateral on Loan Repayment and Loan Completion

Loan day	Mean Unsecured	Secured Treatment	Adverse Selection	Moral Hazard
	(1)	(2)	(3)	(4)
		Panel A: Loan Repayment		
100	0.46	0.13***	0.04	0.09**
		(0.04)	(0.03)	(0.04)
150	0.57	0.13***	0.05	0.09**
		(0.04)	(0.03)	(0.04)
200	0.62	0.11***	0.04	0.07*
		(0.04)	(0.03)	(0.04)
		Panel B: Loan Completion		
110	0.31	0.10**	0.01	0.09*
		(0.05)	(0.04)	(0.05)
150	0.41	0.17***	0.05	0.12**
		(0.05)	(0.04)	(0.05)
200	0.47	0.19***	0.05	0.13***
		(0.05)	(0.04)	(0.05)
n		655	814	593

Note: Standard errors in parentheses. Loan repayment is measured by the cumulative proportion of the loan principal repaid (Panel A). Loan completion describes whether the loan principal has been repaid (Panel B). The above results display the Local Average Treatment Effect (LATE), which measures the average treatment effect on loan repayment (completion) for compliers, using the share of days in compliance as the endogenous variable (see the Appendix for Intent to Treat (ITT) results). The analysis is run on samples at either the 100th, 110th, 150th, or 200th day from loan origination. "Secured Treatment" captures the difference in the repayment (completion) rate between the Unsecured and Secured samples, "Adverse Selection" captures the difference in the repayment (completion) rate between the Unsecured and Surprise Unsecured samples, and "Moral Hazard" captures the difference in the repayment (completion) rate between the Surprise Unsecured and Secured samples. $^{*}\ p < .10$, $^{**}\ p < .05$, $^{***}\ p < .01$

Figure 5: Distribution of Monthly IRRs



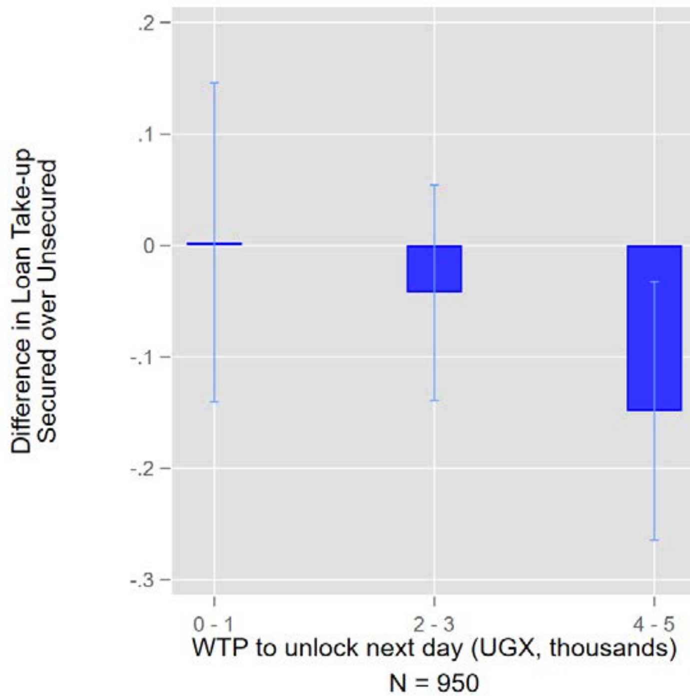
Note: The internal rate of return (IRR) is the discount rate that makes the net present value of cash flows on the loan or the portfolio equal to zero. For a typical 300,000 UGX loan, the initial cash outflow incurred by Fenix is 250,000 UGX. The cash inflows are the periodic repayment made by customers, for which we use the whole repayment history. This figure plots the cumulative probability density of the monthly IRRs of individual loans. Because the IRR is unbounded from below, the distribution is truncated at -30%.

Table 2: Effect of Securing a Loan with Digital Collateral on Loan Repayment and Loan Completion, by Risk Level

	Secured	Adverse Selection	Moral Hazard
	(1)	(2)	(3)
On Loan Repayment at 150 days			
Treatment	0.13**	0.10**	0.02
	(0.06)	(0.05)	(0.05)
Treatment × Median risk or above	0.01	-0.11*	0.13*
	(0.08)	(0.06)	(0.08)
Median risk or above	-0.15***	-0.15***	-0.27***
	(0.04)	(0.04)	(0.04)
Constant	0.63***	0.64***	0.73***
	(0.03)	(0.03)	(0.03)
On Loan Completion at 200 days			
Treatment	0.15**	0.09	0.06
	(0.07)	(0.06)	(0.06)
Treatment × Median risk or above	0.07	-0.07	0.15
	(0.09)	(0.08)	(0.09)
Median risk or above	-0.20***	-0.20***	-0.28***
	(0.05)	(0.05)	(0.05)
Constant	0.56***	0.57***	0.65***
	(0.04)	(0.04)	(0.04)
n	655	814	593

Note: Standard errors in parentheses. Loan repayment is measured by the cumulative proportion of the loan principal repaid. Loan completion describes whether the loan principal has been repaid. The above results display the Local Average Treatment Effect (LATE), which measures the average treatment effect on loan repayment (completion) for compliers, using the share of days in compliance as the endogenous variable (see the Appendix for Intent to Treat (ITT) results). The analysis is run on the sample at the 150th day (for loan repayment) or 200th day (for loan completion) from loan origination. Under "Secured" where the subsample is those who were assigned Secured or Unsecured, "Treatment" captures the treatment effect of Secured. Under "Adverse Selection" where the subsample is those who were assigned Unsecured or Surprise Unsecured, "Treatment" captures the treatment effect of Surprise Unsecured. Under "Moral Hazard" where the subsample is those who were in assigned Surprise Unsecured and Secured, "Treatment" captures the treatment effect of Secured. "Median risk or above" is an indicator for whether the customer had their solar home system locked for 11 percent or more of its history by early May 2019, right before the start of the experiment. The × symbol signals an interaction between two variables. $^{*}\ p < .10$, $^{**}\ p < .05$, $^{***}\ p < .01$

Figure 6: Effect of Secured Treatment on Loan Take-up by Willingness to Pay



Note: This figure covers the sample of 950 individuals, of which 344 are treated with secured loans and 606 are treated with unsecured loans. Individuals treated with surprise unsecured loans are excluded from this figure. Individuals with willingness to pay to unlock next day of 0 or 1,000 UGX are in the first group, of 2,000 or 3,000 UGX in the second group, and of 4,000 or 5,000 in the third group. The differences in take-up between individuals treated with secured and unsecured loans are plotted and 95% confidence intervals are presented along with the bars. Note that 1 USD was equal to approximately 3,704 UGX in 2019 (Source: https://data.worldbank.org/indicator/PA.NUS.FCRF?locations=UG).

Table 3: Education Outcomes, Household-level

	Enrollment		Days absent		Log school expenditures		Education index	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pooled (β)	0.09***		-1.83**		0.37**		0.32***	
	(0.03)		(0.72)		(0.15)		(0.10)	
Secured (β_1)		0.11***		-2.39***		0.47***		0.39***
		(0.03)		(0.77)		(0.16)		(0.10)
Surprise Unsecured (β_2)		0.08***		-1.31*		0.32**		0.27***
		(0.03)		(0.74)		(0.15)		(0.10)
Unsecured (β_3)		0.10***		-2.00***		0.37**		0.33***
		(0.03)		(0.74)		(0.15)		(0.10)
Pooled $\times$ Number of School-Aged Children	-0.02***	-0.02***	0.38**	0.37**	-0.05	-0.05	-0.06**	-0.06**
	(0.01)	(0.01)	(0.19)	(0.19)	(0.04)	(0.04)	(0.02)	(0.02)
Outcome control mean	0.88	0.88	2.77	2.77	81	81	0	0
p-value for $\beta_1 = \beta_3$		0.51		0.34		0.24		0.28
n	1683	1683	1683	1683	1683	1683	1683	1683

Note: Standard errors in parentheses. Results relate to Term 2 outcomes. The above results display the Intent to Treat (ITT) analysis, which measures the average effect of assignment to a loan. "Enrollment" describes the share of school-aged children (SAC; individuals aged 5-20) enrolled in Term 2. "Days absent" describes the average days of school missed per month, per enrolled SAC. "School expenditures" (school fees, supplies, transport, and school meals) describes the average school expenditure per enrolled SAC. "Number of School-Aged Children" denotes the number of SAC in the household at endline. The $\times$ symbol denotes an interaction. The above analysis also includes the number of SAC at endline as a control variable (not shown). 58 observations for days absent and log school expenditures in which students were not enrolled are given value thirty or zero for the above estimations, respectively. School expenditures are in USD (1 USD is equal to approximately 3,704 UGX in 2019). School expenditures are winsorized at the 99th percentile. The outcome control mean for school expenditures is not log transformed. All specifications are conditional on having at least one SAC within the household at endline. Following Anderson (2008) and Casey et al. (2012), "Education index" is created by (i) switching the sign on the days absent outcome, (ii) standardizing enrollment, days absent, and school expenditures (logged) with respect to their control group mean and control group standard deviation, and (iii) weighting outcomes with the appropriate element from the inverse of the covariance matrix, where the matrix is estimated in the control group and zeroes replace negative estimated weights. "p-value for $\beta_1 = \beta_3$" records the p-value from the test that the Secured treatment coefficient is equal to the Unsecured treatment coefficient. * $p < .10$, ** $p < .05$, *** $p < .01$

Table 4: Education Outcomes for School-Aged Children

	Enrollment		Days absent		Log school expenditures		Education index	
	Male	Female	Male	Female	Male	Female	Male	Female
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pooled (β)	0.05	0.08**	-1.91	-2.70**	0.35*	0.30	0.20*	0.25*
	(0.04)	(0.04)	(1.19)	(1.23)	(0.20)	(0.22)	(0.11)	(0.13)
Pooled × Number of School-Aged Children	-0.01	-0.02***	0.21	0.69***	-0.02	-0.04	-0.02	-0.06**
	(0.01)	(0.01)	(0.25)	(0.24)	(0.04)	(0.05)	(0.02)	(0.03)
Outcome control mean	0.89	0.92	4.64	3.84	70	75	0	0
p-value for $\beta_{Male}=\beta_{Female}$		0.57		0.61		0.85		0.75
n	2756	2903	2756	2903	2756	2903	2756	2903

Note: Standard errors in parentheses and are clustered at the household level. Results relate to Term 2 outcomes for males and females. The above results display the Intent to Treat (ITT) analysis, which measures the average effect of assignment to a loan. "Enrollment" captures enrollment in Term 2 for school-aged children (SAC; individuals aged 5-20). "Days absent" describes the average days of school missed per month for Term 2 for SAC. School expenditures captures school fees, supplies, transport, and school meals for Term 2 for SAC. "Number of School-Aged Children" denotes the number of SAC in the household at endline. The × symbol denotes an interaction. The above analysis also includes the number of SAC at endline as a control variable (not shown). 545 observations in total (248 male, 297 female) for days absent and log school expenditures in which students were not enrolled are given value thirty or zero for the above estimations, respectively. School expenditures are in USD (1 USD is equal to approximately 3,704 UGX in 2019). School expenditures are winsorized at the 99th percentile. The outcome control mean for school expenditures is not log transformed. Following Anderson (2008) and Casey et al. (2012), "Education index" is created by (i) switching the sign on the days absent outcome, (ii) standardizing enrollment, days absent, and school expenditures (logged) with respect to their control group mean and control group standard deviation, and (iii) weighting outcomes with the appropriate element from the inverse of the covariance matrix, where the matrix is estimated in the control group and zeroes replace negative estimated weights. "p-value for $\beta_{Male} = \beta_{Female}$" records the p-value from the Chow test that the Pooled treatment effect on an outcome for males is equal to that for females. * $p < .10$, ** $p < .05$, *** $p < .01$

Table 5: Effect on Asset Purchases, Sales, and Money Borrowed in the Last 6 Months

	Asset purchases		Asset sales		Money borrowed		Net difference	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pooled (β)	8		2		23		-17	
	(34)		(16)		(37)		(48)	
Secured (β_1)		15		-10		23		2
		(44)		(20)		(47)		(62)
Surprise Unsecured (β_2)		-23		-4		28		-47
		(39)		(18)		(42)		(55)
Unsecured (β_3)		33		14		17		2
		(39)		(18)		(42)		(55)
Outcome control mean	236	236	96	96	283	283	-143	-143
p-value for $\beta_1 = \beta_3$		0.63		0.18		0.90		1.00
n	1877	1877	1877	1877	1877	1877	1877	1877

Note: Standard errors in parentheses. The above results display the Intent to Treat (ITT) analysis, which measures the average effect of assignment to a loan. "Asset purchases" records the value of asset purchases over the last 6 months. "Asset sales" records the value of asset sales over the last 6 months. "Money borrowed" refers to the the summation of amounts to be repaid (including interest) for new loans acquired in the last 6 months prior to the endline survey, across formal and informal loans. "Net difference" records the difference between asset purchases and asset sales, minus money borrowed. "Asset purchases," "asset sales," and "money borrowed" are winsorized at the 99th percentile. Values are in USD (note that 1 USD was equal to approximately 3,704 UGX in 2019). "p-value for $\beta_1 = \beta_3$" records the p-value from the test that the Secured treatment coefficient is equal to the Unsecured treatment coefficient. * $p < .10$, ** $p < .05$, *** $p < .01$

Table 6: Effect on Household Balance Sheet

	Asset value		Debt		Net difference	
	(1)	(2)	(3)	(4)	(5)	(6)
Pooled (β)	-43		34		-76	
	(143)		(61)		(143)	
Secured (β_1)		34		12		22
		(183)		(78)		(183)
Surprise Unsecured (β_2)		-131		13		-144
		(163)		(70)		(163)
Unsecured (β_3)		-2		65		-67
		(162)		(70)		(162)
Outcome control mean	1819	1819	600	600	1219	1219
p-value for $\beta_1 = \beta_3$		0.82		0.45		0.58
n	1877	1877	1877	1877	1877	1877

Note: Standard errors in parentheses. The above results display the Intent to Treat (ITT) analysis, which measures the average effect of assignment to a loan. "Asset value" records the sum of the household's value of assets at baseline, together with net difference between asset purchases and asset sales over the last 6 months, recorded at endline. "Debt" is the sum of a summary variable that records the amount of money borrowed across all loans (formal and informal) over the 12 months prior to the baseline survey and the summation of amounts to be repaid (including interest) for new loans acquired in the last 6 months prior to the endline survey, across formal and informal loans (recorded at endline). The components for "asset value" and "debt" are winsorized at the 99th percentile. "Net difference" records the difference between "asset value" and "debt." Values are in USD (note that 1 USD was equal to approximately 3,704 UGX in 2019). "p-value for $\beta_1 = \beta_3$" records the p-value from the test that the Secured treatment coefficient is equal to the Unsecured treatment coefficient. * $p < .10$, ** $p < .05$, *** $p < .01$

Table 7: Fraction of School-Fee Loan Days Locked

Percentile	Day 100	Day 150	Day 200
	(1)	(2)	(3)
25th	0.11	0.08	0.06
50th	0.33	0.33	0.25
75th	0.66	0.73	0.78

Note: The above table calculates the fraction of loan days locked at 100, 150, and 200 days from school-fee loan origination, by percentile. The figures are calculated for the sample of 217 secured school-fee loans taken up in the experiment.

Table 8: Liqudity Shocks over the Past 6 Months

	Proportion shocks experienced		Are you worried about coping with this shock?	
	(1)	(2)	(3)	(4)
	Category A: Basic Needs			
Pooled	0.01		0.02	
	(0.02)		(0.02)	
Secured		0.02		0.04
		(0.03)		(0.02)
Surprise Unsecured		-0.01		0.01
		(0.02)		(0.02)
Unsecured		0.02		0.01
		(0.02)		(0.02)
Outcome control mean	0.42	0.42	0.73	0.73
n	1882	1882	1400	1400
	Category B: Health, Unemployment, Accidents, and Disasters			
Pooled	0.003		0.004	
	(0.01)		(0.01)	
Secured		-0.003		0.01
		(0.02)		(0.02)
Surprise Unsecured		-0.01		-0.01
		(0.02)		(0.02)
Unsecured		0.02		0.01
		(0.01)		(0.02)
Outcome control mean	0.34	0.34	0.83	0.83
n	1882	1882	1648	1648

Note: Standard errors in parentheses. The above analysis uses the Intent to Treat (ITT) from loan assignment. Liquidity Shock Category A gathers together the following experiences over the last 6 months: not having enough money for basic needs such as food and clothing; not having enough money for other living home expenses; being unable to educate all of your children; not having enough money for medicines and medical treatment; debts owed to others. Liquidity Shock Category B gathers together the following experiences over the last 6 months: health problems or illness; an accident or disaster; difficulty finding work; death of a family member; job loss; weather affecting your crops. Columns (1) and (2) use the proportion of shocks within a category that one is said to have experienced over the last 6 months as the dependent variable. Columns (3) and (4) use the average value of the likert-scale values transformed to 0-1 scales, out of the shocks experienced within a category, as the dependent variable. The reference group is the Control group that was not assigned any school-fee loan. * $p < .10$, ** $p < .05$, *** $p < .01$

A Supplemental Tables

Table A.1: Descriptive Statistics of Enrollee Characteristics from Administrative Data

Characteristic	Uganda LSMS	SMS sent to	Took up loan
	(1)	(2)	(3)
Proportion of days locked at SMS	-	0.13	0.16***
		(0.15)	(0.15)
Age (years)	45	46***	44**
	(22)	(12)	(11)
Female (proportion)	0.34	0.23***	0.14***
	(0.68)	(0.42)	(0.35)
Married (proportion)	0.70	0.90***	0.92***
	(0.67)	(0.30)	(0.26)
Number of children	3.0	4.3***	3.9***
	(3.3)	(2.9)	(2.5)
Agriculture or Non-employed	0.55	0.37***	0.24***
	(0.73)	(0.48)	(0.43)
Non-professional	0.27	0.39***	0.38
	(0.65)	(0.49)	(0.49)
Other	0.05	0.08***	0.08
	(0.32)	(0.27)	(0.28)
Professional	0.13	0.17***	0.30***
	(0.55)	(0.38)	(0.46)
Central	0.39	0.44***	0.37***
	(0.70)	(0.50)	(0.48)
Eastern	0.28	0.28	0.35***
	(0.68)	(0.45)	(0.48)
Western	0.33	0.28***	0.28
	(0.68)	(0.45)	(0.45)
n	2281	27081	1072

Note: Standard deviations in parentheses. The World Bank Uganda LSMS information in (1) comes from the 2018/2019 wave and uses probability weights. (2) and (3) come from Fenix administrative data. LSMS demographics relate to the household head, while Fenix demographics relate to the customer signing with Fenix. For Occupation using the Fenix data, "Agriculture or Non-employed" includes Cattle Trader, Farmer, Fisherman, and Not Employed; "Professional" includes Accountant, Banker, Broker, Electrician, Engineer, Government / Civil Servant, Health Worker, Journalist, Mechanic / Technician, NGO Worker, Office Work, Police, Security Guard, Teacher, Tour Guide, UPDF, and Uganda Prisons; "Non-professional" includes Boda Boda, Butcher, Carpenter, Construction, Driver, Herbalist, MM Agent, Market Trader, Money Changer, Religious Leader, Shop Keeper, Small Business Owner, Tailor, and Taxi Operator. LSMS sample occupations followed a similar categorization. (3) is a subset of (2). The results from tests of differences comparing (1) to (2) and (2) to (3) are displayed in (2) and (3), respectively. Menu of Choice treatment customers are dropped from (2) and (3), and comprised less than 2% of those samples. * $p < .10$, ** $p < .05$, *** $p < .01$

Table A.2: Baseline Characteristics

Characteristic	Secured	Surprise Unsecured	Unsecured	Control	n
	(1)	(2)	(3)	(4)	
Risk					
Percent of days locked at SMS	15	15	16	14	2130
	(15)	(16)	(15)	(14)	
Household head					
Age (years)	43	44	43	44	2122
	(11)	(11)	(11)	(11)	
Female (proportion)	0.13	0.12	0.11	0.11	2125
	(0.34)	(0.32)	(0.32)	(0.31)	
Married (proportion)	0.89	0.88	0.85	0.86	2125
	(0.32)	(0.32)	(0.35)	(0.34)	
Household head occupation (proportion)					
Family business or farm	0.59	0.56	0.53	0.56	2125
	(0.49)	(0.50)	(0.50)	(0.50)	
Self-employed	0.60	0.63	0.60	0.59	2123
	(0.49)	(0.48)	(0.49)	(0.49)	
Outside the home	0.35	0.36	0.37	0.34	2125
	(0.48)	(0.48)	(0.48)	(0.47)	
Demographics					
Number of people in household	6.6	6.6	6.6	6.6	2130
	(2.7)	(3.0)	(2.7)	(2.7)	
Number of children aged 5-20 enrolled in school	2.7	2.7	2.7	2.7	2125
	(1.9)	(2.0)	(1.9)	(2.0)	
Financial information					
Amount spent on lighting, year (USD)	28	35	42	43	2126
	(73)	(73)	(96)	(99)	
Total household income, year (USD)	1395	1473	1431	1573	2094
	(1271)	(1340)	(1348)	(1484)	
Value of assets (USD)	1755	1599	1705	1767	2127
	(2391)	(2062)	(2425)	(2337)	
Borrowing					
Borrowed in last 12 months (proportion)	0.60	0.60	0.62	0.63	2125
	(0.49)	(0.49)	(0.49)	(0.48)	
Money borrowed in last 12 months (USD)	323	310	357	334	2122
	(739)	(675)	(726)	(666)	
Ever refused for loan in last 12 months (proportion)	0.13	0.14	0.15	0.20	2124
	(0.34)	(0.35)	(0.35)	(0.40)	
Took a microfinance loan in last 12 months (proportion)	0.07	0.06	0.08	0.07	2125
	(0.26)	(0.25)	(0.27)	(0.26)	

Note: Standard deviations in parentheses. The above table contains summary statistics from the baseline survey for the sample at baseline. Monetary values are winsorized at the 99th percentile. Monetary values are in USD (note that 1 USD was equal to approximately 3,704 UGX in 2019).

Table A.3: Baseline Characteristics, p-values from Pairwise Comparisons

Characteristic	Secured - Surprise Unsecured	Secured - Unsecured	Secured - Control	Surprise Unsecured - Unsecured	Surprise Unsecured - Control	Unsecured - Control
	(1)	(2)	(3)	(4)	(5)	(6)
Risk						
Percent of days locked at SMS	0.65	0.18	0.49	0.31	0.22	0.03
Household head						
Age (years)	0.22	0.59	0.47	0.39	0.69	0.75
Female (proportion)	0.48	0.33	0.37	0.76	0.76	0.96
Married (proportion)	0.82	0.15	0.34	0.16	0.40	0.71
Household head occupation (proportion)						
Family business or farm	0.41	0.07	0.52	0.25	0.92	0.27
Self-employed	0.34	0.98	0.84	0.28	0.24	0.80
Outside the home	0.64	0.40	0.90	0.67	0.55	0.33
Demographics						
Number of people in household	0.92	0.88	0.84	0.97	0.91	0.94
Number of children aged 5-20 enrolled in school	0.69	0.92	0.80	0.56	0.91	0.70
Financial information						
Amount spent on lighting, year (USD)	0.14	0.01	0.01	0.14	0.12	0.81
Total household income, year (USD)	0.35	0.67	0.07	0.57	0.27	0.11
Value of assets (USD)	0.26	0.74	0.94	0.39	0.23	0.68
Borrowing						
Borrowed in last 12 months (proportion)	0.86	0.65	0.45	0.46	0.31	0.69
Money borrowed in last 12 months (USD)	0.77	0.47	0.83	0.22	0.58	0.61
Ever refused for loan in last 12 months (proportion)	0.55	0.43	0.01	0.84	0.02	0.03
Took a microfinance loan in last 12 months (proportion)	0.69	0.51	0.84	0.22	0.52	0.68

Note: p-values from t-tests between two different treatment groups are included in the above table (see Table A.2 for the complementary table).

Table A.4: Baseline Characteristics of Endline Sample

Characteristic	Secured	Surprise Unsecured	Unsecured	Control	n
	(1)	(2)	(3)	(4)	
Risk					
Percent of days locked at SMS	15	15	16	13	1883
	(15)	(16)	(15)	(14)	
Household head					
Age (years)	43	44	43	44	1878
	(11)	(11)	(11)	(11)	
Female (proportion)	0.13	0.11	0.11	0.11	1881
	(0.33)	(0.32)	(0.31)	(0.31)	
Married (proportion)	0.89	0.88	0.86	0.87	1881
	(0.31)	(0.32)	(0.35)	(0.34)	
Household head occupation (proportion)					
Family business or farm	0.60	0.57	0.54	0.55	1881
	(0.49)	(0.50)	(0.50)	(0.50)	
Self-employed	0.60	0.64	0.60	0.59	1880
	(0.49)	(0.48)	(0.49)	(0.49)	
Outside the home	0.33	0.35	0.37	0.34	1881
	(0.47)	(0.48)	(0.48)	(0.47)	
Demographics					
Number of people in household	6.6	6.7	6.7	6.6	1883
	(2.7)	(3.0)	(2.8)	(2.7)	
Number of children aged 5-20 enrolled in school	2.8	2.8	2.7	2.7	1881
	(1.9)	(2.0)	(1.9)	(2.0)	
Financial information					
Amount spent on lighting, year (USD)	27	34	42	40	1882
	(75)	(72)	(98)	(96)	
Total household income, year (USD)	1399	1448	1402	1517	1854
	(1283)	(1339)	(1314)	(1450)	
Value of assets (USD)	1689	1563	1657	1678	1881
	(2345)	(1993)	(2367)	(2196)	
Borrowing					
Borrowed in last 12 months (proportion)	0.62	0.61	0.63	0.61	1880
	(0.49)	(0.49)	(0.48)	(0.49)	
Money borrowed in last 12 months (USD)	306	301	364	316	1878
	(684)	(649)	(733)	(621)	
Ever refused for loan in last 12 months (proportion)	0.14	0.14	0.15	0.19	1879
	(0.35)	(0.35)	(0.35)	(0.40)	
Took a microfinance loan in last 12 months (proportion)	0.08	0.07	0.08	0.08	1880
	(0.26)	(0.25)	(0.27)	(0.26)	

Note: Standard deviations in parentheses. The above table contains summary statistics from the baseline survey for the sample at endline. Monetary values are winsorized at the 99th percentile. Monetary values are in USD (note that 1 USD was equal to approximately 3,704 UGX in 2019).

Table A.5: Baseline Characteristics of Endline Sample, p-values from Pairwise Comparisons

Characteristic	Secured - Surprise Unsecured	Secured - Unsecured	Secured - Control	Surprise Unsecured - Unsecured	Surprise Unsecured - Control	Unsecured - Control
	(1)	(2)	(3)	(4)	(5)	(6)
Risk						
Percent of days locked at SMS	0.74	0.37	0.13	0.52	0.047	0.01
Household head						
Age (years)	0.30	0.98	0.44	0.23	0.86	0.38
Female (proportion)	0.56	0.31	0.40	0.62	0.72	0.95
Married (proportion)	0.77	0.18	0.36	0.22	0.46	0.75
Household head occupation (proportion)						
Family business or farm	0.37	0.06	0.23	0.24	0.65	0.58
Self-employed	0.25	0.99	0.78	0.19	0.15	0.74
Outside the home	0.62	0.26	0.89	0.47	0.73	0.33
Demographics						
Number of people in household	0.73	0.64	1.00	0.91	0.73	0.64
Number of children aged 5-20 enrolled in school	0.93	0.74	0.79	0.63	0.71	0.98
Financial information						
Amount spent on lighting, year (USD)	0.17	0.01	0.05	0.10	0.29	0.73
Total household income, year (USD)	0.59	0.97	0.26	0.56	0.46	0.21
Value of assets (USD)	0.39	0.84	0.95	0.46	0.41	0.89
Borrowing						
Borrowed in last 12 months (proportion)	0.89	0.71	0.84	0.55	0.92	0.54
Money borrowed in last 12 months (USD)	0.91	0.23	0.84	0.12	0.73	0.31
Ever refused for loan in last 12 months (proportion)	0.91	0.80	0.06	0.87	0.04	0.05
Took a microfinance loan in last 12 months (proportion)	0.62	0.83	0.99	0.41	0.63	0.82

Note: p-values from t-tests between two different treatment groups are included in the above table (see Table A.4 for the complementary table).

Table A.6: Baseline Characteristics of Those Who Took Up Loans

Characteristic	Secured (1)	Unsecured (2)	n
Risk			
Percent of days locked at SMS	15	16	587
	(14)	(15)	
Household head			
Age (years)	44	43	587
	(11)	(10)	
Female (proportion)	0.13	0.11	587
	(0.33)	(0.31)	
Married (proportion)	0.88	0.85	587
	(0.33)	(0.36)	
Household head occupation (proportion)			
Family business or farm	0.64	0.50***	587
	(0.48)	(0.50)	
Self-employed	0.63	0.60	587
	(0.49)	(0.49)	
Outside the home	0.34	0.36	587
	(0.48)	(0.48)	
Demographics			
Number of people in household	6.8	6.6	587
	(2.7)	(2.8)	
Number of children aged 5-20 enrolled in school	2.8	2.7	587
	(2.0)	(1.9)	
Financial information			
Amount spent on lighting, year (USD)	28	46**	587
	(69)	(102)	
Total household income, year (USD)	1252	1436*	587
	(988)	(1344)	
Value of assets (USD)	1741	1642	587
	(2004)	(2335)	
Borrowing			
Borrowed in last 12 months (proportion)	0.63	0.63	587
	(0.48)	(0.48)	
Money borrowed in last 12 months (USD)	315	360	587
	(727)	(713)	
Ever refused for loan in last 12 months (proportion)	0.13	0.15	587
	(0.34)	(0.35)	
Took a microfinance loan in last 12 months (proportion)	0.07	0.09	587
	(0.26)	(0.28)	

Note: Standard deviations in parentheses. Monetary values are winsorized at the 99th percentile. Monetary values are in USD (note that 1 USD was equal to approximately 3,704 UGX in 2019). The results from tests of differences comparing Secured to Unsecured are displayed above. * $p < .10$, ** $p < .05$, *** $p < .01$

Table A.7: Share of Days in Compliance at Day 200

	Compliance	
	(1)	(2)
Secured	-0.01	
	(0.02)	
Surprise Unsecured	0.01	
	(0.02)	
Percent of days locked at SMS		0.00
		(0.00)
Household head age		-0.00
		(0.00)
Household head female		0.01
		(0.03)
Household head married		0.00
		(0.02)
Household head works family business or farm		-0.00
		(0.02)
Household head works self-employed		0.02
		(0.02)
Household head works outside the home		0.03*
		(0.02)
Number of people in household		-0.00
		(0.00)
Number of children aged 5-20 enrolled in school		-0.00
		(0.01)
Amount spent on lighting, year (USD)		-0.00
		(0.00)
Total household income, year (USD)		-0.00
		(0.00)
Value of assets (USD)		0.00
		(0.00)
Borrowed in last 12 months (prop)		0.01
		(0.02)
Money borrowed in last 12 months (USD)		-0.00
		(0.00)
Ever refused for loan in last 12 months (prop)		-0.01
		(0.02)
Took a microfinance loan in last 12 months		0.05*
		(0.03)
Outcome mean	0.94	0.94
p-value from F-test	0.76	0.28
n	916	916

Note: Standard errors in parentheses. The above analysis uses the Intent to Treat (ITT) from loan assignment. The outcome variable is the share of days in compliance at day 200. Monetary values are winsorized at the 99th percentile. Monetary values are in USD (note that 1 USD was equal to approximately 3,704 UGX in 2019). The reference group in (1) is the Unsecured group of loan takers. In (1) "p-value from F-test" records the p-value from the F-test that the means for the Secured, Surprise Unsecured, and Unsecured groups are equal. In (2) "p-value from F-test" records the p-value from the joint F-test that all coefficients are equal to zero. * $p < .10$, ** $p < .05$, *** $p < .01$

Table A.8: Share of Days in Compliance, by Treatment

Loan day	Secured	Surprise Unsecured	Unsecured
	(1)	(2)	(3)
50	0.93	0.90	0.92
	(0.25)	(0.23)	(0.22)
100	0.93	0.93	0.94
	(0.25)	(0.20)	(0.20)
150	0.93	0.94	0.94
	(0.25)	(0.20)	(0.20)
200	0.93	0.94	0.94
	(0.25)	(0.20)	(0.20)
n	217	376	438

Note: Standard deviations in parentheses. The analysis is run on treatment groups for the share of days in compliance at 50, 100, 150, and 200 days from loan origination. For Secured customers, compliance is introduced when receiving a standard loan with lockout. Non-compliance can be introduced when receiving a "no code" loan (i.e. a loan where customers also did not receive codes in their messaging scheme that would have triggered the lockout capability if inputted into the solar home system) or receiving a set of free days of light meant for assigned Unsecured or Surprise Unsecured customers in the event of not receiving a "no code" loan. Compliance can be re-introduced when receiving an upgrade (i.e. a physical product) during school-fee loan repayment, which activates the lockout capability. Securing upgrades entails (i) going to a Fenix Service Center and (ii) inputting of a code to secure the SHS to begin repayment of the new product. For Unsecured and Surprise Unsecured customers, compliance is introduced when receiving a "no code" loan. Non-compliance can be introduced when receiving a standard loan with lockout or when receiving an upgrade. Compliance can be re-introduced when given a set of free days of light.

Table A.9: Effect of Securing a Loan with Digital Collateral on Loan Repayment and Loan Completion

Loan day	Mean Unsecured	Secured Treatment	Adverse Selection	Moral Hazard
	(1)	(2)	(3)	(4)
		Panel A: Loan Repayment		
100	0.46	0.12***	0.04	0.08**
		(0.03)	(0.03)	(0.03)
150	0.57	0.12***	0.04	0.07**
		(0.03)	(0.03)	(0.04)
200	0.62	0.10***	0.04	0.06*
		(0.03)	(0.03)	(0.03)
		Panel B: Loan Completion		
110	0.31	0.09**	0.01	0.08*
		(0.04)	(0.03)	(0.04)
150	0.41	0.15***	0.05	0.10**
		(0.04)	(0.03)	(0.04)
200	0.47	0.16***	0.05	0.12***
		(0.04)	(0.04)	(0.04)
n		655	814	593

Note: Standard errors in parentheses. Loan repayment is measured by the cumulative proportion of the loan principal repaid (Panel A). Loan completion describes whether the loan principal has been repaid (Panel B). The above results display the Intent to Treat (ITT) analysis, which measures the average effect of treatment assignment on loan repayment (completion). The analysis is run on samples at either the 100th, 110th, 150th, or 200th day from loan origination. "Secured Treatment" captures the difference in the repayment (completion) rate between the Unsecured and Secured samples, "Adverse Selection" captures the difference in the repayment (completion) rate between the Unsecured and Surprise Unsecured samples, and "Moral Hazard" captures the difference in the repayment (completion) rate between the Surprise Unsecured and Secured samples. * $p < .10$, ** $p < .05$, *** $p < .01$

Table A.10: Effect of Securing a Loan with Digital Collateral on Loan Repayment and Loan Completion, by Risk Level

	Secured	Adverse Selection	Moral Hazard
	(1)	(2)	(3)
On Loan Repayment at 150 days			
Treatment	0.11**	0.09**	0.02
	(0.05)	(0.04)	(0.05)
Treatment × Median risk or above	0.01	-0.10*	0.11
	(0.07)	(0.06)	(0.07)
Median risk or above	-0.16***	-0.16***	-0.26***
	(0.04)	(0.04)	(0.04)
Constant	0.64***	0.64***	0.74***
	(0.03)	(0.03)	(0.03)
On Loan Completion at 200 days			
Treatment	0.13**	0.08	0.06
	(0.06)	(0.05)	(0.06)
Treatment × Median risk or above	0.07	-0.06	0.13
	(0.08)	(0.07)	(0.08)
Median risk or above	-0.21***	-0.21***	-0.27***
	(0.05)	(0.05)	(0.05)
Constant	0.58***	0.58***	0.65***
	(0.03)	(0.03)	(0.04)
n	655	814	593

Note: Standard errors in parentheses. Loan repayment is measured by the cumulative proportion of the loan principal repaid. Loan completion describes whether the loan principal has been repaid. The above results display the Intent to Treat (ITT) analysis, which measures the average effect of assignment on loan repayment (completion). The analysis is run on the sample at the 150th day (for loan repayment) or 200th day (for loan completion) from loan origination. Under "Secured" where the subsample is those who were assigned Secured or Unsecured, "Treatment" captures the treatment effect of Secured. Under "Adverse Selection" where the subsample is those who were assigned Unsecured or Surprise Unsecured, "Treatment" captures the treatment effect of Surprise Unsecured. Under "Moral Hazard" where the subsample is those who were in assigned Surprise Unsecured and Secured, "Treatment" captures the treatment effect of Secured. "Median risk or above" is an indicator for whether the customer had their solar home system locked for 11 percent or more of its history by early May 2019, right before the start of the experiment. The × symbol signals an interaction between two variables. * $p < .10$, ** $p < .05$, *** $p < .01$

Table A.11: Effect of Securing a Loan with Digital Collateral on Loan Repayment and Loan Completion, by WTP Level

	Secured	Adverse Selection	Moral Hazard
	(1)	(2)	(3)
On Loan Repayment at 150 days			
Treatment	0.09	0.02	0.07
	(0.07)	(0.06)	(0.07)
Treatment × Median WTP or above	0.10	0.07	0.03
	(0.09)	(0.07)	(0.09)
Median WTP or above	-0.00	0.00	0.07
	(0.05)	(0.05)	(0.05)
Constant	0.58***	0.58***	0.60***
	(0.04)	(0.04)	(0.04)
On Loan Completion at 200 days			
Treatment	0.14*	0.00	0.14*
	(0.08)	(0.07)	(0.08)
Treatment × Median WTP or above	0.09	0.08	0.01
	(0.11)	(0.09)	(0.11)
Median WTP or above	-0.01	-0.00	0.07
	(0.06)	(0.06)	(0.06)
Constant	0.49***	0.50***	0.50***
	(0.05)	(0.05)	(0.05)
n	505	638	469

Note: Standard errors in parentheses. Loan repayment is measured by the cumulative proportion of the loan principal repaid. Loan completion describes whether the loan principal has been repaid. The above results display the Local Average Treatment Effect (LATE), which measures the average treatment effect on either loan repayment or loan completion for compliers, using the share of days in compliance as the endogenous variable. The analysis is run on the sample at the 150th day (for loan repayment) or 200th day (for loan completion) from origination. Under "Secured" where the subsample is those who were assigned Secured or Unsecured, "Treatment" captures the treatment effect of Secured. Under "Adverse Selection" where the subsample is those who were assigned Unsecured or Surprise Unsecured, "Treatment" captures the treatment effect of Surprise Unsecured. Under "Moral Hazard" where the subsample is those who were in assigned Surprise Unsecured and Secured, "Treatment" captures the treatment effect of Secured. "Median WTP or above" is an indicator for whether the customer responded as willing to pay at least 3,000 Ugandan Shillings to unlock their hypothetically-secured solar home system the next day. The × symbol signals an interaction between two variables. * $p < .10$, ** $p < .05$, *** $p < .01$

Table A.12: Effect of Securing a Loan with Digital Collateral on Loan Repayment and Loan Completion, Early Adopters

Loan day	Mean Unsecured	Secured Treatment ITT	Secured Treatment LATE	Adverse Selection ITT	Adverse Selection LATE	Moral Hazard ITT	Moral Hazard LATE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Loan Repayment							
100	0.47	0.15***	0.18***	0.01	0.01	0.14***	0.18***
		(0.05)	(0.07)	(0.05)	(0.06)	(0.05)	(0.07)
150	0.56	0.18***	0.22***	0.05	0.06	0.13**	0.16**
		(0.06)	(0.07)	(0.05)	(0.06)	(0.06)	(0.07)
200	0.62	0.16***	0.19***	0.06	0.07	0.10*	0.13*
		(0.06)	(0.07)	(0.05)	(0.06)	(0.05)	(0.07)
Panel B: Loan Completion							
110	0.33	0.14**	0.18**	-0.01	-0.01	0.15**	0.19**
		(0.07)	(0.08)	(0.05)	(0.07)	(0.07)	(0.08)
150	0.42	0.18***	0.22***	0.05	0.06	0.13*	0.16*
		(0.07)	(0.08)	(0.06)	(0.07)	(0.07)	(0.09)
200	0.49	0.24***	0.29***	0.05	0.06	0.19***	0.23***
		(0.07)	(0.08)	(0.06)	(0.07)	(0.07)	(0.08)
n		247	247	308	308	223	223

Note: Standard errors in parentheses. The samples are further restricted to those individuals who had received the baseline survey after placing the loan deposit or who had not received a baseline survey (Early Adopters). Loan repayment is measured by the cumulative proportion of the loan principal repaid (Panel A). Loan completion describes whether the loan principal has been repaid (Panel B). The Intention to Treat (ITT) measures the average effect of treatment assignment on loan repayment (completion), while the Local Average Treatment Effect (LATE) measures the average treatment effect on loan repayment (completion) for compliers, using the share of days in compliance as the endogenous variable. The analysis is run on samples at either the 100th, 110th, 150th, or 200th day from loan origination. "Secured Treatment" captures the difference in the repayment (completion) rate between the Unsecured and Secured samples, "Adverse Selection" captures the difference in the repayment (completion) rate between the Unsecured and Surprise Unsecured samples, and "Moral Hazard" captures the difference in the repayment (completion) rate between the Surprise Unsecured and Secured samples. * $p < .10$, ** $p < .05$, *** $p < .01$

Table A.13: Probability of Having Any School Aged Children on Treatment Assignment

	Any SAC	
	(1)	(2)
Pooled (β)	0.001	
	(0.018)	
Secured (β_1)		0.003
		(0.023)
Surprise Unsecured (β_2)		0.006
		(0.021)
Unsecured (β_3)		-0.005
		(0.021)
Outcome control mean	0.89	0.89
p-value for $\beta_1 = \beta_2 = \beta_3$		0.82
p-value for $\beta_1 = \beta_3$		0.71
n	1883	1883

Note: Standard errors in parentheses. The above analysis uses the Intent to Treat (ITT) from loan assignment. The outcome variable is the probability of having any school-aged children (individuals aged 5-20) in the household at endline. The reference group is the Control group that was not assigned any school-fee loan. "p-value for $\beta_1 = \beta_2 = \beta_3$" records the p-value from the F-test that all treatment coefficients are equal. "p-value for $\beta_1 = \beta_3$" records the p-value from the test that the Secured treatment coefficient is equal to the Unsecured treatment coefficient. * $p < .10$, ** $p < .05$, *** $p < .01$

Table A.14: Education Outcomes, Household-level, Including Households without School-Aged Children

	Enrollment		Days absent		Log school expenditures		Education index	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pooled (β)	0.06*		-1.32		0.26*		0.16*	
	(0.03)		(0.91)		(0.15)		(0.08)	
Secured (β_1)		0.08**		-1.92*		0.36**		0.22**
		(0.04)		(1.00)		(0.17)		(0.09)
Surprise Unsecured (β_2)		0.05		-0.94		0.23		0.14
		(0.03)		(0.96)		(0.16)		(0.09)
Unsecured (β_3)		0.06*		-1.32		0.24		0.16*
		(0.03)		(0.95)		(0.16)		(0.09)
Pooled × Number of School-Aged	-0.01	-0.01	0.29	0.29	-0.03	-0.03	-0.03	-0.03
	(0.01)	(0.01)	(0.25)	(0.25)	(0.04)	(0.04)	(0.02)	(0.02)
Outcome control mean	0.79	0.79	5.68	5.68	73	73	0	0
p-value for $\beta_1 = \beta_3$		0.40		0.31		0.22		0.27
n	1883	1883	1883	1883	1883	1883	1883	1883

Note: Standard errors in parentheses. Results relate to Term 2 outcomes. The above results display the Intent to Treat (ITT) analysis, which measures the average effect of assignment to a loan. "Enrollment" describes the share of school-aged children (SAC; individuals aged 5-20) enrolled in Term 2. "Days absent" describes the average days of school missed per month, per enrolled SAC. "School expenditures" (school fees, supplies, transport, and school meals) describes the average school expenditure per enrolled SAC. "Number of School-Aged Children" denotes the number of SAC in the household at endline. The × symbol denotes an interaction. The above analysis also includes the number of SAC at endline as a control variable (not shown). 58 observations for days absent and log school expenditures in which students were not enrolled are given value thirty or zero for the above estimations, respectively. 200 observations for enrollment, days absent, and log school expenditures in which no SAC was present are given value zero, thirty, and zero for the above estimations, respectively. School expenditures are in USD (1 USD is equal to approximately 3,704 UGX in 2019). School expenditures are winsorized at the 99th percentile. The outcome control mean for school expenditures is not log transformed. Following Anderson (2008) and Casey et al. (2012), "Education index" is created by (i) switching the sign on the days absent outcome, (ii) standardizing enrollment, days absent, and school expenditures (logged) with respect to their control group mean and control group standard deviation, and (iii) weighting outcomes with the appropriate element from the inverse of the covariance matrix, where the matrix is estimated in the control group and zeroes replace negative estimated weights. "p-value for $\beta_1 = \beta_3$" records the p-value from the test that the Secured treatment coefficient is equal to the Unsecured treatment coefficient. * $p < .10$, ** $p < .05$, *** $p < .01$

Table A.15: Effect on Formal, Informal, and Total Money Borrowed in the Last 6 Months

	Formal money borrowed		Informal money borrowed		Money borrowed		Formal minus informal	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pooled (β)	46		-7		40		53	
	(32)		(12)		(34)		(35)	
Secured (β_1)		57		-19		38		76*
		(41)		(15)		(44)		(44)
Surprise Unsecured (β_2)		52		-7		45		59
		(37)		(14)		(39)		(40)
Unsecured (β_3)		35		1		35		34
		(37)		(14)		(39)		(39)
Outcome control mean	169	169	87	87	256	256	82	82
p-value for $\beta_1 = \beta_3$		0.54		0.14		0.94		0.28
n	1868	1868	1868	1868	1868	1868	1868	1868

Note: Standard errors in parentheses. The above results display the Intent to Treat (ITT) analysis, which measures the average effect of assignment to a loan. "Money borrowed" refers to the summation of amounts to be repaid (including interest) for new loans acquired in the last 6 months prior to the endline survey, across formal and informal loans, where loans could be tied to specific sources. "Formal money borrowed" refers to money borrowed exclusively from formal sources, "informal money borrowed" refers to money borrowed excluseively from informal sources, and "formal minus informal" refers to the loan value from formal sources minus the loan value from informal sources. Formal loans includes loans from the following sources: Commercial bank; Microfinance agency; ReadyPay; Government; and Village bank. Informal loans includes loans from the following sources: Family Member; Friend; Savings group; Moneylender; Workplace; Mobile Money; and Church. Only household observations where all loans that could be attributed to specific loan sources were included in the estimation. Formal money borrowed and informal money borrowed are winsorized at the 99th percentile. All variables refer to the time period over the last six months. Values are in USD (note that 1 USD was equal to approximately 3,704 UGX in 2019). "p-value for $\beta_1 = \beta_3$" records the p-value from the test that the Secured treatment coefficient is equal to the Unsecured treatment coefficient. * $p < .10$, ** $p < .05$, *** $p < .01$

Table A.16: Total Household Adult Income

	Total household adult income	
	(1)	(2)
Pooled (β)	-47	
	(89)	
Secured (β_1)		-96
		(113)
Surprise Unsecured (β_2)		2
		(101)
Unsecured (β_3)		-67
		(100)
Outcome control mean	1449	1449
p-value for $\beta_1 = \beta_3$		0.78
n	1857	1857

Note: Standard errors in parentheses. The above results display the Intent to Treat (ITT) analysis, which measures the average effect of assignment to a loan. "Total household adult income" describes the total income accrued by household members aged 18 to 60 over the last 6 months. Total household adult income is winsorized at the 99th percentile. Total household adult income is in USD (1 USD is equal to approximately 3,704 UGX in 2019). "p-value for $\beta_1 = \beta_3$" records the p-value from the test that the Secured treatment coefficient is equal to the Unsecured treatment coefficient. * $p < .10$, ** $p < .05$, *** $p < .01$

B Theory Appendix

B.1 Competitive Firms

When firms compete for households, they offer the contract that maximizes each household's welfare subject to breaking even. That is, the contract offered to household i solves

$$\begin{aligned} (d_i,p_i) \in & \operatorname*{argmax}_{d,p} U_i(d,p) \\ s.t. \quad & \pi_i(d,p) \geq 0 \end{aligned} \tag{7}$$

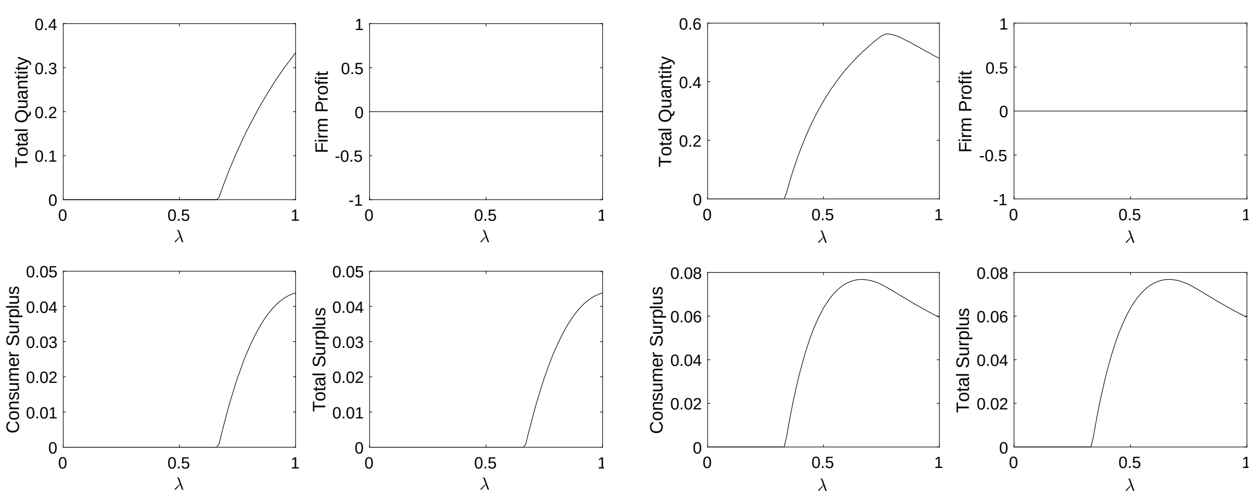
Household expected utility is decreasing in both d and p. However, the deposit is purely a transfer while a higher p destroys more surplus. Therefore, to maximize household utility, firms minimize p_i subject to breaking even.

Proposition 7 (Competitive Equilibrium)**.** *In a competitive equilibrium:*

1. *The household purchases the good if and only if condition (i) or (ii) from Proposition 4 is satisfied. Otherwise, there does not exist a contract such that both the firm breaks even and the household is willing to accept.*

2. *If the household purchases the good then $d_i^c = w$ and p_i^c is the lowest price such that $R_i(p_i^c) = c - w$.*

Notice that the household purchases under the exact same conditions as when the firm is a monopolist. Thus, Corollary 1 also holds with competitive firms and any implications for total surplus apply to both settings. Of course, the price offered by competitive firms is lower for all but the marginal household. Figure B.1 illustrates equilibrium quantities with competitive firms for the same parametric example as in Section 3.3.



(a) Low household wealth, $w = \frac{1}{12}$. (b) High household wealth, $w = \frac{1}{6}$.

Figure B.1: Illustrating the role of lockout with competitive firms.

B.2 Unobservable Risk

The assumption of observable household risk is primarily for tractability. However, this assumption is only used for the results in Section 3.3 (i.e., in determining the equilibrium contract). In general, determining the equilibrium is more involved when household risk is unobservable and restricting the space of contracts to a pair (d,p) is not without loss. The firm may want to offer a menu of contracts as an additional screening device.

That said, it is possible to extend our findings to the model with unobservable risk in certain cases. For example, consider a model with two types of households: low risk (L) and high risk (H). Assume that the firm only wants to lend to low risk households (i.e, $w+R_H(p^*)\leq c\leq w+R_L(p^*)$) and that the condition in Proposition 2 holds (i.e., $S_H(p^*)<w<S_L(p^*)$). Then, in equilibrium, the monopolist offers the contract $(d,p)=(w,p^*)$ and only low risk households accept. This is the same outcome that obtains with observable risk. That is, securing the loan with digital collateral combined with a down payment serves as an effective screening device even if the lender cannot observe household risk.

B.3 Proofs

Proof of Proposition 1. Household i strategically defaults with probability $(1-q_i)F(p/\lambda)$, where $F(\cdot)$ is a cdf and therefore increasing in its argument. Fixing p, as λ increases the argument, p/λ decreases and therefore so too does $(1-q_i)F(p/\lambda)$. □

Proof of Proposition 2. By hypothesis, $S_1(p)=(1-\lambda)\mathrm{E}(\tilde{v}_i)<S_0(p)=\int_{\underline{v}}^{\bar{v}}\max\{v-p,(1-\lambda)v\}dF(v)$. Hence, there must exist v such that the household does not strategically default (i.e., $\bar{v}>p/\lambda$) and therefore $S_i(p)$ is strictly decreasing in q_i. Further, observe that $S_i(p)$ is continuous in q_i. By the intermediate value theorem, there must exist a $q_j\in(0,1)$ such that $S_j(\underline{q})=d\leq w$. From (1), all i such that $q_i\leq q_j$ will purchase and all i such that $q_i>q_j$ will not. Hence, $q_j=\underline{q}$. To see that $\underline{q}$ is decreasing in λ, differentiate both sides of $S_j(p)=d$ with respect to λ to get that

$$\begin{aligned}0&=\frac{dS_j(p)}{d\lambda}\\&=\frac{\partial S_j}{\partial\lambda}+\frac{\partial S_j}{\partial q_j}\frac{\partial q_j}{\partial\lambda}\end{aligned}$$

Hence, $\frac{\partial q_j}{\partial\lambda}=-\frac{\partial S_j}{\partial\lambda}/\frac{\partial S_j}{\partial q_j}<0$, since $\frac{\partial S_j}{\partial\lambda}\leq -q_j\mathrm{E}(\tilde{v}_i)<0$. □

Proof of Lemma 1. We will first show that $d_i=w$ is optimal. First, clearly $d_i<\min\{w,S_i(p_i)\}$ is suboptimal since the monopolist can simply increase d_i and earn more profit. Therefore, $d_i=\min\{w,S_i(p_i)\}$. Next suppose that the monopolist sells to household i and $d_i<w$, which therefore implies $d_i=S_i(p_i)$ and therefore p_i solves $\operatorname{argmax} S_i(p_i)+R_i(p_i)-c$. Since repossession is inefficient (Assumption 2), total surplus is maximized by setting $v(p)=\underline{v}$ or $p_i=\lambda\underline{v}$, but then $d_i+R_i(p_i)<w+R_i(\lambda\underline{v})\leq w+\lambda\underline{v}<c$ (by Assumption 3). Thus, the monopolist would prefer not to sell to household i, a contradiction. Hence, $d_i=w$. □

Proof of Proposition 3. As shown in Lemma 1, when $w\leq S_i(p^*)$ then the monopoly price is $p^*=\lambda v^*$. Conditional on purchasing the good, the probability that household i strategically defaults is therefore $(1-q_i)F(v^*)$. Thus, to prove the result, it suffices to show that v^* is increasing in κ and decreasing in λ. The left-hand side of (4) is independent of the two parameters and increasing in v (by Assumption 4). The right-hand side of (4) is increasing in κ and decreasing in λ. Thus, the point at which the left and right-hand side intersect (i.e., v^*) must increase with κ and decrease with λ. □

Proof of Proposition 4. This result follows from computing when monopoly profits are positive given the optimal prices in Lemma 1. For (i), when $w<S_i(p^*)$, the firm's total profit from selling to household i under the optimal contract is $w+R_i(p^*)-c$. Similarly, for (ii), when $w>S_i(p^*)$, the firms total profit from selling to household i is $w+R_i(S_i^{-1}(w))-c$. □

Proof of Proposition 5. Let F_H and F_L denote two distributions over device values. Suppose that the F_H dominates F_L in the sense of first-order stochastic dominance (FOSD). Let $\underline{q}_t^s$ denote the cutoff income risk type under the distribution F_t. We first show that $\underline{q}_H^s \leq \underline{q}_L^s$. For this result, observe that

$$\begin{aligned}\Pi_{i,r}^s-\Pi_{i,a}^s &= \mathrm{E}[\tilde{v}_i]-(1-q_i)\mathrm{E}[\max\{\tilde{v}_i+\tilde{w}_i-p,0\}]-R \\ &= \int\int (v-(1-q_i)\max\{v+w-p,0\})dF(v)dH(w)-R.\end{aligned}$$

The integrand is an increasing function of v and therefore larger under F_H than F_L (by FOSD). Note also that the integrand is decreasing in $(1-q_i)$ and the threshold type is determined by when the RHS is equal to zero, therefore implying $\underline{q}_H^s \leq \underline{q}_L^s$.

We next show that $\underline{q}^u$ is independent of the value distribution. The payoff to accepting an unsecured loan is given by

$$\begin{aligned}\Pi_{i,a}^u &= R+\mathrm{E}[\tilde{y}_i]+(1-q_i)\mathrm{E}[\max\{\tilde{v}_i+\tilde{w}_i-p,\tilde{v}_i\}]+q_i\mathrm{E}[\tilde{v}_i] \\ &= R+\mathrm{E}[\tilde{y}_i+\tilde{v}_i]+(1-q_i)\mathrm{E}[\max\{\tilde{w}_i-p,0\}]\end{aligned}$$

Therefore, a household accepts an unsecured loan if $R+(1-q_i)\mathrm{E}[\max\{\tilde{w}_i-p,0\}\geq 0$, which holds for all q_i. Thus, $\underline{q}^u=1$ under both F_L and F_H.

To summarize, we have $h(\underline{q}_H^u)=h(\underline{q}_L^u)$, and $h(\underline{q}_H^s)\leq h(\underline{q}_L^s)$. Therefore $h(\underline{q}_H^u)-h(\underline{q}_H^s)\geq h(\underline{q}_L^u)-h(\underline{q}_L^s)$, which implies the adverse selection effect is larger under F_H (since $\Pr(\tilde{w}_i\geq p)$ is independent of the value distribution). The moral hazard effect is the product of two terms. The second term is larger under F_H since $h(\underline{q}_H^s)\leq h(\underline{q}_L^s)$. To see that the first term is also larger under F_H, note that $\Pr(\tilde{v}_i+\tilde{w}_i\geq p)=\int\int 1_{\{v+w\geq p\}}dF(v)dH(v)$. Since the integrand is non-decreasing in v, the integral is larger under F_H (again by FOSD). □

Proof of Proposition 6. The payoff to accepting a secure loan is

$$\Pi_{i,a}=R+(1-q_i)(\mu(\bar{w}+\mathrm{E}[\tilde{v}_i])+(1-\mu)\mathrm{E}[\max\{\tilde{v}_i-p,0\}]),$$

which is increasing in μ. Therefore, $\underline{q}^s$ increases (and $(1-h(\underline{q}^s))$ decreases) with μ. That loan take up increase in μ follows immediately. The moral hazard effect is $(1-\mu)(1-F(p))(1-h(\underline{q}^s))$, which is clearly decreasing in μ. The adverse selection effect is $\mu(h(\underline{q}^u)-h(\underline{q}^s))$. Since $\underline{q}^u=1$ and is independent of μ (see Proof of Proposition 5), the first term in the product increases with μ, while the second term decreases in μ. It is straightforward to construct examples in which the product of the two terms increases with μ (e.g., if $g(q)$ is sufficiently small for q in a neighborhood of $\underline{q}^s$) as well as examples where it decreases (e.g., if the increase in μ leads causes $\underline{q}^s$ to increase to 1 and therefore an adverse selection effect of zero). □

Proof of Proposition 7. It is straightforward to argue that the constraint in (7) binds with equality. If not, then the firm could lower d and increase U_i. We can therefore rewrite the program (7) as

$$\begin{aligned} (d_i, p_i) \in & \operatorname*{argmax}_{d,p} U_i(d,p) + \pi_i(d,p) \\ s.t. \quad & \pi_i(d,p) = 0 \end{aligned} \tag{8}$$

Since d does not enter the objective of (8) and total surplus is decreasing in p, the solution to the above involves the smallest p such that the firm makes zero profit (and then setting $d_i^c = w$), which is precisely as stated in (ii). Statement (i) then follows from computing when the firm profits are non-negative given the prices in (ii). □

C Power, Sample Sizes, and Data Construction

C.1 Power and Sample Sizes

Our sample sizes were based on power calculations. The binding constraint for the three loan categories (Unsecured, Surprise Unsecured and Secured) was the ability to differentiate repayment rates, meaning that sample size requirements for identifying differences in take-up rates were lower. To identify the Adverse Selection effect, we compare repayment rates of Unsecured and Surprise Unsecured and powered to be able to detect a 10 pp difference from an expected Unsecured repayment rate of 50% based on a pilot school-fee loan experiment that Fenix had run. To identify the Moral Hazard effect, we compared rates of Surprise Unsecured and Secured, and powered to be able to detect a 10 pp difference from an expected Secured repayment rate of 86%. Because the expected repayment rates for secured loans were higher, we needed fewer observations in the Secured category.

Our target was to have equal numbers of unsecured and surprise unsecured loans. As the call center reached a larger share of the households that were offered unsecured loans by random chance, the study ended up with more unsecured loans.

C.2 Data Construction

Below we include a table that contains the definition, values taken on, and construction notes for key variables featured in the analysis.

Table C.1: Key Data Construction Description

Variable name	*Definition*	*Values*	*Construction notes*
frac_lpp_maxip	School-fee loan repayment rate	Continuous between 0 and 1	The numerator of this variable comes from the summation of commissions and amount paid towards the loan principal, over the amount that is expected to be paid for the loan.[47] To generate commissions, the difference is first taken between the current loan-day cumulative amount received for the loan and the value for the same variable from the previous loan-day (amtrec_diff). Another difference is taken between the financing amount remaining on the loan from the previous loan-day and the financing amount remaining on the loan from the current day (ltfpr_diff). The difference is then taken between these two variables to generate the daily commission (diff_diff), with a cumulative sum taken over commissions for each loan (cum_diff_diff). This cumulative value for commissions is then summed with the cumulative amount that has been paid towards the principal. This sum is divided by the amount that is expected to be paid towards the principal for the loan, without any commissions. Values for frac_lpp_maxip are then filled down to July 14, 2020 for loans that have reached frac_lpp_maxip equal to one prior to July 14, 2020.

[47] Fenix credits commissions to customers who refer other customers to Fenix. We include payments from these commissions in our analysis of loan repayment, although they account for 0.1% of total payments towards the principal.

Table C.1: Key Data Construction Description

Variable name	*Definition*	*Values*	*Construction notes*
completeloan	School-fee loan completion	0 or 1	A separate loan-specific variable takes value one if the loan was declared "Complete" by Fenix International by July 14, 2020, and zero otherwise (max_frac2). completeloan takes value one for the loan on the day based on the following criteria (i): that the repayment rate equals max_frac2, and (ii) it is the last day in the dataset for the loan, prior to any filling down. Values for completeloan are then filled down to July 14, 2020 for loans that have reached completeloan equal to one prior to July 14, 2020.
accountpercentlocked_may	Percent of days the account was locked	Continuous between 0 and 100	This variable captures the percent of days hat the solar home system was locked, prior to early May 2019, i.e. before the beginning of the experiment. An indicator variable using the median value was used in the analysis.

Table C.1: Key Data Construction Description

Variable name	*Definition*	*Values*	*Construction notes*
compliance_share_wupg	Share of days in compliance	Continuous between 0 and 1	For Secured customers, compliance is introduced when receiving a standard loan with lockout. Non-compliance can be introduced when receiving a "no code" loan (i.e. a loan where customers also did not receive codes in their messaging scheme that would have triggered the lockout capability if inputted into the solar home system) or receiving a set of free days of light meant for assigned Unsecured or Surprise Unsecured customers in the event of not receiving a "no code" loan. Compliance can be re-introduced when receiving an upgrade (i.e. a physical product) during school-fee loan repayment, which activates the lockout capability. Securing upgrades entails (i) going to a Fenix Service Center and (ii) inputting of a code to lock the SHS to begin repayment of the new product. For Unsecured and Surprise Unsecured customers, compliance is introduced when receiving a "no code" loan. Non-compliance can be introduced when receiving a standard loan with lockout or when receiving an upgrade. Compliance can be re-introduced when given a set of free days of light.
locked_share_wupg	Share of days locked	Continuous between 0 and 1	This variable tracks the share of days that the account was locked. This variable was constructed using the share of days in compliance variable as an input.

Table C.1: Key Data Construction Description

Variable name	*Definition*	*Values*	*Construction notes*
irr_loan	Monthly IRR of an individual loan	Continuous	The internal rate of return (IRR) is the discount rate that makes the net present value of cash flows on a loan equal to zero. For a typical 300,000 UGX loan, the initial cash outflow incurred by Fenix is 250,000 UGX. The cash inflows are the periodic repayment made by customers, for which we use the whole repayment history without truncation. We first calculate the daily IRR and then convert it to a monthly measure by multiplying 30. A loan with no repayment ever has an IRR of $-\infty$.
irr_portfolio	Monthly IRR of a portfolio of loans	Continuous	We sort loans within each treatment group into terciles based on the IRRs of individual loans and form portfolios using each tercile. The cash flow of a portfolio on each day is the sum of cash flows of all loans within the portfolio on that day. We then calculate the IRR on these portfolios.

Table C.1: Key Data Construction Description

Variable name	*Definition*	*Values*	*Construction notes*
wtpday	Willingness to pay for one day of electricity	0 UGX, 1000 UGX, 2000 UGX, 3000 UGX, 4000 UGX, or 5000 UGX	The module of the survey capturing willingness to pay begins with the prompt "The following scenario is hypothetical - it will not actually happen. For the purpose of this research, can you please imagine that your ReadyPay device was going to be locked tomorrow for one day only. You won't be able to use your solar home system for one DAY only, or you can pay some money (in UGX) to unlock your device." Survey participants were then led to answer the following questions based on the prompt: (a) Would you be willing to pay 1,000 UGX in order to use your solar home system (SHS) for that one day?; (b) Would you be willing to pay 2,000 UGX in order to use your solar home system (SHS) for that one day?; (c) Would you be willing to pay 3,000 UGX in order to use your solar home system (SHS) for that one day?; (d) Would you be willing to pay 4,000 UGX in order to use your solar home system (SHS) for that one day?; and (e) Would you be willing to pay 5,000 UGX in order to use your solar home system (SHS) for that one day? Note that (b) was only asked if the respondent answered yes to (a), (c) was only asked if there respondent answered yes to (b), and so on. wtpday is assigned the highest value that the individual described as what they would be willing to pay. This variable thus ran from 0 to 5,000 for the sample. An indicator variable using the median value was used in the analysis.
num_520e	Number of children aged 5 to 20 at endline	Continuous	This variable records the number of children aged 5 to 20 (or "school aged children") at the time of the endline survey.

Table C.1: Key Data Construction Description

Variable name	*Definition*	*Values*	*Construction notes*
enroll_t2_fin	Enrollment	0 or 1	This variable describes enrollment of a school-aged child (individual aged 5-20) in Term 2.
missed_month_t2_fin	Absence from school	Continuous between 0 to 30	This variable describes the average days of school missed per month for an enrolled school aged child (individual aged 5-20) in Term 2.
ln_schoolexpend_t2_fin	School expenditures	Continuous	This variable is an aggregate of school expenditures (school fees, supplies, transport, and school meals) for an enrolled school aged child (individual aged 5-20) in Term 2.
outcome_h1	Education index	Continuous	Following Anderson (2008) and Casey et al. (2012), "Education index" is created by (i) switching the sign on the days absent outcome, (ii) standardizing enrollment, days absent, and school expenditures (logged) with respect to their control group mean and control group standard deviation, and (iii) weighting outcomes with the appropriate element from the inverse of the covariance matrix, where the matrix is estimated in the control group and zeroes replace negative estimated weights.
buy_assets_val99p	Asset purchases	Continuous	This variable records the value of asset purchases over the last 6 months
sell_assets_val99p	Asset sales	Continuous	This variable records the value of asset sales over the last 6 months.
total_loans_r	Money borrowed (from Table 5)	Continuous	This variable refers to the the summation of amounts to be repaid (including interest) for new loans acquired in the last 6 months prior to the endline survey, across formal and informal loans.
net_assets_loans_r	Net difference (from Table 5)	Continuous	This variable records the difference between asset purchases and asset sales, minus money borrowed.

Table C.1: Key Data Construction Description

Variable name	*Definition*	*Values*	*Construction notes*
assets_val_end	Asset value	Continuous	This variable records the sum of the household's value of assets at baseline, together with net difference between asset purchases and asset sales over the last 6 months, recorded at endline.
total_loans_end_r	Debt	Continuous	This variable is the sum of a summary variable that records the amount of money borrowed across all loans (formal and informal) over the 12 months prior to the baseline survey and the summation of amounts to be repaid (including interest) for new loans acquired in the last 6 months prior to the endline survey, across formal and informal loans (recorded at endline).
av_tl_end_r	Net difference (from Table 6)	Continuous	This variable records the difference between "asset value" and "debt."
shockAindex	Proportion of Basic Needs Shocks Experienced	Continuous between 0 and 1	This variable captures the proportion of the shocks experienced, for the following shocks: not having enough money for basic needs such as food and clothing; not having enough money for other living home expenses; being unable to educate all your children; not having enough money for medicines and medical treatment; debts owed to others.
scaleAindex	Worry about Basic Needs Shocks Experienced	Continuous between 0 and 1	This variable uses the average value of likert-scale values transformed to 0-1 scales, for the following shocks: not having enough money for basic needs such as food and clothing; not having enough money for other living home expenses; being unable to educate all your children; not having enough money for medicines and medical treatment; debts owed to others.

Table C.1: Key Data Construction Description

Variable name	*Definition*	*Values*	*Construction notes*
shockBindex	Proportion of Health, Unemployment, Accident, and Disaster Shocks Experienced	Continuous between 0 and 1	This variable captures the proportion of the shocks experienced, for the following shocks: health problem or illness; an accident or disaster; difficulty finding work; death of a family member; job loss; weather affecting your crops.
scaleAindex	Worry about Health, Unemployment, Accident, and Disaster Shocks Experienced	Continuous between 0 and 1	This variable uses the average value of likert-scale values transformed to 0-1 scales, for the following shocks: health problem or illness; an accident or disaster; difficulty finding work; death of a family member; job loss; weather affecting your crops.
svyend_before_loan	Baseline survey before loan take up indicator	0 or 1	This variable is an indicator variable that takes value 1 if the survey date-time listed in the raw survey data is earlier than the loan start date-time, and value 0 otherwise. This variable is then used to subset to a group of early adopting households.
amt_forminform_win	Money borrowed (from Table A.15)	Continuous	This variable refers to the summation of amounts to be repaid (including interest) for new loans acquired in the last 6 months prior to the endline survey, across formal and informal loans, where loans could be tied to specific sources.
amt_informal_win	Formal money borrowed	Continuous	This variables refers to money borrowed exclusively from informal sources (Family member, Friend, Savings group, Moneylender, Workplace, Mobile Money, and Church).
amt_formal_win	Formal money borrowed	Continuous	This variables refers to money borrowed exclusively from formal sources (Commercial bank, Microfinance agency, ReadyPay, Government, and Village bank).
diff_fi_win	Difference between formal and informal loans	Continuous	This variable refers to the loan value from formal sources minus the loan value from informal sources.
e_adt_lb_inct	Total household income	Continuous	This variable describes the total income accrued by household members aged 18 to 60 over the last 6 months.