Digital Collateral*

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Abstract

A new form of secured lending utlitizing "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. We find that 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 and find that roughly one-third is attributable to (ex-ante) adverse selection and two-thirds is attributable to (interim or ex-post) moral hazard. Access to school-fee loans significantly increases school enrollment and school-related expenditures without detrimental effects to households' balance sheet.

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1 Introduction

There is a general consensus that households in low and middle income countries (LMICs) have insufficient access to credit. Twenty years ago economists were optimistic that microfinance would fill this void, yet most of the evidence suggests that microfinance loans do not have transformative effects on the average borrower (Banerjee et al., 2015; Meager, 2019).

Traditional microfinance loans are unsecured. In contrast, more than 80% of total household debt in the US is secured by a physical asset.[1] Using collateral to secure debt helps overcome economic frictions, thereby expanding the supply of credit and reducing the cost of credit provision. Yet, secured debt is much less prevalent in poor countries. Why? First, 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 households in remote areas, where the costs associated with locating, repossessing, and redeploying collateral are prohibitive. Second, the primary source of income for many households in LMICs is self-employment, which is subject to more frequent shocks than formal sector wages. As such, they are more likely to default for nonstrategic reasons and may choose to avoid the risk of having assets repossessed.

In this paper, we argue that collateral need not be physically repossessed in order to serve a useful role in access to credit. Recent technological innovations have facilitated the use of digital collateral without the need for costly and inefficient physical repossession. An emerging example is pay-as-you-go financing (PAYGO). 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 financing crucially relies on an embedded "lockout technology" that allows the lender to remotely disable the flow of services from the asset. In other words, the lender can *digitally repossess* the asset without the need to repossess it physically. Digital collateral has several technological advantages: disabling the flow of services is cheap and easily reversible. 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 advantages allow for a richer space of financial contracts involving flexible repayment schedules

[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.

(e.g., pay per usage) and temporary (digital) repossession for non-payment.[2]

We explore this new form of financial contracting within a stylized model and a field experiment. In the model, firms can produce a good at a constant marginal cost. Households have a private value for consuming the good that is realized after they take possession of it. Due to their limited wealth and financial constraints, households cannot afford to purchase the good outright. In order to recoup their costs, firms must offer financing to households. But households cannot credibly commit to repay out of future income. Thus, firms offer a contract that is collateralized by the good: if the household does not repay the loan then the firm repossesses the good.

In the model, repossessing collateral plays 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 incentive to repay the loan or decline the loan offer. In most models of collateralized lending, these two roles are inherently bundled. They need not be. In both our model and experimental setting, repossession via lockout implies a loss in value to households who fail to repay, but does not necessarily involve recovery value for the lender. This decoupling is especially valuable when lenders face a high cost of repossession rendering the recovery role of little (net) value.

Much like traditional collateral, securing loans with digital collateral reduces the firms' 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. Second, when combined with a downpayment, digital collateral serves as a screening mechanism to overcome adverse selection. That is, a borrower that is more likely to face a negative income shock will have less incentive to accept a digitally secured loan. By reducing moral hazard and adverse selection, lenders can offer more financing to credit-worthy borrowers at terms they find acceptable.

In spite of the two aforementioned attributes, 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

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

with the temporary and relatively lenient nature in which lockout is deployed in PAYGO contracts compared to traditional secured lending.

We conduct a field experiment to identify the impact of digital collateral on market frictions and economic outcomes. To conduct the experiment, 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 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 examines the effects of digital collateral with Fenix's most popular follow-up product: a cash loan that is offered to customers near the beginning of each school term when school fees are due.

Our experimental design randomizes the sample into three treatment groups and a control group. In the first treatment, the customer is offered a loan secured with digital collateral. In the second treatment, the customer is offered an unsecured loan. In the third treatment, a customer is offered a secured loan, but if the customer accepts the loan, he or she is (positively) "surprised" and receives an unsecured loan. The "surprise" group is used to disentangle adverse selection from moral hazard a la Karlan and Zinman (2009).

Our experiment yields five main results. First, customer interest and take-up rates are high. More than 12% of the over 27,000 customers who received an SMS about the loan indicated they were interested. Of the 2,200 customers who were offered a loan after expressing interest, 47% accepted the offer and received a loan. These high take-up rates suggest the loan terms were attractive to customers and help to alleviate credit constraints. Second, consistent with our hypothesis that digital collateral reduces adverse selection, the take-up rate was about 6 percentage points (pp) lower for customers offered a (digitally) secured loan than those offered an unsecured loan (45% vs 51%).

Third, securing a loan with digital collateral significantly increases loan repayment. Average repayment increased by 11 pp when the loan was secured with digital collateral compared to an unsecured loan. Furthermore, the fraction of households that fully repaid the secured loan was 19 pp higher than the unsecured loans. About two-thirds of the total effect can be attributed to moral hazard, while one-third is driven by adverse selection. The reduction in moral hazard was concentrated among higher risk borrowers (based on repayment of previous loans), whereas the reduction in adverse selection was concentrated among lower risk borrowers. From a profitability standpoint, digital collateral increased the (annualized) internal rate of return on the loans by 38 pp.

Our finding that moral hazard rather than adverse selection drives the majority of the repayment increase is important because it suggests 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 most of the increase in repayment was due to adverse selection, then digital collateral serves primarily as a screening device and only a select subset of households are both willing and profitable lending opportunities.

Our fourth finding is that the school-fee loan had a positive impact on both enrollment and school-related expenditures (i.e., school fees, uniforms, supplies, transport, and meals). Children in households that were offered a school-fee loan were significantly more likely to be enrolled at school compared to children in the control group. Accounting for loan take-up, the loans reduced the share of children who were not enrolled by half (from 12% to 6%). In addition, households with loans increased school-related expenditures by 44%. Increases in enrollment were concentrated among males, but increases in expenditures were observed for both males and females.

Fifth, the loans did not have significant effects on household balance sheets. Asset purchases (sales) increased (decreased) moderately, but not significantly, and household borrowing was largely unchanged. Our estimates are precise enough to rule out large negative impacts on household balance sheets.

Altogether, our results suggest that digital collateral increases the share of customers to whom a company can profitably offer loans. Moreover, these loans significantly increased school enrollment and expenditures, suggesting that the customers did not have access to other sources of financing to pay for school fees. While our findings are mostly positive, securing loans with digital collateral is not without cost. First, there are costs to integrate and install the lockout technology into a SHS. Second, there is an (ex-post) inefficiency associated with locking devices. In our sample, the SHS was locked for 50 of the first 200 days from loan origination for the median household

(Table 3). On one hand, this could be viewed as a feature of the PAYGO contract; customers need not make payments on days in which they do not require or have a low value for 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.

Our study helps to explain why digital collateral is being employed in a range of emerging applications. For example, PayJoy, a FinTech firm based in San Francisco, developed a lockout technology for smart phones and has been offering digitally secured credit for the purchase of smart phones 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 initial loan by recollateralizing the smart phone. Payjoy has large scale operations in Mexico, and a small but growing customer base in South Africa, India, Indonesia, and Zambia. With the proliferation of smart devices, secured lending via digital collateral could easily be extended to a wide range of devices such as laptops, refrigerators, and televisions. Importantly, the capacity to reuse collateral for future loans (as it has been by Fenix and PayJoy) expands the potential impact of the innovation as a vehicle for affordable access to credit.

A similar technology has been deployed in the United States for subprime auto loans. Several firms have developed 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. These devices have been installed in more than two million vehicles.[3]

Finally, 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., 2021). 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.[4] We believe there is significant potential for utilities to further scale the use of digital collateral in providing affordable access to credit in LMICs.

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

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

2 Related Literature

Our paper relates to several different literatures including the use of collateral in corporate and household finance, microfinance, and education in developing countries.

2.1 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 properties 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.[5] 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).[6]

An extensive empirical literature explores on 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 are liquidation costs after repossession. Assunção et al. (2013) shows 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) finds 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

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

[6] 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).

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

Nevertheless, borrowing secured is not without cost. Exhausting pledgeable assets may mean losing financial flexibility and giving up profitable future investment opportunities (see, e.g., Acharya et al., 2007; Rampini and Viswanathan, 2010, 2013; Li et al., 2016; Donaldson et al., 2019). By pledging collateral, a firm also limits its flexibility to sell or redeploy assets to craft a better business operation. Indeed, Benmelech et al. (2020) document a significant decline in secured debt (as a fraction of total debt) among US firms over the twentieth century attributed in part to these reasons.

2.2 Microfinance

The effectiveness of microcredit as a tool to combat poverty appears to be more modest than advocated by its early proponents and unlikely to be a major pathway out of poverty for much of the population (Banerjee et al., 2015; Meager, 2019). Moreover, microfinance institutions (MFIs) are struggling as the costs of making small loans to poor clients are high, in part due to mediocre repayment (Cull et al., 2018). We demonstrate that securing loans with digital collateral can significantly reduce lending costs and remain both attractive and seemingly beneficial to households.

MFIs turned to joint liability lending as a means to address repayment issues. Under joint liability small groups of borrowers are responsible for the repayment of each other's loans. All group members are treated as being in default when at least one of them does not repay and all members are denied subsequent loans. Because co-borrowers act as guarantors they screen and monitor each other and in so doing reduce agency problems between the MFI and its borrowers (Ghatak and Guinnane, 1999). Theory suggests that joint liability may reduce adverse selection (Ghatak, 1999, 2000; Gangopadhyay et al., 2005) and moral hazard (Stiglitz, 1990; Banerjee et al., 1994; Laffont and Rey, 2003; Besley and Coate, 1995; Bhole and Ogden, 2010).

However, the empirical evidence on the effectiveness of joint liability is mixed. Attanasio et al. (2015) find no differences in repayment rates between joint and individual liability from a field experiment in rural Mongolia. Gine and Karlan (2014) examine the impact of joint liability on repayment through two experiments in the Philippines. They find that joint liability did not affect repayment rates over the ensuing three years. Carpena et al. (2012) exploit a natural experiment in which an MFI in India switched from individual to joint liability and find that joint liability significantly improved repayment.

The downsides to joint-liability lending are that it often involves frequent and time-consuming repayment meetings, making it potentially onerous for borrowers. In addition, it exerts strong social pressure and can suppress efficient risk taking (Giné et al., 2010). For these reasons, many MFIs (such as ASA, Grameen Bank II, and BancoSol) have started to move from joint liability to individual lending (Cull et al., 2009).

Finally, while collateralized lending is not common in microfinance, Jack et al. (2019) use a field experiment to study the potential for asset collateralization to expand access to credit in rural Kenya. They find that a reduction in the down payment on a water tank from 25% to 4% led to a significantly increase in take-up with only a modest increase in default rates, which they attribute almost entirely to selection rather than moral hazard. This is in contrast with our findings that secured lending leads to a drastic increase in repayment primarily driven by a reduction in moral hazard. These differences are likely attributable to differences in study design and the contrast between traditional and digital collateral. In Jack et al. (2019), all loans were secured by collateral—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.

2.3 Education in Developing Countries

Out-of-pocket costs are an important constraint to education in most African countries, as families are asked to pay for things like 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 in African countries (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, Duflo et al. (2019) show that scholarships for students in Ghana, who had already passed the entrance exam but lacked financing, 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 loans are an effective mechanism for increasing K-12 enrollment and school-related expenditures in LMICs. However, for tertiary education, loans are common and have been studied in some 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, our study does not suggest K-12 loans add undue burden to households' balance sheets.

3 Model

In this section, we propose a stylized model of collateralized lending. Our primary contribution is to decompose the repossession technology into two independent parameters in order to isolate and understand the role of each. We use "lockout" to refer to the parameter that controls how much value the household loses in repossession and "recovery" to refer to how much value the firm recovers in repossession.

Our main findings are as follows. First, using lockout to secure a loan increases borrower's repayment incentives thereby reducing the moral hazard problem; more effective lockout implies less moral hazard. Second, when combined with a downpayment, lockout leads to *positive selection*: borrowers with sufficiently high (ex-ante) income risk will be unwilling to take a loan secured with digital collateral. In combination, these findings imply that the lockout technology makes it easier for firms to recover production costs and increases the supply of credit. With a monopolist firm, a stronger lockout technology leads to less strategic default and less repossession in equilibrium, which is in contrast to the effect of a higher recovery value (Proposition 3). Despite the aforementioned attributes, a stronger lockout technology does not necessarily increase welfare, which can explain the lenient nature in which it is deployed in practice.

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 (e.g., 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 production 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.[7]

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 complimentary 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, assume 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 wealth $w_i = w$ for all i and that households are risk-neutral utility maximizers with a discount factor normalized to 1.[8]

Firms. There are $N \geq 1$ identical firms. Each firm has the technology to produce a good that generates value for households at date 1. Each firm has a marginal production cost c. Firms also have the ability to provide financing to their customers. At the beginning of date 0, firms first decide whether to enter (pay c to produce the good). Conditional on entry, firms design 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.[9]

[7] A higher realization of $\tilde{v}_i$ can be interpreted either as deriving from 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.

[8] Risk-neutrality simplifies the space of relevant contracts since there is no demand for intra- nor inter-temporal consumption smoothing.

[9] We take the form of contract as given because it is representative of what is used in practice by PAYGO providers and in our experiment. If households are identical (e.g., $q_i = q$ for all i) or risk is observable, then, under the Myerson's (1981) regularity condition, 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.

Repossession. Should the borrower fail to repay, 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 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 facilitates a decoupling of the two roles by providing incentives without the cost 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.[10]

As discussed earlier, physical repossession is costly in economies with weak creditor rights and limited enforcement. Therefore, a (traditional) collateralized 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., $\lambda>0$). Our primary interest will be to explore how an an increase in λ (i.e., a more effective lockout technology) affects outcomes.

We make the following parametric assumptions.

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

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 even without lockout 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 household values, which is commonly used in auction theory and mechanism design.

[10] One can interpret λ as the probability with which the good is successfully repossessed from the borrower and $(1-\kappa)/\lambda$ as the rate of depreciation or the cost of repossession the good (as a fraction of c).

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

3.1 Household Behavior

We begin by considering the behavior of households taking the contract (d,p) 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:

$$\tilde{v}_i \geq \frac{p}{\lambda}. \tag{1}$$

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.*

Consider now the purchase decision of households. The expected date-1 surplus to household i is given by

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

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

$$d \leq \min\{w, S_i(p)\}. \tag{2}$$

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* $\underline{q} \in (0,1)$ *such that only households with income risk* $q_i \leq \underline{q}$ *accept the contract. Moreover,* $\underline{q}$ *is decreasing in* λ.

This results shows that in combination with a downpayment, lockout leads to *positive selection*. Households with more credit risk prefer not to make a downpayment for the good because they anticipate a higher chance of being locked out.

3.2 Firm Profits

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

$$v(p) = \begin{cases} \underline{v} & p \leq \lambda \underline{v} \\ p/\lambda & p \in (\lambda \underline{v}, \lambda \bar{v}) \\ \bar{v} & p \geq \lambda \bar{v}. \end{cases} \tag{3}$$

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

$$\pi_i(d,p) = \begin{cases} d + R_i(p) - c & \text{if } d \leq \min\{w, S_i(p)\} \\ 0 & \text{otherwise.} \end{cases} \tag{4}$$

3.3 Equilibrium

The equilibrium will naturally depend both on the degree of competition among firms as well as whether firms can observe households' risk type. In this section, we consider both the monopolistic and competitive equilibrium with observable household risk.

3.3.1 Monopolist Firm

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

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

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 lowest type that strategically defaults, $v = p/\lambda$. The marginal revenue to the firm of increasing v is

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

and the first order condition is

$$v^* - \frac{1-F(v^*)}{f(v^*)} = \frac{\kappa c}{\lambda}, \tag{5}$$

which has a unique solution by Assumption 4. Notice 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; higher κ gives the firm more incentive to repossess which increases v^*, whereas higher λ decreases v^*.

Equation (5) is intimately linked to the monopoly price. In particular, when households' financial constraints are severe, 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*

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

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, 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., $w < S_i(p^*)$:*

- *More efficient recovery (higher κ) leads to **more** strategic default and repossession.*
- *More effective lockout (higher λ) leads to **less** strategic default and less 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 empirical evidence from a natural experiment (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 it is optimal for the firm to sell to household i. Otherwise, the household will reject any offer that the firm is willing to make.

Proposition 4 (Monopoly Quantities)**.** *The monopolist 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) $w + R_i(S_i^{-1}(w)) \geq c$ *otherwise.*

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 suplus. The total surplus in the economy is given by

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

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

3.3.2 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

$$\begin{aligned} (d_i, p_i) &\in \underset{d,p}{\operatorname{argmax}} U_i(d,p) \\ s.t. \quad \pi_i(d,p) &\geq 0 \end{aligned} \tag{6}$$

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 5 (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.

Parametric Example Suppose that both $\tilde{v}_i$ and q_i are uniformly distributed on [0,1]. Let $\kappa = 0$ and $c = \frac{1}{4}$, and let w and λ be free parameters. Then $v^* = \frac{1}{2}$, $p^* = \frac{\lambda}{2}$, and

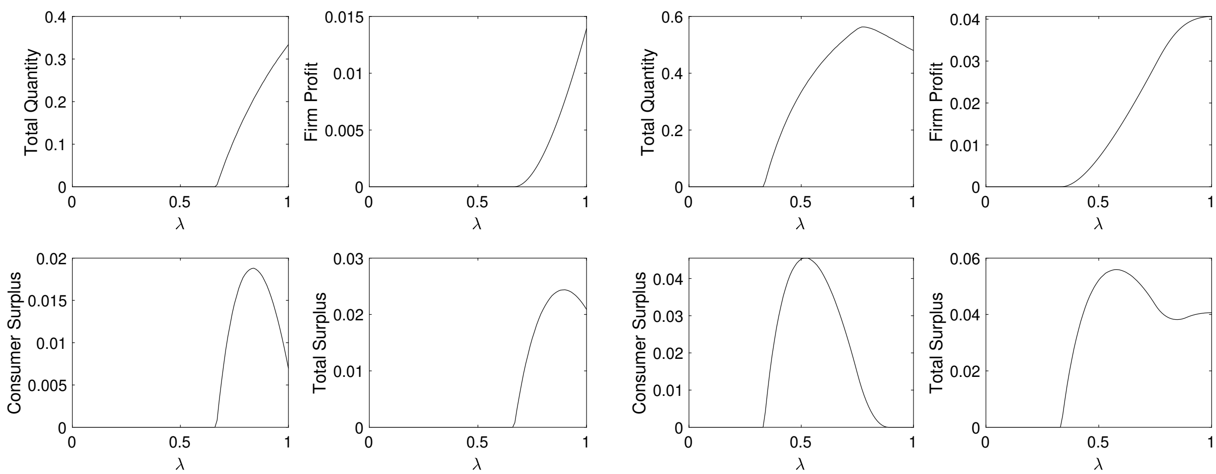
$$R_i(p^*) = \frac{1}{4}\lambda(1-q_i),$$

$$S_i(p^*) = \frac{1}{2} - \frac{\lambda(3+q_i)}{8}.$$

There are two possible cases depending on λ relative to $c-w$.

(i) For $\lambda < 4(c-w)$, then $q^* = 0$ meaning that no households purchase.

(ii) For $\lambda \geq 4(c-w)$, $q^* = 1 - \frac{4(c-w)}{\lambda}$ and the mass of households that purchase is $G(q^*) = 1 - \frac{4(c-w)}{\lambda}$.



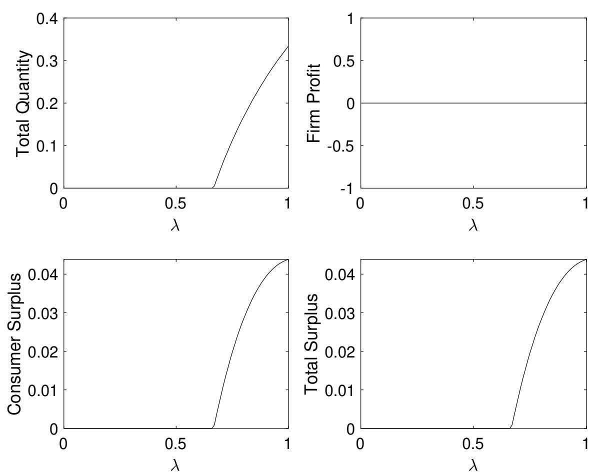
(a) Low household wealth, $w = \frac{1}{12}$.

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

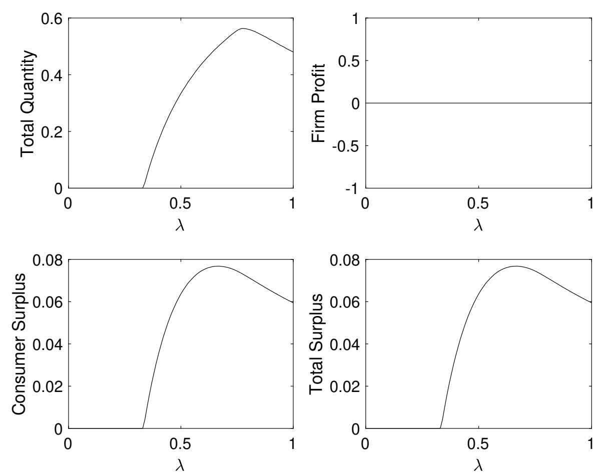
Figure 1: Illustrating the role of lockout with a monopolist firm.

Quantity and profit is increasing in λ as illustrated in the top panels of Figure 1. 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 1(b), 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.

The decrease in household welfare and total surplus can also obtain when firms are perfectly competitive as illustrated in Figure 2(b). These findings suggest that a more lenient repossession policy may be preferable. For example, the firm could reposess 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. Failure to make a payment results in a punishment that is proportional to the flow value of consuming the good rather than the stock value (i.e., physical repossession).



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



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

Figure 2: Illustrating the role of lockout with competitive firms.

3.4 Reusing digital collateral

The households in our experiment have already purchased the good and completed payments on the loan. The product that they are offered is a follow-up loan for school fees in which some fraction of the households are required to (re)-pledge the SHS as collateral in order to be eligible for the loan. It is straightforward to extend most of the results above to this setting.

Increasing λ reduces both moral hazard and adverse selection. Yet, higher λ destroys more surplus after negative income shocks and therefore may reduce overall welfare.

Unlike the model above, a downpayment on a follow-up loan is not necessary to get positive selection—repledging collateral serves the role of the downpayment. Nevertheless, a feature of the loan product offered in our experiment is that it requires households to make a cash deposit (several days in advance) when the loan funds are disbursed, which can serve as an additional screening device.[11]

4 Experimental Setting

We test 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 6 countries in Sub-Saharan Africa.[12] They are the largest SHS provider in Uganda.[13] Fenix's most popular system is 10 Watts and is able to power LED lamps and a radio, and charge cell phones.[14] Fenix's SHSs differ in several ways from the solar panels on homes in the US and Western Europe. First, they are roughly two orders of magnitude smaller than the typical solar panel installation on a US or Western European home. Second, they are standalone systems, meaning they are not connected to a grid.

Like most SHS providers, Fenix sells most of its units through a PAYGO model.[15] Customers make a small down payment, less than \$10, to take possession of the SHS. Subsequently,

[11] To illustrate this claim, consider a three-date model, in which the household receives some income at date 0, has an investment opportunity at date 1, and receives additional income at date 2. The household owns a good that delivers value $\tilde{v}$ at date 2 and can be pledged as collateral for a loan at date 1. The firm offers a contact (d,L,p), where d is the downpayment at date 0, L is the amount of the loan at date 1, and p is the price the household must pay at date 2 in order to avoid repossession. If income is persistent then being able to make the downpayment at date 0 is a positive signal about the household's ability to repay the loan at date 2 and serves as an additional screening device above and beyond household's willingness to pledge their collateral at date 1.

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

[13] 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.

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

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

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 uses the remote payment and locking technology to offer products upgrades and additional loans. Their most popular follow-up product is a school-fee loan. These are cash loans offered to the better-paying customers three times a year at the beginning of school terms. As with the original SHS loan, customers make a small down payment and then Fenix transfers money to the customer's mobile money account. The deposit covers administrative fees and gives the customer a seven day grace period before the device is subject to being locked. After the grace period, if the customer does not make a daily payment, the system will lock and the customer will not be able to use it until they make their next payment.

Our study focused on a 300,000 Ugandan Shilling (UGX) loan ($81).[16] Obtaining the loan requires customers make a deposit of 20% (60,000 UGX, or $16).[17] Several days after making the deposit, the funds are disbursed to the customer via mobile money. Customers receive seven free days of light after which they are responsible for making daily payments of 3,000 UGX (less than $1) for 100 days. Most customers choose to pay for several days or a week of light at a time rather than make daily payments. Fenix considers the loan to be paid off as long as the customer makes nominal payments totaling $81 (not including the deposit) within 145 days of the loan issue date. This arrangement implies that customers who take longer to repay face a lower effective interest rate. For instance, a customer who makes a payment every day pays an annual percentage rate (APR) of 168%, whereas a customer who makes a payment only two out of every three days pays an APR of only 112%. Of course, the latter APR does not reflect the cost of losing access to the SHS on locked days.

Customers who do not pay off the loan within 45 days of the target repayment date face interest charges of 2% per month on any remaining principal. In addition, failure to repay the loan in a timely manner renders customers ineligible for futures loan offers. After 180 days of no payments, the loan is considered to be in default and Fenix reserves the right to repossess

[16]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.

[17]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. (2021).

the SHS system. In practice, only a very small fraction of defaults (less than 5%) result in physical repossession, which is consistent with our hypothesis that the traditional repossession technology is expensive and ineffective in this setting.

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 government and privately run schools. In 2016, the most recent year for which data are available, 80% of primary-aged students attended government-run schools and 20% attended privately run schools. At the secondary level, over 50% of children attend private schools.[18] 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, school lunches and other supplies.

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 Living Standards Measurement Survey. 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

Figure 3 illustrates our experimental design. Our universe of eligible loan recipients consisted of Fenix customers that repaid the initial loan on their solar home system and did not have an outstanding school-fee loan. In May 2019 we sent an SMS message to the 27,081 eligible

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

customers inviting them to reply if they were interested in a school-fee loan. 3,300 customers (12%) responded affirmatively. Table A.1, columns (1) and (2) uses administrative data to compare our sample of Fenix customers to population-wide statistics from rural Uganda based on the 2019 World Bank Living Standards Measurement Study (LSMS). Fenix customers are more likely to be male and married and have more children than the typical 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.

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 collateral ("Unsecured"), and a treatment group that were offered the same terms as the Secured treatment group, but were later (positively) "surprised" that they would not have to post collateral after accepting the loan offer ("Surprise Unsecured").[19]

Following Karlan and Zinman (2009), this surprise 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 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.

Our call center attempted to reach the households in each treatment group using the phone number to which we had sent the SMS messages. The call center reached over 80% of households in the treatment groups. The call center explained that the customers were 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 collateral.

Field teams administered a baseline survey to the set of customers that were offered a

[19] The experiment also included a small group of customers that were given the choice between a secured and unsecured loan, which we do not discuss in this paper due to space constraints.

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 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.

All households who received a loan were sent regular SMS payment reminders: on the payment due date, if they were two days late, and again if they were one week late in making a payment. This is standard practice for Fenix and is useful to rule out alternative hypothesis as we discuss in Section 7. We also conducted an endline survey six months after the loans had been disbursed.

6 Experimental Results

We delineate our experimental results into three categories: (i) take-up rates, (ii) repayment and profitability, and (iii) educational and balance sheet outcomes.

6.1 Take-up Rates

Take-up rates were high across all treatment groups. 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. Consistent with our model, we see a clear indication that requiring households to post digital collateral serves as a screening device: 45% of households take the secured loan compared to 51% who take the unsecured loan.

Table A.2 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 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.

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).[20] 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 is consistently higher than repayment in either Unsecured group. Overall, digital collateral increased repayment by 13 pp at both 100 days (from 46% to 59%) and 150 days (57% to 70%). 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. Moral hazard accounts for the bulk of the overall effect: 9 pp at both 100 and 150 days. The adverse selection effect is derived by comparing repayment in the Surprise group to the Unsecured group; this accounts for 4-5 pp of the overall effect.

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

$$r_{it} = \alpha_t + \beta_t * Treatment\ group_i + \epsilon_{it}, \tag{7}$$

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 who were supposed to be locked were unlocked for some days and vice versa).[21] The column labeled "Secured" captures the total effect of securing loans with digital collateral. Specifications in this column include households in the Secured and Unsecured groups, where $Treatment\ group_i$ is equal to one for households in the Secured group. Specifications in the column labeled "Adverse Selection" include households in the Surprise and Unsecured groups, where $Treatment\ group_i$ is equal to one for households in the Surprise group. Specifications in

[20] Fenix credits commissions to customers who refer other customers to Fenix, and we include payments from these commissions, although they account for less than 0.05% of total payments towards principal.

[21] Altogether, fewer than 10% of the loan days were not in compliance. There were two general types of imperfect compliance: (1) administrative errors at the beginning of the experiment, and (2) customers who had additional transactions with Fenix over the study period, for example to upgrade their solar home system, and were sometimes switched to the wrong locking arrangement. See Appendix A Tables A.5 and A.6 for more details and for the Intent to Treat (ITT) estimates of the specifications reported in Table 1, respectively.

the columns labeled "Moral Hazard" include households in the Secured and Surprise 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 from origination. The last column provides the p-values for the hypothesis test that the moral hazard effect is equal to the adverse selection effect. The standard errors indicate that the overall lockout 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.

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. Lockout leads to a 19 pp increase 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) on loan portfolios.[22] Table 2 summarizes the results and shows that using digital collateral increased the monthly IRR by 3.2 pp (38 pp annualized). When we restrict attention to loans with perfect compliance (Table A.8), the increase in profitability is even larger 4.5 pp (54 pp annualized). We sorted households into terciles based on their repayment history prior to taking the school-fee loan (i.e., account percent locked).[23] Loans in each tercile are formed into a portfolio. The first tercile corresponds to households with the highest repayment rates prior to taking the school-fee loan. Table 2 illustrates that digital collateral increased profitability by more for the first two terciles (3.9 pp and 3.8 pp, respectively) than it did for the third tercile (1.8 pp).

It is noteworthy that all of the unsecured loan terciles have a negative IRR and only the first tercile of secured loans has a positive IRR. There are several takeaways from this finding. First,

[22]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.

[23]Account percent locked is the percentage of days in which the household's SHS was locked due to non-repayment of loans prior to taking the school-fee loan. While all had completed payments on the original SHS loan, some took longer to do so and thereby were locked a higher percentage of days.

the unsecured lending contract is not profitable even among households who have previously been good repayers. Second, securing a loan with digital collateral does not ensure profitability. Screening remains a necessary component of a sustainable lending business. For the purposes of this study, we expanded Fenix's eligibility criterion and increased the loan size. Under Fenix's usual business practices, (i) all school-fee loans are secured, (ii) only households with above median repayment history (among our sample of loans) would be eligible for a school-fee loan, and (iii) as first-time borrowers, they would only be eligible for a loan one-third of the size.[24] Thus, our findings are consistent with Fenix's usual business practices being value maximizing.

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 based on repayment history. As illustrated by the bottom row of Table 2), the prior school-fee loans have significantly better repayment history and are considerably more profitable. The monthly IRR is 6.6%, 6.0%, and 3.2% across the three terciles with an average monthly IRR of 5.1%.

Heterogeneity across households Table 4 analyzes the treatment impact on repayment rates and loan completion for households that were above and below median number of days locked on the original SHS loan. This allows us to assess the extent to which households with higher a priori risk had lower repayment and loan completion rates because of selection or moral hazard. The coefficients on the interaction term in Table 4 suggest that digital collateral increased repayments and completion slightly more for higher risk households. Interestingly, virtually all of the increase in repayment for higher risk households is due to moral hazard and not selection, whereas the opposite is true for lower risk households.

Second, we analyze heterogeneity in willingness to pay (WTP) for the electricity provided by the SHS. If we incorporated this heterogeneity into our model, it would predict that households with a higher WTP would be less willing to accept a locked loan compared to lower WTP households. Figure 5 analyzes loan take-up by respondent's stated WTP for a extra day of

[24]Our study offered 300,000 UGX ($81) loans to customers who had never had a school-fee loan, while the prior school-fee loans were smaller (100,000 UGX, $27) for first-time borrowers. Fenix offers larger loan sizes to customers after they have successfully paid off their first school-fee loan.

access to their SHS.[25] We group the responses into three categories (low, medium, and high). Indeed, households with the highest WTP are significantly less likely to accept a secured loan compared to an unsecured loan, while households in the low and medium groups are equally likely to accept them. Also consistent with our model, we found the effect on repayment is larger for households with above median WTP for solar (see Table A.21). For instance, the effect of requiring digital collateral is 10 pp higher at 150 days for households with above (vs below) median willingness to pay.

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. It is possible that the households who made the deposit after they were notified were different than the households in the Secured treatment group.[26] To understand by how much this potential selection affects our decomposition results, 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 are reported in Table A.7. Interestingly, the overall effect of digital collateral on repayment is almost two times as large among this set of people, pointing to considerable heterogeneity. Nevertheless, the overall conclusion that moral hazard explains the bulk of the effect remains.

6.3 Schooling and Household Balance Sheet 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 for households (e.g., schooling). On the other hand, loans with high interest rates, especially if they are misunderstood by customers, may have detrimental effects on households'

[25] 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.

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

balance sheet. We first examine schooling outcomes and then present results on households' balance sheet.

Schooling outcomes 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 equations:

$$y_i = \alpha + \beta * Loan\ Offer_i + \epsilon_i \tag{8}$$

$$y_i = \alpha + \beta * \widehat{Loan}_i + \epsilon_i, \tag{9}$$

where y_i is an outcome variable for household i. Equation (8) yields the intent to treat (ITT) estimates, where $Loan\ Offer_i$ is an indicator for a household that was offered a loan through one of the three (locked, surprise unlocked, unlocked) groups. Equation (9), estimated by instrumenting for $Loan_i$ with $Loan\ Offer_i$, yields the local average treatment effect (LATE) for households that accepted loans.[27] In what follows, we focus on discussing the LATE estimates, and the ITT estimates are reported in the Appendix.

Table 5 reports results from estimates of (9) for several schooling-related outcomes. The first two columns report impacts on the share of 5 to 20-year-old children within a household who are enrolled in school. The sample is restricted to households that had at least one child in that age range at the endline survey. The results indicate that the loan increased the fraction of households who enrolled all of their school-aged children by 6 pp. 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 just over half.[28]

[27]We also estimated specifications that allowed the loan impacts to vary by treatment group but saw no significant differences in the effect size across the treatment groups.

[28]Enrollment rates among households in our sample appear roughly comparable to enrollment rates for the population. According to the Living Standards Measurement Survey, nationwide 91% of primary school-aged

The third column on Table 5 analyzes the impact on monthly absences from school for households that had at least one child enrolled. The coefficients are precisely estimated and suggest no meaningful impact on days absent. The fourth column shows that expenditures for school-related items (including school fees, uniforms, supplies, transport and meals) increased by 34.6% for households who received a loan.[29] The increase in school-related expenditures corresponds to roughly 44% of the loan amount (net of the deposit) or $29.7.

Table 6 presents the LATE 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 the increased enrollment was concentrated among male children, who have a lower base rate (control mean) of enrollment, possibly because they were more likely to be working. The loan then may have not only been used to cover school costs but also used to offset lost income from reduced child labor supply. The loan was associated with a significant increase in school expenditures for both males (29 pp) and females (46 pp) by a similar magnitude to the household-level results.

In summary, Fenix's loans had an economically meaningful and statistically significant impact on educational outcomes. These findings suggest that households did not have another source of liquidity to use for schooling-related expenditures. The Living Standards Measurement Survey (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.

Household balance sheet Table 7 reports results on household asset purchases, sales, and borrowing in the six months prior to endline survey. The effect of the loan on households balance sheet is not statistically significant effect in any category. Moreover, based on the standard errors, we can rule out large negative impacts on households that took loans, such as a significant increase in asset sales or reduction in purchases. We repeated the analysis

children and 68% of secondary school-aged children are enrolled at school.

[29]The estimated coefficient of the loan on log expenditures is 0.297. So, the percentage increase in expenditures for households who received a loan is $e^{0.297}-1=34.6\%$.

using endline asset, loans and balance sheet level variables in Table 8. The estimated effect of the loan on household net balance is small and is not statistically different from zero. For additional perspectives on households' financial position, we asked a series of questions about shocks households had experienced, including financial shocks, and their ability to endure those shocks. The results are summarized in Table A.11. Again, we see no systematic or significant differences between households that were offered loans and the control group.

7 Discussion

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 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 (secured or unsecured) 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 digital collateral is applied.[30] If the set of households with a high continuation value overlaps with the set of households that responds to the incentives from lockout, then our estimate is biased downward.[31]

To get a sense for the magnitude of the bias, suppose a fraction q of such households have a high continuation value and complete payments within 120 days regardless of whether or not

[30]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.

[31]We are grateful to Antoinette Schoar for pointing out the potential for a downward bias.

lockout is applied. Absent this high continuation value, the true effect of lockout on increasing loan completion is m.[32] If continuation value and willingness to pay are independently distributed, then we would estimate the (moral hazard) effect on loan completion to be $(1-q)m$. Under the assumption of independence, we can provide an upper bound on m using the observation that 40% of households in the surprise unlocked treatment complete the loan within 120 days. Thus, q is at most 0.4 and m is at most two thirds larger than the effect size that we estimate.

Our finding that adverse selection accounts for a smaller portion of the increase in repayment than does moral hazard can partially be attributed to the fact that our sample has 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 initial SHS loan. The adverse selection effect is likely to be larger on the initial loan. Second, eligible school-fee loan customers are 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 a screening device (Gertler et al., 2021).

In addition to reducing moral hazard and adverse selection, there are other potential benefits of loans secured 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 savings. This savings vehicle can be particularly valuable to households who lack self control because there is an added incentive to save (Laibson, 1994)—failure to do so means facing 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 borrowers without any reciprocal benefit to lenders, it may raise ethical questions especially if the primary reason for

[32] Within the context of the model from Section 3, if we consider a locked loan to have $\lambda=1$ and an unlocked loan to have $\lambda=0$, then $m=1-F(p)$ is simply the fraction of households with v_i greater than the price.

nonpayment 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?[33] 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 can be significantly less punitive than physical repossession, a practice that is widely accepted. 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.

8 Conclusion

In this paper, we explore a novel form of financial contracting that uses lockout technology to create digital collateral, which does not require 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 collateralized 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 effects on educational outcomes and did not have negative effects on households' balance sheet.

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.

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

Our field experiment also demonstrates the potential for private institutions to offer digitally collateralized loans to pay for schooling, resulting in increased enrollment and expenditures without placing a significant financial burden on the household. 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 utilized 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, refrigerators, automobiles, and farming equipment. Importantly, the capacity to reuse collateral for future loans (as it has been by Fenix and PayJoy) 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 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 in LMICs.

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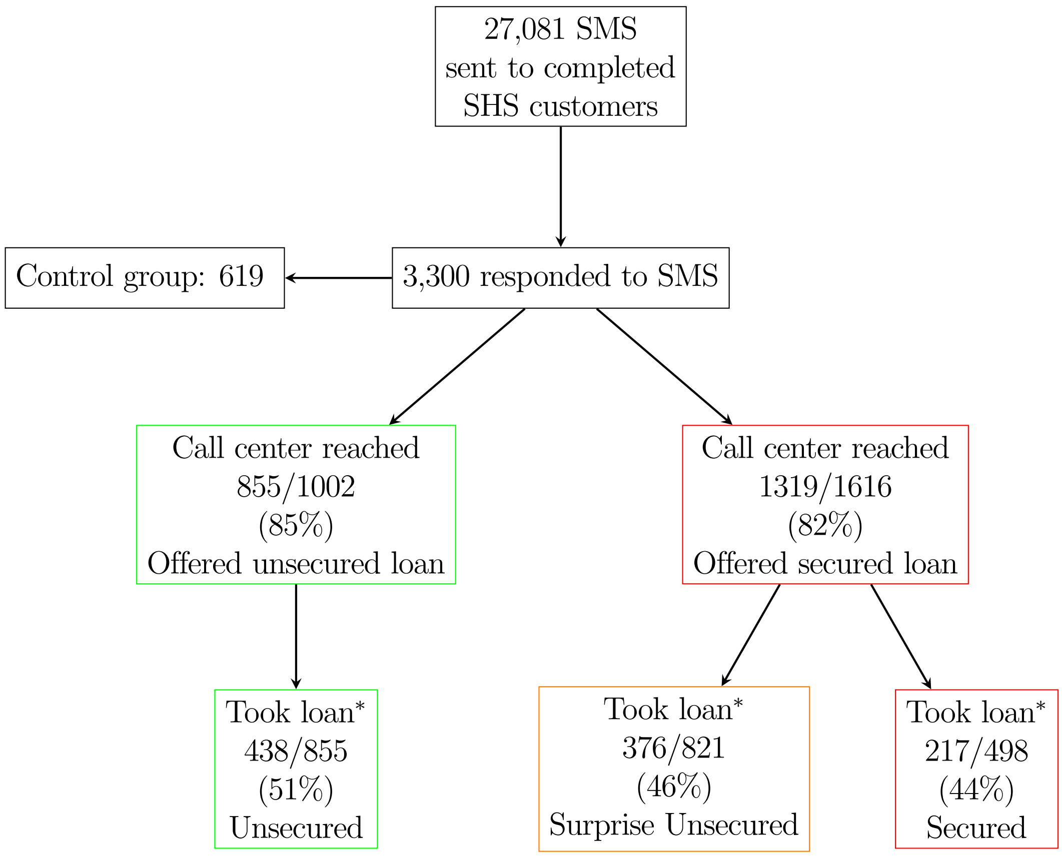
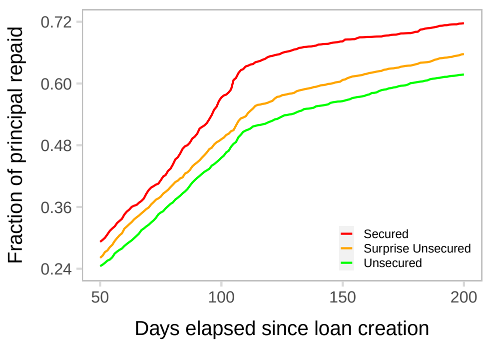
9 Figures and Tables

Figure 3: Consort Statement

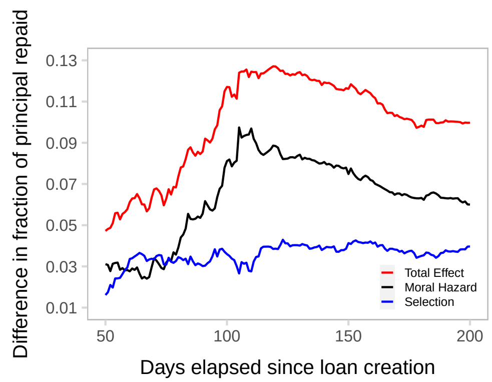


* Took loan refers to accepting the loan, completing the necessary paperwork, and paying the deposit.

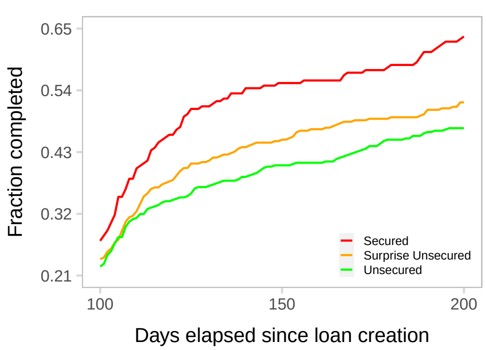
Figure 4: Loan Repayment and Completion



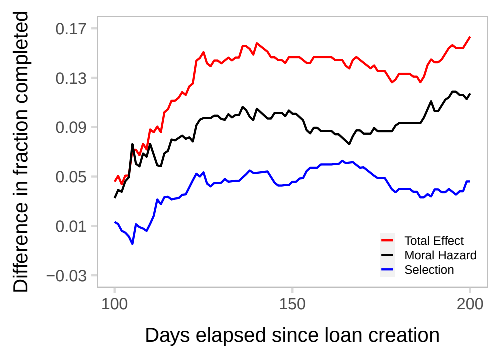
(a) Loan repayment



(b) Differences in repayment



(c) Loan completion



(d) Differences in completion

Note: Panel (a) plots average fraction of principal repaid by days elapsed since loan origination for each treatment group. Panel (b) plots the difference in average fraction of principal repaid by days elapsed for each treatment group. Panel (c) plots average fraction of customers completed by days elapsed for each treatment group. The difference in average fraction of customers 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 principal repaid (customers completed) between the Secured and Unsecured groups, "Moral Hazard" displays the difference in average fraction of principal repaid (customers completed) between the Secured and Surprise Unsecured groups, and "Selection" displays the difference in average fraction of principal repaid (customers completed) between the Surprise Unsecured and Unsecured groups. (Differences in) both the fraction of principal repaid and fraction of customers 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: Tests of Lockout, Adverse Selection and Moral Hazard on Loan Repayment and Loan Completion (LATE)

Loan day	Mean Unsecured	Lockout	Adverse Selection	Moral Hazard	p-value diff
		Panel A: Loan Repayment			
100	0.46	0.13***	0.04	0.09**	0.29
		(0.04)	(0.03)	(0.04)	
150	0.57	0.13***	0.05	0.09**	0.46
		(0.04)	(0.03)	(0.04)	
200	0.62	0.11***	0.04	0.07*	0.65
		(0.04)	(0.03)	(0.04)	
		Panel B: Loan Completion			
110	0.31	0.10**	0.01	0.09*	0.21
		(0.05)	(0.04)	(0.05)	
150	0.41	0.17***	0.05	0.12**	0.31
		(0.05)	(0.04)	(0.05)	
200	0.47	0.19***	0.05	0.13***	0.19
		(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 origination. "Lockout" 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-value diff" records the p-value from testing the equality of the differences between the Adverse Selection and Moral Hazard LATE models. * $p < .10$, ** $p < .05$, *** $p < .01$

Table 2: Monthly IRRs of Loan Portfolios

Treatment Group	Account percent locked			All	n
	1st tercile	2nd tercile	3rd tercile		
Secured	0.2%	-2.5%	-8.4%	-3.7%	217
	[0.00, 0.06]	[0.06, 0.19]	[0.19, 0.57]	[0.00, 0.57]	
Unsecured	-3.7	-6.3	-10.2	-6.9	438
	[0.00, 0.05]	[0.05, 0.19]	[0.19, 0.64]	[0.00, 0.64]	
Prior School Fee Loans (Secured)	6.6	6.0	3.2	5.1	1377
	[0.00, 0.04]	[0.04, 0.13]	[0.13, 0.30]	[0.00, 0.30]	

Note: Loans in each treatment group are sorted by proportion of days locked at SMS and divided into equal-sized terciles. Loans in each tercile are formed into a portfolio. The internal rate of return (IRR) is the discount rate that makes the net present value of cash flows on the portfolio equal to zero. The IRRs of portfolios formed using all loans in each treatment group are also reported. The range of the fraction of days locked is reported in square brackets.

Table 3: Fraction of School Fee Loan Days Locked

Percentile	Day		
	100	150	200
25th	0.11	0.08	0.06
50th	0.33	0.33	0.25
75th	0.66	0.73	0.78

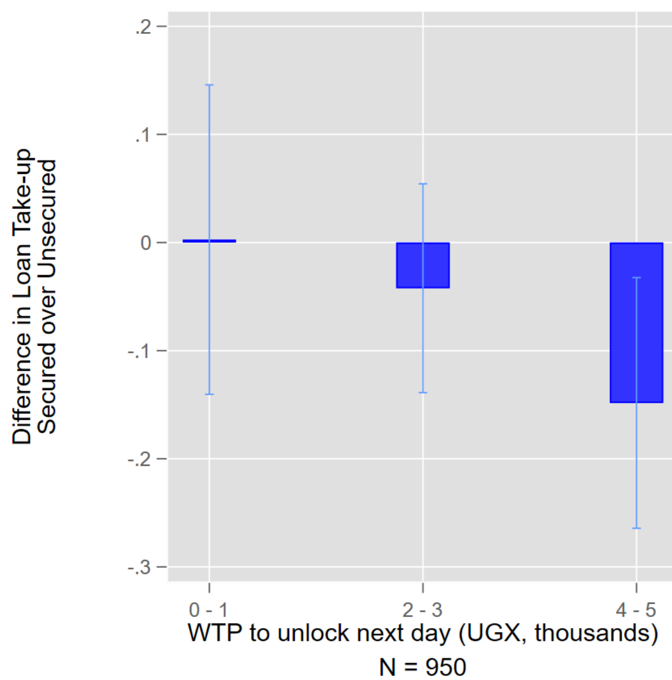
Note: The above table calculates the fraction of loan days locked at 100, 150, and 200 days from school-fee loan origination, by percentile. The figures are calculated for the sample of 217 Secured school-fee loans involved in the experiment.

Table 4: Tests of Lockout, Adverse Selection, and Moral Hazard, Risk (Interactions Model) (LATE)

	Lockout	Adverse Selection	Moral Hazard
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 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 "Lockout" 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. * $p < .10$, ** $p < .05$, *** $p < .01$

Figure 5: Effect of Lockout 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 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 5: Education Outcomes, Household-level (LATE)

	Enrollment	Days absent	Log school expenditures
Loan	0.0556*	0.0319	0.297**
	(0.0299)	(0.345)	(0.127)
Outcome control mean	0.88	1.28	85.85
n	1683	1625	1625

Note: Standard errors in parentheses. Results relate to Term 2 outcomes. The above results display the Local Average Treatment Effect (LATE), which measures the average treatment effect for compliers, using actual receipt of a school-fee loan as the endogenous variable (see the Appendix for Intent to Treat (ITT) results). "Enrollment" describes the share of school-aged children (SAC; individuals aged 5-20) enrolled in Term 2, and is conditional on having at least one SAC within the household at endline. "Days absent" describes the average days of school missed per month, per enrolled SAC, and is conditional on having at least one SAC enrolled at endline in Term 2. "School expenditures" (school fees, supplies, transport, and school meals) describes the average school expenditure per enrolled SAC and is conditional on having at least one SAC enrolled at endline in Term 2. School expenditures are in USD (1 USD is equal to approximately 3704 UGX in 2019). School expenditures are winsorized at the 99th percentile. The outcome control mean for school expenditures is not log transformed. * $p < .10$, ** $p < .05$, *** $p < .01$

Table 6: Education Outcomes for School Aged Children (LATE)

	Enrollment		Log school expenditures	
	Male	Female	Male	Female
Loan	0.0593*	-0.0403	0.253*	0.381**
	(0.0343)	(0.0325)	(0.145)	(0.176)
P value from Chow test		0.03		0.48
Outcome control mean	0.89	0.92	79.33	83.07
n	2756	2903	2508	2606

Note: Standard errors in parentheses and are clustered at the household level. Results relate to Term 2 outcomes. The above results display the Local Average Treatment Effect (LATE), which measures the average treatment effect for compliers, using actual receipt of a school fee loan as the endogenous variable (see the Appendix for Intent to Treat (ITT) results). School expenditures (school fees, supplies, transport, and school meals) are conditional on enrollment at endline in Term 2. School expenditures are in USD (1 USD is equal to approximately 3704 UGX in 2019). School expenditures are winsorized at the 99th percentile. The p value from the Chow test compares the treatment effect for males to that of females. The outcome control mean for school expenditures is not log transformed. * $p < .10$, ** $p < .05$, *** $p < .01$

Table 7: Effect on Asset Purchases, Sales, and Money Borrowed in the Last 6 Months (LATE)

	Asset purchases (IHST)	Asset sales (IHST)	Money borrowed (IHST)	Net difference (IHST)
Loan	0.113	-0.216	0.061	0.060
	(0.380)	(0.301)	(0.405)	(0.407)
Outcome control mean (USD, level)	238	96	234	-234
n	1836	1836	1836	1836

Note: Standard errors in parentheses. The above analysis uses the Local Average Treatment Effect (LATE) to derive semi-elasticities. The LATE measures the average treatment effect for compliers, using actual receipt of a school fee loan type (or any school fee loan) as the endogenous variable (see the Appendix for Intent to Treat (ITT) results). "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 were converted to USD prior to IHST transformation (note that 1 USD was equal to approximately 3,704 UGX in 2019). Winsorizing at the 99th percentile takes place before IHST transformation. For 31 individuals who reported Fenix as a creditor, the amount of the school fee loan was added back into the total amount reported to have been borrowed. Loan refers to the semi-elasticity calculated following the exact method from Bellemare and Wichman (2019), following arguments from Halvorsen and Palmquist (1980), Kennedy (1981) and Giles (1982). * $p < .10$, ** $p < .05$, *** $p < .01$

Table 8: Effect on Household Balance Sheet (LATE)

	Asset value (IHST)	Money borrowed (IHST)	Net difference (IHST)
Loan	-0.160	0.114	-0.014
	(0.172)	(0.417)	(0.756)
Outcome control mean (USD, level)	1810	553	1258
n	1830	1830	1830

Note: Standard errors in parentheses. The above analysis uses the Local Average Treatment Effect (LATE) to derive semi-elasticities. The LATE measures the average treatment effect for compliers, using actual receipt of a school fee loan type (or any school fee loan) as the endogenous variable (see the Appendix for Intent to Treat (ITT) results). "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. "Money borrowed" is the sum of the amount borrowed over the 12 months prior to the baseline survey (recorded at baseline) and the amount over the 6 months prior to the endline survey (recorded at endline). The components for "asset value" and "money borrowed" are winsorized at the 99th percentile prior to IHST transformations. "Net difference" records the difference between "asset value" and "money borrowed." Values were converted to USD prior to IHST transformation (note that 1 USD was equal to approximately 3,704 UGX in 2019). For 31 individuals who reported Fenix as a creditor, the amount of the school fee loan was added back into the total amount reported to have been borrowed. Loan refers to the semi-elasticity calculated following the exact method from Bellemare and Wichman (2019), following arguments from Halvorsen and Palmquist (1980), Kennedy (1981) and Giles (1982). The number of observations differs from that in Table 7 because the outcomes in this table relies on having reported values at baseline. * $p < .10$, ** $p < .05$, *** $p < .01$

A Appendix (For Online Publication Only)

A.1 Supplemental Tables and Figures

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

Characteristic	(1) Uganda LSMS	(2) SMS sent to	(3) Took up loan
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: Characteristics of those who take-up loans

	Secured	Unsecured	N
Percent of days locked at SMS	15.8	14.9	505
	(15.5)	(14.3)	
Household head characteristics			
Age (years)	42.7	44.0	505
	(9.9)	(11.1)	
Female (proportion)	0.10	0.11	505
	(0.31)	(0.32)	
Household head occupation (proportion)			
Family business or farm	0.51	0.65***	505
	(0.50)	(0.48)	
Self-employed	0.61	0.63	505
	(0.49)	(0.48)	
Outside the home	0.36	0.33	505
	(0.48)	(0.47)	
Number of school aged children	3.0	3.2	505
	(2.1)	(2.0)	
Annual household income per adult (USD)	336	298	505
	(333)	(248)	
Value of assets per adult (USD)	354	389	505
	(489)	(481)	
WTP for SHS next day (USD)	0.81	0.77	505
	(0.40)	(0.40)	
Hours to nearest ReadyPay Service Center	0.9	1.0	505
	(0.8)	(0.8)	

Note: Standard deviations in parentheses. The above table presents group averages for various characteristics, and does not include individuals in the Surprise Unsecured treatment group. "Percent of days locked at SMS" describes the percentage of days that the customer was locked on their solar home systems (SHS) at the time that the initial SMS was sent to customers inviting them to take up a school fee loan. School aged children are children between the ages of 5 and 20, inclusive. USD values are winsorized at the 99th percentile. "WTP for SHS next day" describes customers' reported willingness to pay to unlock their SHS for the next day. "Hours to nearest ReadyPay Service Center" describes the amount of time customers reported taking to go to the nearest Fenix ReadyPay Service Center. Values were converted to USD (note that 1 USD was equal to approximately 3,704 UGX in 2019). Tests of differences in means are carried out between Unsecured and Secured. * $p < .10$, ** $p < .05$, *** $p < .01$

Table A.3: Baseline Characteristics

Characteristic	Secured	Surprise Unsecured	Unsecured	Control	n
Risk					
Percent of days locked at SMS (%)	14.7	15.2	16.0	14.0	2130
	(15.3)	(15.5)	(15.2)	(14.5)	
Household head					
Age (years)	43.0	43.8	43.3	43.5	2122
	(11.0)	(11.1)	(10.6)	(11.1)	
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. USD values are winsorized at the 99th percentile. Values were converted to USD (note that 1 USD was equal to approximately 3,704 UGX in 2019).

Table A.4: Baseline Characteristics, p-values from pairwise comparisons

Characteristic	Secured - Surprise Unsecured	Secured - Unsecured	Secured - Control	Surprise Unsecured - Unsecured	Surprise Unsecured - Control	Unsecured - Control
Risk						
Percent of days locked at SMS (%)	0.648	0.177	0.489	0.312	0.222	0.032
Household head						
Age (years)	0.222	0.595	0.466	0.395	0.687	0.752
Female (proportion)	0.484	0.330	0.373	0.764	0.764	0.962
Married (proportion)	0.822	0.150	0.338	0.156	0.395	0.713
Household head occupation (proportion)						
Family business or farm	0.410	0.067	0.516	0.248	0.922	0.274
Self-employed	0.343	0.983	0.836	0.279	0.240	0.798
Outside the home	0.638	0.400	0.904	0.672	0.548	0.331
Demographics						
Number of people in household	0.919	0.882	0.843	0.966	0.915	0.939
Number of children aged 5-20 enrolled in school	0.691	0.925	0.802	0.563	0.908	0.704
Financial information						
Amount spent on lighting, year (USD)	0.137	0.013	0.014	0.139	0.117	0.810
Total household income, year (USD)	0.354	0.667	0.074	0.568	0.272	0.113
Value of assets (USD)	0.264	0.742	0.942	0.388	0.226	0.682
Borrowing						
Borrowed in last 12 months (proportion)	0.858	0.647	0.448	0.460	0.307	0.689
Money borrowed in last 12 months (USD)	0.767	0.466	0.834	0.222	0.580	0.607
Ever refused for loan in last 12 months (proportion)	0.547	0.434	0.009	0.839	0.019	0.027
Took a microfinance loan in last 12 months (proportion)	0.687	0.514	0.836	0.220	0.524	0.675

Note: p-values from t-tests between two different treatment groups are included in the above table.

Table A.5: Share of Days in Compliance, by Treatment

Loan day	Secured	Surprise Unsecured	Unsecured
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 samples of the share of days in compliance at 50, 100, 150, and 200 days from origination.

Table A.6: Tests of Lockout, Adverse Selection and Moral Hazard on Loan Repayment and Loan Completion (ITT)

Loan day	Mean Unsecured	Lockout	Adverse Selection	Moral Hazard	p-value diff
		Panel A: Loan Repayment			
100	0.46	0.12***	0.04	0.08**	0.16
		(0.03)	(0.03)	(0.03)	
150	0.57	0.12***	0.04	0.07**	0.33
		(0.03)	(0.03)	(0.04)	
200	0.62	0.10***	0.04	0.06*	0.55
		(0.03)	(0.03)	(0.03)	
		Panel B: Loan Completion			
110	0.31	0.09**	0.01	0.08*	0.11
		(0.04)	(0.03)	(0.04)	
150	0.41	0.15***	0.05	0.10**	0.18
		(0.04)	(0.03)	(0.04)	
200	0.47	0.16***	0.05	0.12***	0.08
		(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 assignment on loan repayment (completion). The analysis is run on samples at either the 100th, 110th, 150th, or 200th day from origination. "Lockout" 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-value diff" records the p-value from testing the equality of the differences between the Adverse Selection and Moral Hazard ITT models. * $p < .10$, ** $p < .05$, *** $p < .01$

Table A.7: Tests of Lockout, Adverse Selection, and Moral Hazard on Loan Repayment and Loan Completion, Early Adopters

Loan day	Mean Unsecured	Lockout ITT	Lockout LATE	Adverse Selection ITT	Adverse Selection LATE	Moral Hazard ITT	Moral Hazard LATE	p-value diff
				Panel A: Loan Repayment				
100	0.47	0.15***	0.18***	0.01	0.01	0.14***	0.18***	0.01
		(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**	0.16
		(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*	0.40
		(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**	0.02
		(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*	0.22
		(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***	0.02
		(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 assignment on loan repayment, while the Local Average Treatment Effect (LATE) measures the average treatment effect on loan repayment 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 origination. "Lockout" 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-value diff" records the p-value from testing the equality of the differences between the Adverse Selection and Moral Hazard ITT models. * $p < .10$, ** $p < .05$, *** $p < .01$

Table A.8: Monthly IRRs of Loan Portfolios, Compliers Only

Treatment Group	Account percent locked			All	n
	1st tercile	2nd tercile	3rd tercile		
Secured	-0.5%	-3.0%	-7.4%	-3.7%	202
	[0.00, 0.05]	[0.06, 0.18]	[0.18, 0.57]	[0.00, 0.57]	
Unsecured	-5.3	-7.1	-11.8	-8.2	358
	[0.00, 0.05]	[0.05, 0.20]	[0.20, 0.64]	[0.00, 0.64]	
Prior School Fee	6.6	6.0	3.2	5.1	1377
Loans (Secured)	[0.00, 0.04]	[0.04, 0.13]	[0.13, 0.30]	[0.00, 0.30]	

Note: In this analysis, we exclude customers with imperfect compliance (i.e., customers who were supposed to be locked were unlocked for some days and vice versa). Loans in each treatment group are sorted by proportion of days locked at SMS and divided into equal-sized terciles. Loans in each tercile are formed into a portfolio. The internal rate of return (IRR) is the discount rate that makes the net present value of cash flows on the portfolio equal to zero. The IRRs of portfolios formed using all loans in each treatment group are also reported. The range of the fraction of days locked is reported in square brackets.

Table A.9: Education Outcomes, Household-level (ITT)

	Enrollment	Days absent	Log school expenditures
Loan	0.0251*	0.0144	0.134**
	(0.0135)	(0.156)	(0.0567)
Outcome control mean	0.88	1.28	85.85
n	1683	1625	1625

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, and is conditional on having at least one SAC within the household at endline. "Days absent" describes the average days of school missed per month, per enrolled SAC, and is conditional on having at least one SAC enrolled at endline in Term 2. "School expenditures" (school fees, supplies, transport, and school meals) describes the average school expenditure per enrolled SAC and is conditional on having at least one SAC enrolled at endline in Term 2. School expenditures are in USD (1 USD is equal to approximately 3704 UGX in 2019). School expenditures are winsorized at the 99th percentile. The outcome control mean for school expenditures is not log transformed. * $p < .10$, ** $p < .05$, *** $p < .01$

Table A.10: Education Outcomes for School Aged Children (ITT)

	Enrollment		Log school expenditures	
	Male	Female	Male	Female
Loan	0.0276*	-0.0182	0.120*	0.176**
	(0.0158)	(0.0146)	(0.0688)	(0.0804)
P value from Chow test		0.03		0.51
Outcome control mean	0.89	0.92	79.33	83.07
n	2756	2903	2508	2606

Note: Standard errors in parentheses and are clustered at the household level. Results relate to Term 2 outcomes. School expenditures are conditional on enrollment at endline in Term 2. The above results display the Intent to Treat (ITT) analysis, which measures the average effect of assignment to a loan. School expenditures (school fees, supplies, transport, and school meals) are conditional on enrollment at endline in Term 2. School expenditures are in USD (1 USD is equal to approximately 3704 UGX in 2019). School expenditures are winsorized at the 99th percentile. The p value from the Chow test compares the treatment effect for males to that of females. The outcome control mean for school expenditures is not log transformed. * $p < .10$, ** $p < .05$, *** $p < .01$

Table A.11: Shocks over the past 6 months

	(1) Proportion shocks experienced	(2) Proportion shocks experienced	(3) How worried are you about this?	(4) How worried are you about this?
	Shock Category A: Problem With Money			
Assigned Secured loan	0.0151		0.0369	
	(0.0255)		(0.0233)	
Assigned Surprise Unsecured loan	-0.00584		0.0111	
	(0.0227)		(0.0210)	
Assigned Unsecured loan	0.0216		0.00819	
	(0.0226)		(0.0206)	
Assigned any loan		0.00973		0.0157
		(0.0199)		(0.0183)
Constant	0.415***	0.415***	0.729***	0.729***
	(0.0180)	(0.0180)	(0.0165)	(0.0165)
n	1882	1882	1400	1400
	Shock Category B: Money Matters For Coping			
Assigned Secured loan	-0.00302		0.00955	
	(0.0169)		(0.0186)	
Assigned Surprise Unsecured loan	-0.00625		-0.00607	
	(0.0150)		(0.0168)	
Assigned Unsecured loan	0.0157		0.00901	
	(0.0149)		(0.0166)	
Assigned any loan		0.00314		0.00352
		(0.0132)		(0.0146)
Constant	0.342***	0.342***	0.832***	0.832***
	(0.0119)	(0.0119)	(0.0132)	(0.0132)
n	1882	1882	1648	1648
	Shock Category C: Money Doesn't Help			
Assigned Secured loan	-0.00675		0.0646	
	(0.0121)		(0.0466)	
Assigned Surprise Unsecured loan	-0.0111		0.0577	
	(0.0107)		(0.0410)	
Assigned Unsecured loan	-0.0148		0.0312	
	(0.0107)		(0.0406)	
Assigned any loan		-0.0116		0.0486
		(0.00942)		(0.0353)
Constant	0.0886***	0.0886***	0.695***	0.695***
	(0.00851)	(0.00851)	(0.0315)	(0.0314)
n	1882	1882	455	455

Note: Standard errors in parentheses. 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. 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. Shock Category C gathers together the following experiences over the last 6 months: problems at home with relatives; problems with people in other tribes; idleness of your children or spouse; alcohol consumption of your children or spouse. 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. * $p < .10$, ** $p < .05$, *** $p < .01$

Table A.12: Effect on Asset Purchases, Sales, and Money Borrowed in the Last 6 Months, Regressions, IHST Transformation (LATE)

	Asset purchases (IHST)	Asset purchases (IHST)	Asset sales (IHST)	Asset sales (IHST)	Money borrowed (IHST)	Money borrowed (IHST)	Net difference (IHST)	Net difference (IHST)
Assigned Secured loan	0.0173		-0.0522		-0.0481		0.0568	
	(0.390)		(0.426)		(0.436)		(0.438)	
Assigned Surprise Unsecured loan	-0.104		-0.495		0.0616		-0.0648	
	(0.332)		(0.363)		(0.372)		(0.373)	
Assigned Unsecured loan	0.300		-0.00113		0.0879		-0.0880	
	(0.308)		(0.336)		(0.344)		(0.346)	
Assigned any loan		0.107		-0.234		0.0587		-0.0580
		(0.342)		(0.372)		(0.381)		(0.383)
Outcome control mean (level)	238	238	96	96	234	234	-234	-234
n	1836	1836	1836	1836	1836	1836	1836	1836

Note: Standard errors in parentheses. The above analysis uses the Local Average Treatment Effect (LATE). The LATE measures the average treatment effect for compliers, using actual receipt of a school fee loan type (or any school fee loan) as the endogenous variable. "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. Winsorizing takes place before IHST transformation. Values were converted to USD prior to IHST transformation (note that 1 USD was equal to approximately 3,704 UGX in 2019). For 31 individuals who reported Fenix as a creditor, the amount of the school fee loan was added back into the total amount reported to have been borrowed. The above analysis uses the Intent to Treat (ITT). * $p < .10$, ** $p < .05$, *** $p < .01$

Table A.13: Effect on Asset Purchases, Sales, and Money Borrowed in the Last 6 Months, Regressions, IHST Transformation (ITT)

	Asset purchases (IHST)	Asset purchases (IHST)	Asset sales (IHST)	Asset sales (IHST)	Money borrowed (IHST)	Money borrowed (IHST)	Net difference (IHST)	Net difference (IHST)
Assigned Secured loan	0.00850		-0.0256		-0.0236		0.0279	
	(0.192)		(0.209)		(0.214)		(0.215)	
Assigned Surprise Unsecured loan	-0.0533		-0.254		0.0317		-0.0333	
	(0.171)		(0.186)		(0.191)		(0.192)	
Assigned Unsecured loan	0.166		-0.000621		0.0484		-0.0485	
	(0.170)		(0.185)		(0.190)		(0.191)	
Assigned any loan		0.0468		-0.103		0.0258		-0.0254
		(0.150)		(0.163)		(0.167)		(0.168)
Outcome control mean (level)	238	238	96	96	234	234	-234	-234
P value from K-W H test	0.585		0.521		0.937		0.914	
P value from M-W U test		0.998		0.509		0.900		0.907
n	1836	1836	1836	1836	1836	1836	1836	1836

Note: Standard errors in parentheses. The above analysis uses the Intent to Treat (ITT) from loan assignment. "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. Winsorizing takes place before IHST transformation. Values were converted to USD prior to IHST transformation (note that 1 USD was equal to approximately 3,704 UGX in 2019). For 31 individuals who reported Fenix as a creditor, the amount of the school fee loan was added back into the total amount reported to have been borrowed. * $p < .10$, ** $p < .05$, *** $p < .01$

Table A.14: Effect on Household Balance Sheet, Regressions, IHST Transformation (LATE)

	Asset value (IHST)	Asset value (IHST)	Money borrowed (IHST)	Money borrowed (IHST)	Net difference (IHST)	Net difference (IHST)
Assigned Secured loan	0.0124		-0.00858		0.274	
	(0.232)		(0.426)		(0.873)	
Assigned Surprise Unsecured loan	-0.223		-0.103		0.0140	
	(0.198)		(0.364)		(0.747)	
Assigned Unsecured loan	-0.151		0.318		-0.185	
	(0.184)		(0.339)		(0.694)	
Assigned any loan		-0.171		0.108		-0.0150
		(0.204)		(0.374)		(0.767)
Outcome control mean (level)	1810	1810	553	553	1258	1258
n	1830	1830	1830	1830	1830	1830

Note: Standard errors in parentheses. The above analysis uses the Local Average Treatment Effect (LATE). The LATE measures the average treatment effect for compliers, using actual receipt of a school fee loan type (or any school fee loan) as the endogenous variable (see the Appendix for Intent to Treat (ITT) results). "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. "Money borrowed" is the sum of the amount borrowed over the 12 months prior to the baseline survey (recorded at baseline) and the amount over the 6 months prior to the endline survey (recorded at endline). The components for "asset value" and "money borrowed" are winsorized at the 99th percentile prior to IHST transformations. "Net difference" records the difference between "asset value" and "money borrowed." Values were converted to USD prior to IHST transformation (note that 1 USD was equal to approximately 3,704 UGX in 2019). For 31 individuals who reported Fenix as a creditor, the amount of the school fee loan was added back into the total amount reported to have been borrowed. The number of observations differs from that in Table A.12 because the outcomes in this table relies on having reported values at baseline. * $p < .10$, ** $p < .05$, *** $p < .01$

Table A.15: Effect on Household Balance Sheet, Regressions, IHST Transformation (ITT)

	Asset value (IHST)	Asset value (IHST)	Money borrowed (IHST)	Money borrowed (IHST)	Net difference (IHST)	Net difference (IHST)
Assigned Secured loan	0.00611		-0.00421		0.135	
	(0.114)		(0.209)		(0.429)	
Assigned Surprise Unsecured loan	-0.114		-0.0529		0.00716	
	(0.102)		(0.187)		(0.383)	
Assigned Unsecured loan	-0.0826		0.174		-0.102	
	(0.101)		(0.186)		(0.381)	
Assigned any loan		-0.0746		0.0472		-0.00655
		(0.0892)		(0.164)		(0.335)
Outcome control mean (level)	1810	1810	553	553	1258	1258
P value from K-W H test	0.521		0.547		0.728	
P value from M-W U test		0.221		0.953		0.458
n	1830	1830	1830	1830	1830	1830

Note: Standard errors in parentheses. The above analysis uses the Intent to Treat (ITT) from loan assignment. "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. "Money borrowed" is the sum of the amount borrowed over the 12 months prior to the baseline survey (recorded at baseline) and the amount over the 6 months prior to the endline survey (recorded at endline). The components for "asset value" and "money borrowed" are winsorized at the 99th percentile prior to IHST transformations. "Net difference" records the difference between "asset value" and "money borrowed." Values were converted to USD prior to IHST transformation (note that 1 USD was equal to approximately 3,704 UGX in 2019). For 31 individuals who reported Fenix as a creditor, the amount of the school fee loan was added back into the total amount reported to have been borrowed. The number of observations differs from that in Table A.13 because the outcomes in this table relies on having reported values at baseline. * $p < .10$, ** $p < .05$, *** $p < .01$

Table A.16: Effect on Household Balance Sheet, Regressions, Levels (LATE)

	Asset value	Asset value	Money borrowed	Money borrowed	Net difference	Net difference
Assigned Secured loan	119		26		93	
	(375)		(149)		(376)	
Assigned Surprise Unsecured loan	-221		-10		-211	
	(321)		(128)		(322)	
Assigned Unsecured loan	-7		61		-68	
	(299)		(119)		(300)	
Assigned any loan		-72		32		-104
		(330)		(131)		(331)
Outcome control mean (level)	1810	1810	553	553	1258	1258
n	1830	1830	1830	1830	1830	1830

Note: Standard errors in parentheses. The above analysis uses the Local Average Treatment Effect (LATE). The LATE measures the average treatment effect for compliers, using actual receipt of a school fee loan type (or any school fee loan) as the endogenous variable (see the Appendix for Intent to Treat (ITT) results). "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. "Money borrowed" is the sum of the amount borrowed over the 12 months prior to the baseline survey (recorded at baseline) and the amount over the 6 months prior to the endline survey (recorded at endline). The components for "asset value" and "money borrowed" are winsorized at the 99th percentile. "Net difference" records the difference between "asset value" and "money borrowed." Values were converted to USD (note that 1 USD was equal to approximately 3,704 UGX in 2019). For 31 individuals who reported Fenix as a creditor, the amount of the school fee loan was added back into the total amount reported to have been borrowed. The number of observations differs from that in Table A.12 because the outcomes in this table relies on having reported values at baseline. * $p < .10$, ** $p < .05$, *** $p < .01$

Table A.17: Effect on Household Balance Sheet, Regressions, Levels (ITT)

	Asset value	Asset value	Money borrowed	Money borrowed	Net difference	Net difference
Assigned Secured loan	58		13		46	
	(185)		(73)		(185)	
Assigned Surprise Unsecured loan	-113		-5		-108	
	(165)		(65)		(165)	
Assigned Unsecured loan	-4		33		-37	
	(164)		(65)		(164)	
Assigned any loan		-31		14		-45
		(144)		(57)		(145)
Outcome control mean (level)	1810	1810	553	553	1258	1258
P value from K-W H test	0.532		0.529		0.728	
P value from M-W U test		0.221		0.945		0.458
n	1830	1830	1830	1830	1830	1830

Note: Standard errors in parentheses. The above analysis uses the Intent to Treat (ITT) from loan assignment. "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. "Money borrowed" is the sum of the amount borrowed over the 12 months prior to the baseline survey (recorded at baseline) and the amount over the 6 months prior to the endline survey (recorded at endline). The components for "asset value" and "money borrowed" are winsorized at the 99th percentile. "Net difference" records the difference between "asset value" and "money borrowed." Values were converted to USD (note that 1 USD was equal to approximately 3,704 UGX in 2019). For 31 individuals who reported Fenix as a creditor, the amount of the school fee loan was added back into the total amount reported to have been borrowed. The number of observations differs from that in Table A.13 because the outcomes in this table relies on having reported values at baseline. * $p < .10$, ** $p < .05$, *** $p < .01$

Table A.18: Effect on Asset Purchases, Sales, and Money Borrowed in the Last 6 Months (ITT)

	Asset purchases (IHST)	Asset sales (IHST)	Money borrowed (IHST)	Net difference (IHST)
Loan	0.048	-0.102	0.026	0.026
	(0.157)	(0.153)	(0.172)	(0.173)
Outcome control mean (USD, level)	238	96	234	-234
n	1836	1836	1836	1836

Note: Standard errors in parentheses. The above analysis uses the Intent to Treat (ITT) estimates to derive semi-elasticities. "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 were converted to USD prior to IHST transformation (note that 1 USD was equal to approximately 3,704 UGX in 2019). Winsorizing at the 99th percentile takes place before IHST transformation. For 31 individuals who reported Fenix as a creditor, the amount of the school fee loan was added back into the total amount reported to have been borrowed. Loan refers to the semi-elasticity calculated following the exact method from Bellemare and Wichman (2019), following arguments from Halvorsen and Palmquist (1980), Kennedy (1981) and Giles (1982). * $p < .10$, ** $p < .05$, *** $p < .01$

Table A.19: Effect on Household Balance Sheet (ITT)

	Asset value (IHST)	Money borrowed (IHST)	Net difference (IHST)
Loan	-0.072	0.047	-0.007
	(0.083)	(0.171)	(0.333)
Outcome control mean (USD, level)	1810	553	1258
n	1830	1830	1830

Note: Standard errors in parentheses. The above analysis uses the Intent to Treat (ITT) from loan assignment. "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. "Money borrowed" is the sum of the amount borrowed over the 12 months prior to the baseline survey (recorded at baseline) and the amount over the 6 months prior to the endline survey (recorded at endline). The components for "asset value" and "money borrowed" are winsorized at the 99th percentile prior to IHST transformations. "Net difference" records the difference between "asset value" and "money borrowed." Values were converted to USD prior to IHST transformation (note that 1 USD was equal to approximately 3,704 UGX in 2019). For 31 individuals who reported Fenix as a creditor, the amount of the school fee loan was added back into the total amount reported to have been borrowed. Loan refers to the semi-elasticity calculated following the exact method from Bellemare and Wichman (2019), following arguments from Halvorsen and Palmquist (1980), Kennedy (1981) and Giles (1982). The number of observations differs from that in Table A.18 because the outcomes in this table relies on having reported values at baseline. * $p < .10$, ** $p < .05$, *** $p < .01$

Table A.20: Tests of Lockout, Adverse Selection, and Moral Hazard, Risk (Interactions Model) (ITT)

	Lockout	Adverse Selection	Moral Hazard
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 or loan completion. The analysis is run on the sample at the 150th day (for loan repayment) or 200th day (for loan completion) from origination. Under "Lockout" 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. "×" represents an interaction. * $p < .10$, ** $p < .05$, *** $p < .01$

Table A.21: Tests of Lockout, Adverse Selection, and Moral Hazard, WTP (Interactions Model) (LATE)

	Lockout	Adverse Selection	Moral Hazard
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

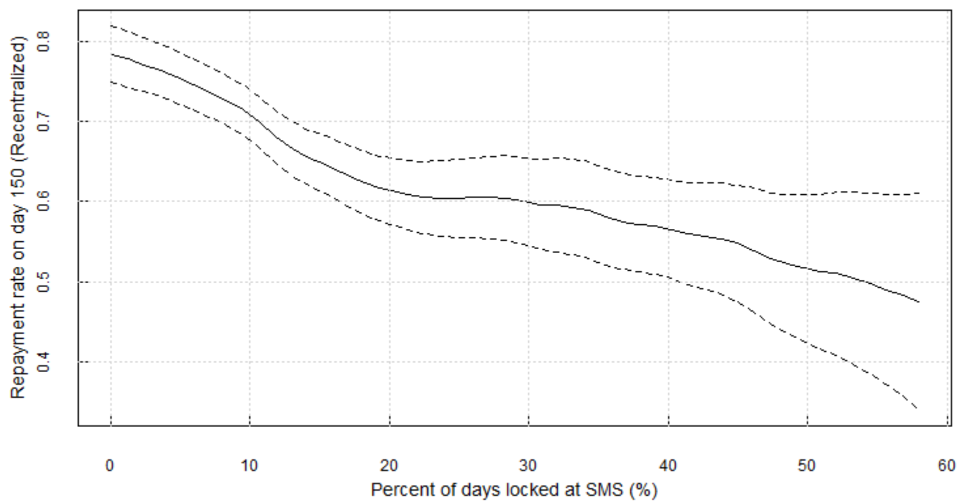
Note: Standard errors in parentheses. Loan repayment is measured by the cumulative proportion of the loan principal repaid. Loan completion describes whether the loan principal has been repaid. The above results display the Local Average Treatment Effect (LATE), which measures the average treatment effect on either loan repayment or loan completion for compliers, using the share of days in compliance as the endogenous variable (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 origination. Under "Lockout" 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-locked solar home system the next day. "×" represents an interaction. * $p < .10$, ** $p < .05$, *** $p < .01$

Table A.22: Tests of Lockout, Adverse Selection, and Moral Hazard, WTP (Interactions Model) (ITT)

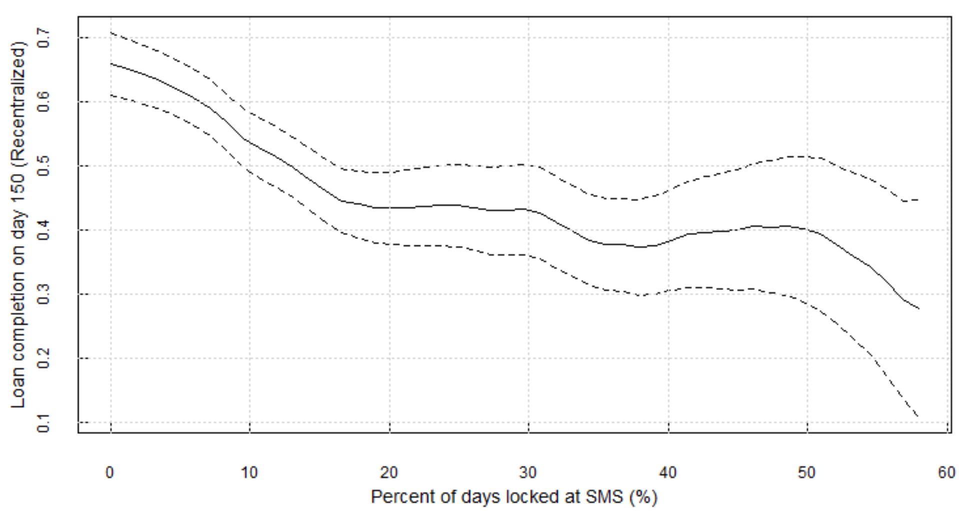
	Lockout	Adverse Selection	Moral Hazard
On Loan Repayment at 150 days			
Treatment	0.08	0.02	0.06
	(0.06)	(0.05)	(0.06)
Treatment × Median WTP or above	0.09	0.06	0.03
	(0.08)	(0.07)	(0.08)
Median WTP or above	0.01	0.01	0.07
	(0.05)	(0.05)	(0.05)
Constant	0.58***	0.58***	0.60***
	(0.04)	(0.04)	(0.04)
On Loan Completion at 200 days			
Treatment	0.13*	0.00	0.12*
	(0.07)	(0.06)	(0.07)
Treatment × Median WTP or above	0.08	0.07	0.01
	(0.09)	(0.08)	(0.09)
Median WTP or above	0.00	0.00	0.07
	(0.06)	(0.06)	(0.06)
Constant	0.50***	0.50***	0.50***
	(0.04)	(0.04)	(0.04)
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 Intent to Treat (ITT) analysis, which measures the average effect of assignment on loan repayment or loan completion. The analysis is run on the sample at the 150th day (for loan repayment) or 200th day (for loan completion) from origination. Under "Lockout" 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-locked solar home system the next day. "×" represents an interaction. * $p < .10$, ** $p < .05$, *** $p < .01$

Figure A.1: Loan Repayment (Completion) by Percent of Days Locked on Day 150



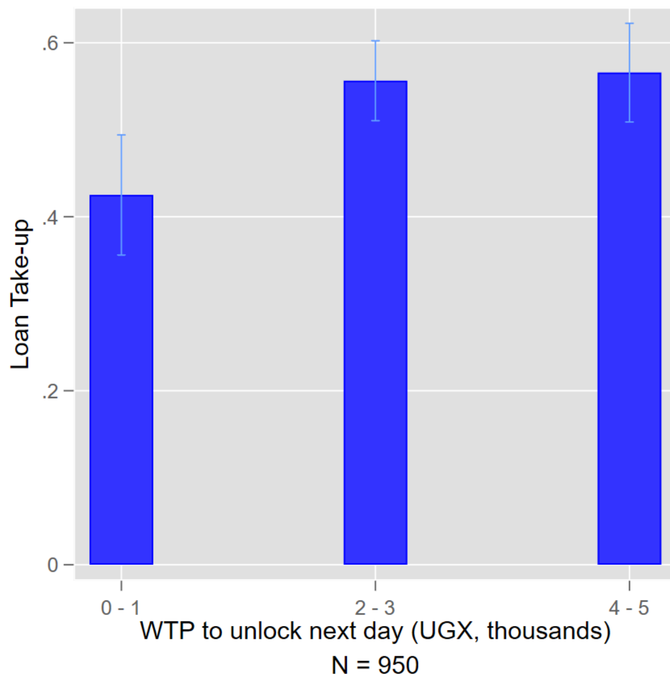
(a) Loan repayment



(b) Loan completion

Note: 95% confidence intervals (displayed with dotted lines) are obtained via bootstrapping. Percent of days locked at SMS is trimmed at 1% and 99%. Repayment (completion) rate on day 150 is residualized to remove the effects of treatments and recentralized to the mean of the Secured group.

Figure A.2: 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 being 0 or 1,000 UGX are in the first group, being 2,000 or 3,000 UGX in the second group, and being 4,000 or 5,000 in the third group. The average loan take-up by willingness to pay is plotted and 95% confidence intervals are 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).

A.2 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 $(1-q_i)F(p/\lambda)$. $\square$

Proof of Proposition 2. By hypothesis, $S_1(p)=(1-\lambda)\mathbb{E}(\tilde{v}_i)<S_0(p)=\int_{\underline{v}}^{\overline{v}}\max\{v-p,(1-\lambda)v\}dF(v)$. Hence, there must exist v such that the household does not strategically default (i.e., $\overline{v}>p/\lambda$) 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 (2), 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 $\frac{\partial S_j}{\partial\lambda}\leq -q_j\mathbb{E}(\tilde{v}_i)<0$. $\square$

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 $\text{argmax} S_i(p_i)+R_i(p_i)-c$. 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, $d_i=w$. $\square$

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 (5) is independent of the two parameters and increasing in v (by Assumption 4). The right-hand side of (5) 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. $\square$

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 $w+R_i(S_i^{-1}(w))-c$. $\square$

Proof of Proposition 5. It is straightforward to argue that the constraint in (6) binds with equality. If not, then the firm could lower d and increase U_i. We can therefore rewrite the program (6) as

$$\begin{aligned}(d_i,p_i)\in&\underset{d,p}{\text{argmax}}\,U_i(d,p)+\pi_i(d,p)\\ s.t.\quad&\pi_i(d,p)=0\end{aligned}\tag{10}$$

Since d does not enter the objective of (10) 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). $\square$