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by

Eilin Liz Francis

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The Dissertation of Eilin Liz Francis
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Abstract

Essays in the Economics of Development and Behavior

by

Eilin Liz Francis

This dissertation consists of three self-contained chapters in economics.

In the first chapter, I study the demand for, and welfare impacts of, costly self-control. I offer Malawian micro-entrepreneurs solar lamps for purchase, for which payment can be completed either in weekly installments or as a single deferred lump sum payment. An incentive-compatible willingness-to-pay experiment reveals that individuals are willing to pay a premium of nearly 22 percent of the price of the solar device to pay for it in weekly installments. Lack of access to secure savings technologies, and demand for self control rules can both drive demand for the installments plan. To identify the relative importance of each of these factors, I induce experimental variation in access to a secure savings technology. Despite a 15 percent reduction in the premium among those given the savings technology, it remains large and significant indicating that there are barriers to saving beyond access to basic savings products. Paying in installments increases the probability of timely completion of payment by 13 percentage points, but defaulters are hurt more by the installments plan than the lump sum plan.

The second chapter is co-authored work with Shilpa Aggarwal and Jonathan Robinson. Many farmers in the developing world lack access to effective savings and storage devices. Such devices might be particularly valuable for farmers since income is

received as a lump sum at harvest but expenditures are incurred throughout the year, and because grain prices are low at harvest but rise over the year. We experimentally provided two saving schemes to 132 ROSCAs in Kenya, one designed around communally storing maize and the other around saving cash for inputs. About 56% of respondents took up the products. Respondents in the maize storage intervention were 23 percentage points more likely to store maize (on a base of 69%), 37 percentage points more likely to sell maize (on a base of 36%) and (conditional on selling) sold later and at higher prices. We find no effects of the individual input savings intervention on input usage, likely because baseline input adoption was higher than expected.

The final chapter is co-authored with Joshua Blumenstock and Jonathan Robinson. In the past few years, digital credit has emerged as an alternative mechanism for providing short-term loans. In this chapter, we summarize the current state of digital credit, focusing primarily on the currently dominant form of credit ? consumer loans offered through mobile money systems, often backed by a financial institution. We summarize the current landscape, and we discuss various ways in which digital credit will represent a change from previously available forms of credit, in particular microcredit or bank loans. We conclude with some possible directions for further research.

To Ijja, Thatha, Amma, and Kippy.

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1

Paying to Repay? Experimental Evidence on Repayment Commitment

1.1 Introduction

Self control can be elusive – rarely persistent, and always difficult. Consequently, many choose to restrict choice sets of future behavior. This strategy is at least weakly dominated from a neo-classical perspective, but it can often be an effective way to reduce the effort cost of resisting temptation. For example, individuals may choose contracts that commit to future provision of effort [17, 119] even when such contracts are costly [164], and may not always be optimal [14].[1] Failure at self control can have

[1] The classical perspective of decision utility assumes that preferences that are consistent with each other, and with the axioms of rational choice are utility-maximizing. A behavioral framework of decision-making, on the other hand, does not assume that utility is always maximized. As [111] discuss, individuals do not always make accurate predictions of future outcomes when making choices, and hence choices may not always maximize utility. For example, [14] find that students set deadlines to force self control rules. While the deadlines improve performance, students do not select optimal deadlines.

negative consequences, and these consequences can be particularly severe for the poor[2] by preventing them from making useful and necessary investments.[3] In this paper, I study the demand for, and welfare impacts of, costly self control among Malawian micro-entrepreneurs. The study population is offered a solar lamp for purchase – a very useful investment for this population who are overwhelmingly disconnected from the electric grid. Then, among those who receive the offer to purchase the solar lamp, I elicit willingness to pay for the lamp with one of two types of deferred payment plan.

With the deferred payment plan, the solar lamp has to be completely paid either in eight equal, weekly installments or as a single lump sum paid *end* of eight weeks. The installments plan is designed to be a costly repayment strategy in this experiment. First, the solar light supports a technology that causes the light to become "inactive" every time a scheduled payment is not fulfilled. An inactive device does not provide energy and remains unusable until outstanding payment is covered completely. So, those who choose to pay in installments face the risk of the lamp switching to inactive status each time they are unable to adhere by the weekly payment schedule. Next, for those with investment opportunities with a positive return, the most obvious cost of the installment plan is foregone returns on investment, which is usually quite high among micro-enterprises in the developing world.[4] Paying in installments also

[2]Moreover, exercising self control can be more effortful for the poor. The cognitive load of pressing, and persistent budgetary concerns may make the poor more likely to fail at exercising self-control [129].

[3]The literature provides several examples of useful and cost-effective investments that require large lump sums. A behavioral model can explain why individuals may find it difficult to save to fulfil some of these investments needs, for example in agriculture [71, 29] or health [76, 160]

[4]For example, [64] and [117].

leads to less liquidity. This can be a considerable cost with serious impacts for the poor or those with limited access to liquidity or credit.[5] Finally, the experimental installment price is often higher than the lump price, resulting in the installment plan being straightforwardly more expensive.

An incentive-compatible willingness-to-pay (WTP) experiment is used to measure revealed preference to pay in installments. In this exercise, individuals choose whether to pay the lump sum price, $P_L =$MWK 20,000,[6] as one deferred lump sum amount, or an installment price $P_{ins} = P_L(1 + r)$ in equal, weekly installments. Every respondent makes this choice for each $r \in$ (-0.10, 0, 0.10, 0.20, 0.25, 0.30). Next, to compare demand with installment and lump sum plan, every respondent is asked whether she would purchase the lamp at P_{ins} paid as a deferred lump sum at the end of eight weeks. Thus, the WTP exercise records twelve responses for each individual in the deferred payment group. Before they make these choices, all respondents are informed that the solar lamp will be shut off when a payment is not completed. The results indicate that individuals are willing to pay a premium for the rigid installments plan. At installment prices that are equal to or greater than the lump sum price, 92 percent of the population choose to pay in installments. When the installment price is strictly greater than the lump sum price, 75 percent of the population still choose to pay in installments. And, at every price, demand is far greater if payment is completed in installments rather than

[5] [105] and [77] provide evidence that poor households respond to shocks by reducing schooling and increasing child labor.

[6] At the time of the experiment, the exchange rate was roughly MWK 720/USD 1.

a deferred lump sum.[7]

Demand for installments may be driven by at least two challenges to save – lack of a secure place to hold savings, and intra-personal conflicts that undermine savings plans. In the absence of a secure place to hold savings, individuals may worry about theft of their savings, especially liquid savings. In fact, 12 percent of respondents cite this as the reason for choosing the installments plan (Table A1). The installments plan can also help impose self control rules. Abandoning self control rules, and succumbing to temptation is usually associated with positive utility in the contemporaneous period, and negative or zero utility in the future. The installments plan distorts this outcome by generating immediate negative utility (of the lamp turning off) when breaking self control rules. This, in turn, reduces the benefit of giving in to temptation, and consequently, the effort cost associated with resisting temptation is lowered. Second, individuals may be tempted to spend savings that are at their disposal, especially when these savings are accumulated in small denominations. The installments plan is an effective way to prevent future selves from diverting savings to other uses. In this sample, 70 percent of respondents report choosing the installments plan as a mechanism to impose self control.

In order to distinguish between these drivers of the demand for installments,

[7]Time-payments are popular in other contexts because they allow for relatively low-cost experimentation of unfamiliar technology [141]. However, in this study setting choosing the lump sum plan is the cheaper contract to experiment with solar technology, because with this plan the lamp can be used without any payment for eight weeks.

I provide access to a secure savings technology – a lockbox (with padlock and key)– to one half of the population, and encourage them to use this lockbox to save for the solar lamp. Importantly, the lockbox is provided before the WTP experiment is implemented. Because respondents retain access to the key, the lockbox is unlikely to have a meaningful impact on exercising self control.[8] I compare the premium that individuals with and without the box are willing to pay for the installments plan and find that respondents who are not offered the lockbox are willing to pay about 22 percent of the lamp's price as a premium for the installments plan. In the group that is offered the box, this premium reduces by a significant 15 percentage points – a reduction that is attributable to gaining access to a secure place to hold savings. Despite this reduction, the demand for installments continues to be significant. Thus, lack of access to a secure place is an important, but not the only, reason to demand the installments plan. The costly task of imposing self control rules continues to be an important determinant of the demand for installments.

Paying in installments can be helpful for some people. The probability of completely paying for the lamp within the scheduled time increases by 10-13 percent in the installments group. But, commitment can be utility-reducing. This experiment is designed to measure one way through which the repayment plan affects individual-utility

[8] [76] show that a lockbox can be helpful in increasing savings by offering a secure storage technology. In the present experiment, users retain access to the key. Hence, they can access money in the lockbox quite easily. And while withdrawing money from the lockbox may induce some transactional cost (relative to accessing money on the person, for example) or some psychic cost (associated with mental accounting), these costs may not provide strong self control rules.

– the probability of having a solar lamp that is fully paid for at the end of the study period. This strategy allows precise, albeit narrow, measure of the welfare impacts of the installment plan. The installment plan increases probability of having an active lamp by about 10-13 percentage points. But, those who failed to complete payment were hurt more by the installments plan than the lump sum plan. On average, 65 percent of those who failed to complete payment in the installment group made at least one installment payment towards the lamp. And, defaulters on the installment plan had the light shut-off for nearly three weeks due to incomplete payment. Everyone who failed to complete paying for the lamp in the lump sum group was able to use it for eight weeks, without making any payment.[9]

After completing the WTP exercise, the solar lamp is offered for purchase at MWK 20,000 and on a randomly determined repayment plan (either installments or deferred lump sum) or, for a random 10 percent of the population, at one of the choices of the WTP exercise. Purchase decisions indicate that, in addition to the challenges to save, credit constraints are important in driving the decision to invest in solar technology.[10] Purchase of the solar lights is 4 percent in the group assigned to

[9] Qualitative evidence suggests that people feel optimistic about being able to complete payment for the solar lamp at a later date. At the end of the eighth week, defaulting respondents received a surprise offer to return the lamp back to receive some repayment against the payment they made. Individuals who made at least one payment but were unable to complete full payment against the lamp should use this offer to get their money back (or some fraction of it if the solar lamp is not returned in good condition). No one who made at least some payment against the solar lamp took up this offer. The most commonly cited reason for this was that people planned to complete payment for the lamp at our partner's office at a later date. As of the first week of November (roughly 7 weeks after the end of the study), 17.5 percent of respondents paid the outstanding balance on their solar lamps.

[10] [68] provide evidence that access to credit increases willingness-to-pay for private water connection in Morocco. Relieving credit constrains has also had significant demand for several other health-improving products, like ceramic water filters [93] and fuel-efficient cookstoves [126].

payment-at-purchase, whereas 49 percent of those assigned to deferred payment group decide to take a solar lamp. This measure is roughly comparable with documented purchase rates of goods with lumpy upfront costs and relatively long stream of benefits [15, 56, 160].

The reminder of the paper is organized as follows. I describe how this research builds on, and contributes to the existing literature in section 2. After describing the background for this study in section 3, I lay out a basic framework to motivate demand for the installments plan in section 4. The experimental design is explained in section 5. I present results that show demand for installments, and outcomes related to purchase in section 6, and then conclude in section 7.

1.2 Relationship to the Literature

This paper contributes to the literature on the demand for self control rules to overcome undesirable behavior, like procrastination, impatience or poor health practices. [16] provide evidence of demand for commitment savings accounts among women, and the accounts' effectiveness in increasing savings among bank clients. Demand for commitment to save can manifest as demand for less conventional savings products. In this paper, this is preference to pay for the solar lamp in several, smaller payments. This interpretation of the demand for installments as a commitment to repay adds to the literature that shows how behavioral devices and arrangements may help overcome the challenges posed by difficult self control to saving [92, 59]. Frequency of repayment is a salient mechanism in behavioral approaches to saving. For example, [27] provide evidence that some part of the popularity for microcredit loans stems from how these loans impose discipline to savings behavior.[11] They show that women with need for self control are more likely to choose microcredit over traditional forms of credit for which repayment has to be completed in a single installment.

Further, this paper adds to the nascent evidence base that shows willingness to pay for commitment contracts [51, 153]. Further, demand for commitment that is as rigid as in this experiment is striking. The installments plan is a rigid repayment contract because individuals are effectively pledging their access to a functioning solar light for the study period of eight weeks. In addition to the disutility of the lamp turning off during the experimental period, and the associated monetary costs of paying for other forms of lighting makes the installment plan potentially quite punitive. The installments plan also leads to less liquidity. What makes the installment plan rigid relative to other commitment devices in the literature is that respondents cannot choose to revise how much they are willing to pay for self control on the intensive margin after they select into a commitment plan. Commonly studied commitment contracts offer some flexibility to soften the blow of failing at self control by allowing individuals to refine their commitment contract on the intensive margin, for example by depositing less money into a designated account when users feel that they may fail at the commitment

[11] [27] show that present-biased preferences increase the probability of selecting microcredit, instead of credit with less frequent repayment cycles, as the vehicle for borrowing.

rule.[12]

Temptation to save less can undermine long-term plans, and commitment can help against this.[13] Welfare in the current experiment is defined to be ownership of a solar device that is paid for in full. This focused definition of welfare allows me to measure how individuals fare when they choose to self-impose commitment. My results show that commitment can help achieve savings goals, but that those who fail at commitment can be hurt more than those who do not when they fail at their commitment goals. A related work is [109] who offers savings accounts with the option to commit to make weekly or bi-weekly deposits. The instalment commitment increased savings, but 55 percent of the clients who committed to make frequent payments defaulted on their contract and incurred penalties.

This paper also adds to the literature on the impact of financial access by demonstrating the access to savings technology can have an immediate, perceptible impact on beliefs about future behaviors and outcomes. Access to a financial account or savings technology has been shown to lead to a host of beneficial downstream outcomes, like reduction in poverty [46], better education and consumption outcomes [**?**, 147], improved firm-level outcomes [75], and reduced debt [118]. In this project, access to the

[12] For example, [86] offer smokers a savings account which restricts access to deposits for six months. Deposits in this account will be returned to study participants who pass a test that verifies smoking cessation, and is otherwise donated to charity. Despite the possibility of not regaining money deposited into the account, 11 percent take up the product, but the amount they deposit into the account is self-selected.

[13]. [71] find that farmers who are able to purchase fertilizer at the time of harvest, and well in advance of the next planting season, are much more likely to use fertilizer when planting next.

savings technology leads to a significant increase in the probability of purchasing the lamp, in the range of 13-20 percent. The downward revision in demand for the costly self control mechanism of paying in installments with access to the lockbox adds to the evidence base on how financial accounts can also have less tangible, but nevertheless important, impacts. Another example of the behavioral impacts of financial accounts is reported by [50] who demonstrate that savings accounts increased increased willingness to take risks and to delay gratification among households in Nepal.

Finally, I estimate the effects of solar lamp usage. This is one of a handful of studies that look at the impact of entry-level solar lights. I use daily records to evaluate the impact of treatment on outcome variables of interest. Treated individuals experience significant reduction in off-grid lighting expenditures at home and business. They also report a significant reduction in the number of hours that their phone is without charge, and a 96 percent reduction in phone recharging costs. I do not find a significant impact on business outcomes.[14] In a field experiment in Kenya, [150] offered households the option to purchase solar lights and find that adults' working hours and children's study hours are not significant affected by usage. They too find a significant reduction in off-grid lighting expenditure.[15]

[14] [2] offer Tanzanian households varying subsidy-levels for solar lights, and find impacts on expenditure on lighting and mobile phone charging as well as labor outcomes.

[15] [8] also find no socioeconomic impacts of solar technology despite strong electrification and expenditure effects.

1.3 Background

Policymakers working to bring power to the 1 billion people who live without electricity today are shifting their focus towards clean, renewable energy to bring sustainable access to power. Malawi is one of the least electrified countries in the world (World Bank Global Electrification Database). In the study sample, about 80 percent of homes, and 90 percent of business are not connected to the electric grid. And, those connected to the grid spend 2 percent of monthly household income on electricity expenditure. Non-grid lighting is more commonly used – 69 (59) percent use battery-operated lights, and 38 (14) percent use candles to light their homes (shops), and the average household spends 4 percent of its monthly income on lighting needs for the home and shop. Solar technology is a compelling alternative to expensive, and often dangerous and unreliable, fuel-based lighting. For example, in the study setting users of the product are able to recoup the lamp's price in about three months.

Solar devices come in a broad range of sizes and functionalities. The smaller devices, for example, consist of a single bulb, whereas larger solar modules can power appliances like fans and televisions. Solar lights offer a stream of monetary benefit, among other possible benefits, accrued as savings on energy expenditure. But, these savings are not available at the time of purchasing solar devices, making even a basic solar light prohibitively expensive for those in most need of them. Pay-as-you-go services have made many useful products more affordable for large numbers of people in developing countries by allowing inter-temporal reallocation of debt. This inter-temporal reallocation of debt can be especially useful when making investments that offer a stream of income or savings in the future, like a solar lamp.[16]

Another reason for the popularity of these plans, as the present study shows, could be that they allow consumers to commit to self control rules. As reported in Table A1, nearly 71 percent of the respondents who preferred the installments plan reported that this is to control their spending habits. The next most-frequently cited reason is the threat of theft (12 percent). Other evidence show that social pressure to share income can have strong impacts on women [106, 13]. Inter-personnel demands to share income does not seem to be an important reason to demand installments in this largely-male study population.

The solar light used in this project is the ovPilot X, manufactured by Omnivoltaic and distributed by SunnyMoney in Malawi (Figure A2). This product has both lighting and mobile charging capabilities. At full charge, the light is functional for 8 hours at 100 lumens, 16 hours at 50 lumens, and and 38 hours at 29 lumens.[17] This product is particularly well-suited for payment-by-installments. The solar light can be sold in "locked" status. A locked lamp can be set to remain turned on and functional until the next installment is due. Every installment payment tops-up the solar device with

[16] Global PAYG revenue was USD 41.5 million in the second half of 2016, and half of the products were sold in Sub-Saharan Africa. Currently, more than 85 million people are using off-grid solar technology devices [87].

[17] By way of context, a 40-watt incandescent bulb gives about 450 lumens of light.

enough energy credit for the device to remain functional until the following payment date. Making each scheduled payment, then, tops up the device with energy credits to keep the device active. When the solar device is completely paid for, the device achieves "unlocked" status and can be used without further toping up.

While solar lights have been available in Malawi for several years now, pay-as-you-go (PAYG) financing became viable just recently after introduction of the technology which allows for incremental payments for time-limited access to solar energy.[18] At the time of this study, the PAYG product was quite new to Malawi, and approximately 1,000 lights had been sold country-wide. A large fraction of the study participants knew of solar technology (64.4 percent), but very few owned a solar device (4.5 percent).

1.4 A Framework to Motivate Preference for Installments

Consider a credit-constrained individual with hyperbolic preferences. There are two time periods, $t = 1, 2$. During each of these time periods, the individual receives non-stochastic income 1, which she can choose to spend on a single consumption good. The behavioral agent is modelled as having time-specific selves, each with different preferences. Time-0 self is the planner with no contemporaneous consumption. In all other periods, future consumption is discounted at $\beta < 1$. So, time-1 utility, for example,

[18] Prior to the described PAYG technology, a similar light from the same manufacturer was available for purchase at MWK 20,000 paid upfront and in full. The non-PAYG version of the light has only two light settings-8.5 hours at 74 lumens or 35 hours at 12 lumens. The older model, too, has mobile charging capability.

is given by:

$$U(c_1) + \beta U(c_2), \tag{1.1}$$

and time-0 utility is given by:

$$\mathbb{E}[U(c_1) + U(c_2)]. \tag{1.2}$$

Here U is increasing, concave and continuously differentiable.

The individual may experience a taste shock, which increases the marginal utility of present-period consumption, with probability $\Theta = \{\theta_B, \theta_S, \theta_{NS}\}$. These shocks are private information to the time-specific selves. With probability θ_B, the individual faces a big shock and she consumes all that she has on hand. And, with probability θ_S, she experiences a small shock and consumes half of what is available to her. Finally, with probability $\theta_{NS} = (1 - \theta_B - \theta_S)$, the individual faces no taste shock. All possible states of the world are equally likely.

1.4.1 Frequency of Repayment

At time 0, the individual decides whether to purchase a durable on one of two types of deferred payment plans. The durable is available for use immediately at no payment. The durable's price is $p = 2/3$, has to be paid within time 2. If she buys the durable, she has to save some part of her income to pay for the durable.

With the first repayment plan, the installments plan (subscripted I in all expressions below), the individual enjoys benefit b in time 1. She continues to receive b in time 2 if and only if she makes a payment of at least $p/2$ within time 2 (so, either in $t = 1$ or $t = 2$). I assume that $b = p/4$. With the second repayment plan, the lump sum plan (subscripted L in all expressions below), the individual enjoys benefit b in both times 1 and 2 without having to make any payment, and is instead required to pay p as one lump sum at time 2. If the durable is completely paid for within time 2, the individual enjoys lifetime utility $U(D)$, such that $\beta U(D) = 1$.

A. No Shock in time 1

Consider the ex-ante first-best allocation in the state with no shock, $c_1 = c_2 = 1-p/2$ as the benchmark allocation. If self 1 experiences no shock, she saves $p/2$ and makes this payment for the durable at the end of time 1 with the installment plan. The individual holds on to this saving, $p/2$, if she buys the durable on the lump sum plan. Thus, self 2 receives b in time 2 with both the installments plan and the lump sum plan. Self 2 can choose to save $p/2$ for the durable, or, alternatively, she can choose to quit saving for the durable. In time 2, the individual may experience a big shock, a small shock or have another period of no shock.

First, consider that self 2 experiences big shock. She consumes everything and utility under each of the repayment plans are,

$$\mathbb{E}[U^2_{I,\theta_B}(\Theta)] = U(1+b),$$
$$\mathbb{E}[U^2_{L,\theta_B}(\Theta)] = U(1+b+p/2). \tag{1.3}$$

Expected lifetime utility at time-0 is maximized from choosing to buy the durable on the lump sum plan. This is because savings from time 1 can be consumed in time 2 with the lump sum plan, but not with the installments plan.

With probability θ_S, self 2 experiences a small shock. In time 2, the individual spends half of her income in response to the taste shock. The outstanding payment against the durable is $p/2 = 1/3$, and self 2 consumes the rest. And, if she quits saving for the durable, she receives b since she paid $p/2$ in time 2. With the lump sum plan, self-2 has $1 + p/2 = 4/3$ on hand. She spends half of this to respond to the taste shock, and is left with 2/3 which is used in entirety to pay for the durable. Alternatively, self 2 can quit saving for the durable and spend her income and previous period savings on the consumption good.

$$U^2_{I,\theta_S,save}(\Theta) = U(1 - 1/2 - p/2 + b) + \beta U(D),$$
$$U^2_{I,\theta_S,quit}(\Theta) = U(1 - 1/2 + b),$$
$$U^2_{L,\theta_S,save}(\Theta) = U(1 + p/2 - 1/2 - p/4 + b) + \beta U(D),$$
$$U^2_{L,\theta_S,quit}(\Theta) = U(1 + p/2 + b). \tag{1.4}$$

Under both plans, continuing to save for the durable is the dominated choice. But, lifetime utility is maximized with the installments plan, and thus self 2 chooses to purchase the durable on the installments plan.

Finally, if both selves 1 and 2 experience periods of no shock, utility in time 2 from saving for the durable and quitting to save are,

$$\begin{aligned}
&U^2_{I,\theta_{NS},save}(\Theta) = U(1 - p/2 + b) + \beta U(D), \\
&U^2_{I,\theta_{NS},quit}(\Theta) = U(1 + b). \\
&U^2_{L,\theta_{NS},save}(\Theta) = U(1 - p/2 + b) + \beta U(D), \\
&U^2_{L,\theta_{NS},quit}(\Theta) = U(1 + p/2 + b).
\end{aligned} \tag{1.5}$$

Again, self 0 would prefer to buy the durable on the installments plan because the probability of continuing to save is at greater with this plan.

B. Small shock in time 1

Consider that self 1 experiences small-shock. She saves $p/2$ out of her income 1, but then claims half of this saving to respond to the taste shock. Thus, she makes a payment of $p/4$ in time 1 with the installments plan. She holds on to this saving if she bought the durable on the lump sum plan. If self 2 chooses to save for the durable, she has to put away $3p/4$ from her time-2 income to compensate for the shortcoming in savings in time 1.

If self 2 experiences a big shock, she consumes everything on hand. Time-2 utility with the installments and lump sum plan are, respectively,

$$\begin{aligned} U^2_{I,\theta_B}(\Theta) &= U(1), \\ U^2_{L,\theta_B}(\Theta) &= U(1+p/4+b). \end{aligned} \tag{1.6}$$

If the individual faces small shock in time 1 and then a big shock in time 2, self-0 would maximize utility by choosing to buy the durable on the lump sum plan.

Instead, consider that self-2 experiences a small shock. She responds to the small shock by consuming half of her available savings. In the case of the installments plan, available savings is what was set aside in time 2 whereas with the lump sum plan, available savings is the sum of savings from time 1 and time 2. With the installments plan, self 2 is left with 1/2 after responding to the preference shock and uses this in entirety to pay for the durable. With the lump sum plan, self 2 has $1 + p/4 = 7/6$ on hand. After responding to the prefrnece shock, she is left with less than p and is thus unable to complete payment for the durable.

$$\begin{aligned} U^2_{I,\theta_S,save}(\Theta) &= U(1-1/2+3p/4+b) + \beta U(D), \\ U^2_{I,\theta_S,quit}(\Theta) &= U(1), \\ U^2_{L,\theta_S,save}(\Theta) &= U(1+p/2-1/2-p/4+b), \\ U^2_{L,\theta_S,quit}(\Theta) &= U(1+p/4+b). \end{aligned} \tag{1.7}$$

Self 2 continues to save for the durable with the installments plan, but not with the lump sum plan. Thus, self 0 would choose to buy the durable on the installments plan in this case.

If self 2 does not experience a taste shock, her utility from saving for the durable and quitting to save for the durable are,

$$
\begin{aligned}
&U^2_{I,\theta_{NS},save}(\Theta) = U(1 - 3p/4 + b) + \beta U(D), \\
&U^2_{I,\theta_{NS},quit}(\Theta) = U(1), \\
&U^2_{L,\theta_{NS},save}(\Theta) = U(1 - 3p/4 + b) + \beta U(D), \\
&U^2_{L,\theta_{NS},quit}(\Theta) = U(1 + p/4 + b).
\end{aligned}
\tag{1.8}
$$

Self 0 would choose to buy the durable on the installments plan because the probability of completing payment against it is greater with the installments plan.

C. Big shock in time 1

Consider that self 1 experiences big shock. She consumes everything on hand and does not save for the durable. If self 2 chooses to save for the durable, she has to put away p from her time-2 income to compensate for the shortcoming in savings in time 1.

If self 2 also experiences big shock, she too consumes everything. Time-2 utility with the installments and lump sum plan are, respectively.

$$\begin{aligned} U^2_{I,\theta_B}(\Theta) &= U(1), \\ U^2_{L,\theta_B}(\Theta) &= U(1+b). \end{aligned} \tag{1.9}$$

Self 0 would choose to buy the durable on the lump sum plan in order to enjoy b in times 1 and 2.

Instead, consider that self-2 experiences small shock after a period of big shock in time 1. In both repayment plans, she claims half of her time-2 income to respond to the taste shock. She can pay just one installment and receive b, but this choice is dominated by the choice to stop saving for the durable. The utility of continuing to save and quitting are:

$$\begin{aligned} U^2_{I,\theta_S,save}(\Theta) &= U(1-1/2-p/2+b), \\ U^2_{I,\theta_S,quit}(\Theta) &= U(1), \\ U^2_{L,\theta_S,save}(\Theta) &= U(1-1/2-p/2+b), \\ U^2_{L,\theta_S,quit}(\Theta) &= U(1+b). \end{aligned} \tag{1.10}$$

With both plans, the individual receives b in time 2 if she continues to save for the durable. And, with the lump sum plan, she receives b even when she quits saving for the lamp. Continuing to save is the dominated choice here because it does not lead to complete repayment of the durable. Thus, self 0 chooses to buy the durable on the lump sum plan.

If self 2 does not experience a taste shock, her utility from saving for the durable and quitting to save for the durable with the installments and lump sum plan are, respectively.

$$
\begin{aligned}
&U^2_{I,\theta_{NS},save}(\Theta) = U(1-p+b) + \beta U(D),\\
&U^2_{I,\theta_{NS},quit}(\Theta) = U(1),\\
&U^2_{L,\theta_{NS},save}(\Theta) = U(1-p+b) + \beta U(D),\\
&U^2_{L,\theta_{NS},quit}(\Theta) = U(1+b).
\end{aligned}
\tag{1.11}
$$

In this case, saving for the lamp in time 2 leads to an increase in lifetime utility by $\beta U(D)$. Self 0 would now choose to purchase the durable on the installments plan because the probability of completing payment against the lamp is at least greater with the installments plan.

Summing across choices in each of these outcomes, the installments plan is the dominating choice for a larger set of states of the world. Given that each state is equally probable, self 0 maximizes lifetime utility by choosing to buy the durable on the installments plan. Extending the insights to the experiment, we should expect to see greater demand for the installments plan relative to the lump sum plan.

1.5 Experimental Setup and Data

1.5.1 Experimental Design

I conducted a census of 93 urban and semi-urban market centers in Lilongwe and Dowa districts of Malawi (Figure A1). For the purpose of sample selection, a micro-entrepreneur is defined to be engaged in business as primary occupation, to have no more than 2 separate businesses and to be present at the business at least 3 days in a week. Because randomization occurs at the individual-level, no more than roughly 20 percent of micro-entrepreneurs in each of these markets was enrolled in the study. The sample was restricted to micro-entrepreneurs who were literate because participants are required to maintain daily logbooks. Solar light agents and mobile money agents were not enrolled at census.[19]

There are four treatments in this experiment (see Figure 4.1). The first treatment distinguishes between groups offered the lamp for purchase and a group that serves as the *Control* group. Second, I randomize financing offers for the lamp. Of those who were offered the lamp, one-third had to pay the full price of the lamp upfront at the time of purchase (*Upfront lump sum* group). The *Upfront lump sum* group had up to one week after the baseline survey to take-up the offer for purchase. The other two-third

[19]The initial design was to provide mobile money accounts to save for the solar lights. But this involved larger monetary costs and posed some logistical challenges with registering participants on the mobile-money network within the study period. Consequently, lockboxes were used instead of mobile money savings account as the savings technology. A relatively small fraction of micro-entrepreneurs (2.5 percent) were from the sample during censusing because they were mobile money agents. No business that we identified at census was a solar light agent.

of the sample could begin using the solar lamp immediately with no requirement for immediate payment. So, effectively, anyone who took up the offer in this group was able to try out the lamp for free. This treatment is to test whether credit constraints when the population wants to make a lumpy investment.

Third, I randomize access to a lockbox to individuals who qualified for the financing treatment and could try out the solar lamp for free (Figure A3). The lockbox is a secure savings technology, and individuals are encouraged to use it to save for the solar lamp. Everyone in the *Box* group knows that the box is theirs to keep even if they decide not to try out the solar lamp. Fourth, cross-cut with the Box-treatment, the group that receives the financing offer is ranodmized into one of two repayment frequencies. The experimental price was held fixed at MWK 20,000, and respondents were randomly assigned to pay this amount in eight weekly installments or as one deferred lump sum payment at the end of eight weeks. The box-treatment and the installments-treatment are applicable only to those who were randomized into the financing group.

All respondents (other than *Control* and *Upfront lump sum* groups) are asked to complete an incentive-compatible willingness-to-pay exercise (see Figure A4 for an example). Importantly, the *Box* group was asked these questions *after* they had received the savings technology, and were encouraged to use it to save for the solar lamp. And, of course, the randomly assigned payment plan and experimental offer was revealed only after the exercise was completed. Every respondent is asked whether she prefers to buy the lamp and pay one lump sum price of P_L at the end of eight weeks, an installment price $P_{ins} = P_L(1 + r)$ completed in eight equal, weekly payments or to not purchase the lamp. The lump sum price was always P_L = MWK 20,000. The interest rate on the installments plan ranged from negative, through 0 to positive rates, such that the six installment prices were $P_{ins} \in (18000, 20000, 22000, 24000, 25000, 26000)$. Next, demand is elicited for each P_{ins} paid as one lump sum amount at the end of eight weeks.

Thus, every respondent answered 12 questions about WTP for the solar lamp. All respondents were informed that the solar lamp would be shut off when a payment was not completed. So, if they bought the lamp on the installments plan, it would be shut off anytime an installment payment was incomplete. If, instead, the lamp was bought on the lump sum, the lamp would shut off if they did not complete payment for the lamp in full at the end of eight weeks. The elicitation exercise was designed to be incentive compatible. All respondents knew that the price at which the lamp would be available for purchase would be decided at random, and that the price which is assigned to them could, with some positive probability, be their choice to one of the twelve questions.[20] At the end of the elicitation exercise, *Box* and *No Box* respondents are informed of the experimental price and repayment frequency at which the lamp was available to them for purchase.

The experiment was implemented from from May-September, 2017. Out of the

[20]Those who purchase the light at one of their selected prices from the price elicitation exercise are excluded from all outcome variables analysis.

targeted 500 micro-entrepreneurs, 444 (88 percent) were enrolled in the baseline survey. The solar light was introduced to all groups that qualified to purchase the light during the baseline survey. The field team explained how the product could be used for lighting and to charge phones. They demonstrated how the device was to be recharged using the solar panel, and informed all respondents about the manufacturer's two year warranty on the product. *Upfront lump sum* respondents were then told that they could buy the lamp from the project at MWK 20,000 due at the time of purchase, and that the offer would be available to them for one week. Deferred payment plan groups decided whether they wanted to try out the solar lamp at the randomly assigned repayment plan. After completion of the baseline survey, all respondents were given logbooks and instructed how to fill them in. We met study participants twice during the study period to record logbook entries.[21]

1.5.2 Data

There are five main sources of data for this study. First, at census, individuals are asked to make a series of choices between receiving some amount of money at a sooner date and a smaller, equal or larger amount of money at a later date. The sooner date is either the day of the census or a week later, and the later date is always one week away from the sooner date. The responses are used to construct a measure of time discounting. The second source of data is the baseline survey. In addition to basic

[21] Specifically, we met respondents after week 1 and after week 5. Responses from the first week are not used in the analysis because they were intended to ensure that respondents understood our instructions and were filling out the logbooks accurately. At the second meeting, we collected records maintained for all days until then. At each of these meetings, respondents who maintained logbook records were compensated with a gift (soap or sugar) of monetary value of about USD 0.75.

household demographics, and business practices and outcomes, the baseline survey also contains the incentive-compatible willingness-to-pay exercise. Third, my main outcomes of take-up and repayment are measured using administrative data. Fourth, the impact of using solar lights on business outcomes, and expenditure on lighting is measured using daily logbooks records. Fifth, an endline survey was administered to a random sub-sample of respondents who chose to purchase the solar light from us. The survey measures user perception of the solar lights.

1.6 Results

Table 4.1 presents summary statistics by treatment group, and results from tests to confirm that intervention groups are comparable at baseline. Columns 1-4 present sample means and standard deviations for each group. P-values of F-tests of equality of means between *Box* and *No Box* groups is presented in column 5, between *Upfront lump sum* and deferred payment groups is presented in column 6, and between the *Control* group and those offered the lamp for purchase in column 7. The intervention groups appear fairly well-balanced. The number of instances of significant difference across treatment groups is what can be expected by chance.

The population of micro-entrepreneurs in this study setting is largely male (68 percent) and married (78 percent). The average micro-entrepreneur is nearly 35 years old, with close to 2 children, and has completed 8.8 years of education. Most respondents are financially excluded – 27 percent have a bank account, and 36 percent participate in at least one informal financial group, like rotating savings and credit associations, or village savings and loan associations. Many people use mobile money accounts; 55 percent report having an active mobile money account, of which 41 percent share the mobile money account with their spouse. Credit is expensive; the average micro-entrepreneur pays 23 percent as interest for a one-month loan. On average respondents pay MWK 1744 (USD 2.4) for grid lighting at home, MWK 835 (USD 1.1) for grid lighting at business, and MWK 3959 (USD 5.5) for non-grid lighting in a regular month. This is a significant cost, average monthly expenditure on non-grid lighting is 26 percent of business profit in a good week, and 45 percent of business profit in a bad week. Finally, while many know of solar lights (64 percent), very few own one (4.5 percent).

1.6.1 WTP Exercise

Responses to the elicitation exercise described above is used to construct measures of willingness to pay for the lamp at each experimental price. The results of the WTP exercise are presented in Figure 4.3. As motivated in the framework in Section 3, there is a strong demand to pay in installments. At all prices, demand decreases monotonically with price. The familiar, downward sloping demand curve indicates that respondents understand repayment options and prices. Strikingly, preference for installments is so strong that respondents are willing to pay a higher price to pay for the lamp in installments – 85 percent of respondents chose to pay in installments at one of the prices in the elicitation exercise, and 78 percent of respondents chose to pay in installments even when the installment price is at least weakly greater than the lump sum price.[22] The demand for installments when the installment price is greater than the lump sum price indicates some large, negative discount rates (Figure 4.4). The negative discount rates would be consistent with some part of savings being lost to temptation spending, demands from others, or theft.

Figure 4.3b distinguishes demand of *Box* and *No Box* groups with lump sum and installment payments. Demand for installments is always measured as preference to pay P_{ins} in installments relative to paying MWK 20,000 as a deferred lump sum. Access to the lockbox lowers demand for the installments plan. As P_{ins} increases, the *Box* group is less likely to buy the lamp on installments, and instead switch to the deferred lump sum plan. Further, when the price of the solar lamp is paid as a deferred lump sum, demand for the solar lamp is always higher in the *Box* group. The following regression is estimated to formalize how preference for installments is affected by access to the savings technology.

$$Y_i = \alpha_1 + \delta_1 Box_i + X_i' \theta_1 + \epsilon_{1i}. \tag{1.12}$$

Here Y_i measures outcome variable of interest for respondent i, Box_i is a dummy equal to 1 if individual i is offered the lockbox, and X_i is a vector of individual

[22] The choices reported in this WTP exercise largely matches actual purchase decision (see Table A5) indicating that most respondents are not engaging in cheap talk.

and business characteristics. The outcomes of interest here are (i) preference to pay in installments, and (ii) preference to pay in installments when installments price is higher than lump sum price, and (iii) willingness to pay premium over lump sum price of MWK 20,000 to pay in installments. Table 4.2 presents results of the regression. All outcomes are measured from responses to the WTP exercise.

Echoing the result in Figure 4.3, 85 percent of choices indicate preference for installments over paying in lump sum. As prefaced in Figure 4.3, the *Box* group is more likely to want to buy the solar lamp. Consistent with this result, the *Box* group is somewhat more likely to prefer installments when the installment price is lower than the lump sum price. But, demand across *Box* is somewhat lower than, though not statistically distinguishable from, the *No Box* group when installment price is strictly greater than the lump sum price.

I construct a measure of the premium that someone is willing to pay for the lamp in installments as the difference between maximum installment price that an individual is willing to pay and the fixed lump sum price of MWK 20,000 . So, the minimum value of premium is -2000 and maximum value is 6000. Mean value of premium in the *No Box* group is MWK 4385, which is 22 percent of the lump sum price of the lamp. While this premium reduces by a statistically significant 15 percent in the *Box* group, the premium continues to be large at about MWK 3740. The results indicate that access to a a secure savings technology is an important barrier to saving, but it at least not perceived to be the largest barrier to saving in this population.

1.6.2 Take-up of Solar Lamp

The following regression is estimated to study take-up across three treatments: offer to purchase the lamp on deferred payment, offer to purchase the lamp on installments, and access to the savings technology. The framework outlined in Section 3 predicts that both the lockbox treatment and the installments treatment should at least wekaly increase the probability of trying out the solar lamp. The take-up decision for the *Upfront lump sum* group is really a purchase decision. For the groups that receive the deferred payment plan, the results of the regression indicate the decision to try out the solar lamp.

$$Y_i = \alpha_2 + \beta_2 Def_i + \gamma_2 I_i + \delta_2 Box_i + \zeta_2 I_i \times Box_i + X_i' \theta_2 + \epsilon_{2i}. \tag{1.13}$$

For respondent i, Def_i is 1 if she was offered the lamp for purchase on a deferred payment plan. The variables I_i and Box_i indicate whether respondent i was offered the lamp for purchase on installments plan, and whether she received the savings technology, respectively. The combined effect of the cross-cutting Box and $Installments$ treatments is given by ζ_2. Baseline measures of individual and business characteristics are controlled for in vector X_i. The results are presented in Table 4.3.

Credit constraints severely dampens demand for solar light. Those offered the solar light on deferred repayment plans are 48 percent more likely to take-up the offer. Importantly, the *Upfront lump sum* group is not significantly different from the deferred payment in their willingness to buy the solar lamp at a positive price (see Table A4). This increases confidence in the result that it is in fact credit constraints, and not differences in subjective valuation of the product (on the extensive margin), that is driving the difference in purchase rates between groups offered the light for purchase with upfront payment and deferred payment.

Next, restricting attention to those offered the lamp on deferred payment plan, access to the very simple savings technology of a box increases probability of take-up by 13-19 percent. After controlling for the offer to pay in installments, those offered the savings technology are 17-20 percent more likely to want to try out the solar lamp. The strong increase in probability of take-up with the lock box is quite remarkable because the outcome of interest is change in belief about future behavior, and not future change in behavior. The effects reported here imply that access to the savings technology has an important contemporaneous impact by changing belies about future outcomes. Further, the box was actively used to save for the solar lamp (Table **??**). In the *Box* group, everyone took up the product and nearly 97 percent of respondents made at least one deposit into the box. The box was used almost exclusively to save for the solar lamp, which is perhaps unsurprising given the short duration of the repayment period On average, individuals saved nearly 77 percent of the experimental price of the lamp in the lockbox, and median savings in the lockbox is equal to the price of the solar lamp.

The treatment of repayment frequency, on the other hand, does not lead to significantly different behaviors across the two groups. While the coefficient on the indicator for the option to repay in weekly installments, instead of one deferred lump sum payment, is positive, it is not statistically significant. Finally, the combined treatment of having the box and the offer to repay in installments has no significant impact on take-up decision. Perhaps, it is unsurprising that the installments treatment does not have a strong impact on the decision to try out the solar lamp because everyone who chooses to take up the purchase offer is given the lamp immediately, and payment is not due for one week (when paying in installments) or eight weeks (when paying as a lump sum). Someone who does not plan to make any payments for the solar lamp is assured a working light for at least one week. Thus, conditional on the solar lamp bringing positive utility, the optimal choice is always to purchase the light for either repayment frequency.[23]

1.6.2.1 Correlates of Purchase Decision

Correlates presented in Table A4 indicate several noteworthy trends. First, it does not appear that wealthier or more educated households are more likely to adopt this technology. Individuals who may be wealthier based on baseline indicators like education, business revenue, or material used to construct home are not significantly more likely to purchase a solar light. Baseline lighting expenditure is statistically

[23] At the lowest price, 23 respondents did not want to purchase the light with deferred payment. Of this, 87 percent reported that they would not be able to afford the lamp even with deferred payment.

significant in explaining purchase decision. After controlling for baseline wealth, a doubling of non-grid lighting costs increases the probability of solar light purchase by 2 percent. While not significant, individuals with prior knowledge about solar lights are more likely to buy a solar light and those who already own solar lights are less likely to buy another one. Finally, the strong, significant correlation between number of children and probability of purchase of solar light suggest that the people are likely to use the light for children's study. Having one more child is associated with a 5 percent increase in the probability of purchase. At the same time, increase in household size after controlling for number of children, is not significantly correlated with purchase decision.

Echoing results presented in Table 4.3, access to a transactional or savings account is correlated with a significant and positive impact on purchase probability. While not causal evidence, ownership of mobile money accounts, bank accounts, and participation in informal financial groups is associated with higher probabilities of taking up the offer for the solar lamp. For example, those with a mobile money account and those who participate in an informal financial group are respectively 8 percent and 10 percent more likely to want to try out the solar lamp on a deferred payment plan.

The solar lights are easily mobile, and a little more than 50 percent of the individuals report using it both at home and in the business. Respondents are asked what is the largest quality-of-life impact that the solar lamp has had on their lives, besides energy savings. Nearly 44 percent of individuals report that they work longer, even though the number of hours worked are not statistically different across the treatment groups as reported in the logbooks (A10).

1.6.3 Completing Repayment

When a lamp is completely paid for, the device achieves "unlocked" status. A "locked" device, on the other hand, turns off when payment is due. Any lamp that is not completely paid for at the end of the study period remains turned off until a payment is made against the outstanding balance. The impact of the cross-cutting treatments on the probability of having an unlocked device at the end of eight weeks is measured using the following regression:

$$Y_i = \alpha_3 + \beta_3 Def_i + \gamma_3 I_i + \delta_3 Box_i + \zeta_3 I_i \times Box_i + X_i' \theta_3 + \epsilon_{3i}. \tag{1.14}$$

As reported in Table 4.4, both access to savings technology and frequent repayment leads to higher probability of having an unlocked and functional solar lamp at the end of the study period. The *Box* treatment increases probability of completing payment by 12-14 percent. Paying back in installments increases probability of repayment by 10-13 percent. The impact of the combined treatment of box and installments on repayment is not statistically distinguishable from zero. On average, the installments group paid MWK 17,000 against completing the payment of MWK 20,000 within eight weeks. Average payment for the lamp in the deferred lump sum group is MWK 11,724.

But, this masks heterogeneity in how the installments plan had negative impacts for those who were unable to complete paying for the lamp. As reported in Table A2, restricting attention to those who were unable to finish paying for the lamp, the installment group paid MWK 9,218.75 whereas the lump sum group paid 0. And, the solar light was shut-off every time someone in the installment group missed a weekly payment. Consequently, on average, the installment group had access to the light for nearly three weeks lesser than the lump sum group, despite paying more to use the light during the study period (Table A3). At the same time, individuals who choose the installments plan are significantly about 30 percent more likely to finish paying for the solar lamp and have a functioning light at the end of the study period. And, those who are randomly offered the installment plan when they expressed preference the lump sum plan are less likely to have an active light at the end of the study period Table 4.5.

1.6.4 Impact of Solar lamps

I estimate the effect of owing the solar lamp on the following outcomes: expenditure on grid and non-grid lighting for the home and business, mobile phone outcomes, and working hours. Understanding the savings accrued by users of solar light is important to understand the profitability of the investment. I use the following specification to understand the impact of using the solar lamp:

$$Y_i = \alpha_3 + \mu Use_i + X_i'\theta_3 + \epsilon_{3i}. \tag{1.15}$$

Here Use_i is an indicator variable for using the solar lamp, and is instrumented with experimental treatment as follows:

$$Use_i = \omega + Treat_i'\psi + \nu_i. \tag{1.16}$$

Experimental treatment have a strong effect on the decision to try out the solar lamp and yields a strong first stage (Table A7).

The solar lamps are easily portable, and are used both at businesses and homes. On average, 31 percent of the respondents used the light at the home, 17 percent at their business, and 52 percent at both home and business (Table A6). The light have an immediate effect on the most obvious outcomes that are expected to change – lighting expenditure and mobile phone usage outcomes. The results for lighting expenditure are presented in Table 4.6. Treated individuals spend considerably less on off-grid lighting at the home and business. Daily expenditure on off-grid lighting for the home reduces by nearly 95 percent from the control mean. This translates to a daily reduction of MWK 136 on a base of MWK 158.80. Daily expenditure on off-grid lighting for business reduces from MWK 133.60 to MWK 132.44. Expenditure on grid lighting does not appear to be affected significantly by the treatment for the small fraction who are connected to the grid.

The average respondent's mobile phone battery is out of charge for about one and a half hours every day. For the treatment group, this time reduces by 60 percent.

Commonly, respondents rely on recharging centres to get their mobile phones recharged at a cost. On average, individuals spend MWK 45.05 for this service everyday. The treatment group stops relying on this paid service almost entirely. Mobile recharge expenditure in this group reduces by about MWK 43, a reduction of nearly 96 percent. Summing across savings on lighting and recharging mobile phone, the treatment group saves about MWK 242 (Table 4.7). At this rate of saving, the solar lamp's experimental price of MWK 20,000 can be regained with about twelve weeks of use.

Finally, having access to the solar light does not have a significant impact on business hours, revenue, or children's study hours in this sample (Table 4.8). While qualitative evidence suggests that some types of businesses operated longer (tailors, restaurants) the study was not designed to detect differences across business types. The null effect on children's study hours is not informative in this setting because, unfortunately, the study period coincided with annual school holidays in Malawi.

1.7 Conclusion

This paper presents prima facie puzzling evidence that individuals prefer to pay for a lumpy investment in several installments, rather than one deferred lump sum, even when the installment price is as much as 30 percent higher than the lump sum price. These choices imply some large and negative returns to saving. Negative returns to saving can be motivated as, for instance, some fraction of savings being lost to temptation spending or theft. This interpretation resonates with the large evidence base that shows that the poor are often unable to save to make investments that can be very useful to them. In this paper, I address two impediments to save – lack of a secure place to hold savings, and intra-personal conflict that undercut savings plans.

The installments plan can help along two fronts – it makes it easier to impose self control by physically relinquishing access to savings, and it can provide a secure means to hold savings to pay for the solar lamp. I am interested in understanding how much of the demand for installments is driven by the desire for self control rules. I measure this by inducing experimental variation in access to a secure savings technology leads. While access to the savings technology leads to a meaningful reduction in the premium that individuals are willing to pay for the installments plan, it continues to remain large and significant. The installments plan offers a commitment mechanism to complete payment against the solar lamp by both moving savings out of the home and by increasing the disutility of reneging on savings plan by having the lamp shut off when periodic payment is not fulfilled. It is, therefore, individuals' desire for commitment savings that is driving the demand for installments after they gain access to the savings technology.

Access to commitment repayment through installments increases the probability of paying for the lamp. This suggests that policymakers can impact the poor's ability to make useful, lumpy investments by restructuring how these investments are made. The scope of impact of nuanced policy, like structuring payment plans to mimic commitment accounts, can be quite broad and significant. And, it can compliment the impact of more traditional solutions to bring financial empowerment, like increasing access to a secure savings technology.

At the same time, we need to remain mindful of heterogeneity in impacts of such policies. For example, at least in the short run and in the context of this experiment, many are hurt by choosing the installments plan – they end up paying more for fewer days of access to solar lights. And, within 6 weeks of the end of the study, about 18 percent of individuals completed arrears on the solar lamp. This is an intersting result in its own right because respondents often have to make a a long and costly journey of about 40 miles in round-trip to making this payment in-town. Longer-term outcomes of interest are how the experimental groups vary in repayment. For example, preliminary evidence indicates that individuals with the box and those who paid in installments are more likely to come back later to fulfil outstanding payment. Another line of further study is whether we can predict ex ante who will benefit from the installments plan.

2

Grain Today, Gain Tomorrow: Evidence from a Storage Experiment with Savings Clubs in Kenya

2.1 Introduction

Prices of many agricultural commodities display large fluctuations over the season in rural areas of developing countries, from post-harvest lows to pre-harvest peaks,[1] presenting a seemingly straightforward opportunity for inter-temporal arbitrage. However, many smallholder farmers are unable to exploit this opportunity, and sell output immediately after harvest at low prices, sometimes even buying maize later in the season when prices have risen (i.e. [47]). [2]

[1] See [85] and [47] for recent evidence summarizing price gaps across multiple countries.

[2] Beyond the obvious income implications, an emerging literature shows that seasonality in consumption (arising due to high food prices in the pre-harvest period) during childhood can have health and cognitive impacts even in the long-run [1, 55].

One important reason why intertemporal returns remain unexploited might be that farmers lack access to a good storage technology. In our study context of Western Kenya, storage facilities are very limited: many farmers report storing maize in their homes in plain sight, and such storage ends up imposing many pecuniary, social, and psychological costs. Farmers report that stored maize may be eaten by pests or livestock, spoiled by fungus, or may in rare cases be stolen. Many farmers are often asked for assistance from friends or relatives, and may find it hard to refuse such requests when maize is available in the home. Many farmers also report that they themselves get tempted when maize is easily accessible in their home, and consume more than they planned to. These issues are similar to those faced by households while trying to save cash, and many recent studies have shown that providing these types of households with savings accounts can increase cash savings.[3] There has been much less research on providing storage technologies for saving grain, however.

To help fill this gap, we designed an experiment that provided Rotating Savings and Credit Associations (ROSCAs) in Kenya with a technology for storing grain, which we called the Group Savings and Reinvestment Account (GSRA). Specifically, we encouraged randomly selected ROSCAs to set aside maize together in communal bags, stored at a single member's house (usually the ROSCA treasurer). In order to facilitate this, we provided GSRA ROSCAs with storage supplies, namely triple-layered plastic bags

[3] See Prina (2015) and Dupas et al. (2017) for a review of recent savings studies.

capable of being hermetically sealed and designed specifically for the purpose of storing grain[4] and a heavily subsidized wooden stand to keep the maize elevated from the ground (and less susceptible to pests and water damage). We hypothesized that moving the maize out of farmers' homes would make it less prone to being claimed by others or falling prey to temptation. Moreover, separating this portion of their maize-holding from the rest of the stock, and mentally allocating it to the purpose of later sale ("labeling") might increase savings [5] The "technology" that we evaluate in this paper is thus an amalgam of the physical technology (bags and stand) aimed at minimizing spoilage, the mental accounting aspect from labeling, and the social or interpersonal channel due to the ROSCA storing grain as a collective.[6] The ultimate goal of this combined technology is to increase the amount of maize stored for later use and to increase cash income from maize sales.

We have three main findings. First, take-up was high: records kept by the ROSCAs suggest that 57 percent of all respondents made at least 1 deposit of maize in the common pool [7] This measure of take-up is somewhat higher than the average

[4]Specifically, we provided them with the Purdue Improved Crop Storage (PICS) bags: https://ag.purdue.edu/ipia/pics/Pages/home.aspx. These bags have been found so effective at arresting postharvest losses that a USAID initiative in Kenya has projected that if a million farmers in Kenya adopt them by 2019, domestic supply of maize would increase by 450,000 tons (https://www.fintrac.com/sites/default/files/HST_A3_11.16.pdf).

[5]See [161] on mental accounting, and [76] for evidence on labeling savings in Kenya.

[6]While the idea of harnessing mental accounting and peer pressure through communal grain storage is novel, storing grain communally has precedent. Historically, many communities have had such systems, largely to ensure food security for everyone; more recently, the Millennium Villages project also supported cereal banks with a similar objective. In the 1970s, several NGOs sponsored the setting up of communal grain storage geared towards weathering poor market conditions, especially in West Africa and the Sahel (World Bank, 2011).

[7]The take-up at the ROSCA-level was nearly universal, i.e., 96 percent the treatment ROSCAs agreed to participate in the study and paid the subsidized price for the wooden stand.

among recent savings interventions.[8] Second, individuals in the GSRA were significantly more likely to store maize: while 69 percent of the control group reported storing maize to realize price increases (which we defined as saving maize for at least a month after harvest), the percentage increased to 92 percent in the treatment group. Total storage increased by 18% in the treatment group, significant at the 10% level. Third, treatment farmers were much more likely to have sold maize in the market by endline – only 36% of the control group sold maize, compared to 74% in the treatment group. Conditional on selling, treatment farmers sold later: sales in the GSRA group were on average 1 month later than in the control group, and fetched 4 percent higher prices.

Our paper makes several contributions. First, it is an addition to the literature which examines the reasons behind why large intertemporal arbitrage gains are not exploited. So far, this literature has mainly focused on financial constraints, namely credit constraints [156, 47], or liquidity constraints [125, 157, 69], or high alternative returns to capital [133]. An older literature has looked at price risk as a potential explanation [152, 24]; however, the current consensus among academics as well as policy-makers is that this is largely implausible given how predictable and regular these price increases are.

Second, by evaluating the effect of a novel savings scheme, but one that is focused around saving harvest grain, we contribute to the voluminous savings literature,

[8] See Table 3 in Prina 2015 and Dupas et al. 2017.

which has almost exclusively focused on cash savings, especially among microentrepreneurs.[9] Our study is one of only a handful to show a statistically significant effect on *total* savings or storage since savings is a noisy outcome, few studies are powered to find effects on total savings, and instead infer a change in savings behavior from changes in downstream outcomes (see Table 9 in [73] for a discussion). The closest paper to ours is [26], which offered households free weather sealed storage drums and storage sacks or lean-season consumption loans to be repaid after harvest, and which finds that the storage interventions increased an index of consumption and income, in both the harvest and lean seasons. Our paper is complementary in several ways. First, we provide another data point in favor of storage as an effective intervention and validate their findings in a different setting. Second, our data allows us to look at mechanisms through which storage is effective. We find that it is not only the technological improvement of reduced harvest losses which was effective, but also the mental accounting of setting aside maize. In particular, while a majority (53%) said that the GSRA was effective because it reduced spoilage, large minorities also said it helped them consume less (38%) or give away less to others (24%).[10] Lastly, we show that income gains were also not solely from reducing spoilage, but occurred because farmers were more likely to sell maize, and sold maize later in the season at higher prices. Another related paper is [47] which worked with an NGO to offer loans to farmers in the post-harvest period and observed that farmers sold less maize immediately after harvest and more in the lean

[9] Our design has similarities to studies such as [44], though our focus is on realizing seasonal gains in prices rather than in setting aside income for future input use.

[10] Multiple responses were allowed. People also cited as reasons the ability to share costs and that they were able to allocate money to agricultural inputs.

season. Since that study did not change storage technology, the interpretation is that conditional on the existing storage technology, farmers sell some maize out of liquidity needs.[11]

Finally, our project is related to the nascent literature on ASCAs/VSLAs, which has tended to show large positive effects from such groups (see [122, 28, 88, 116]). The key distinction with financing agricultural inputs is that all participants are on the same agricultural cycle, making within-group lending for agricultural loans difficult. Communal storage, by contrast, intertemporally transfers group-level resources from harvest to later in the agricultural cycle.

The rest of the paper proceeds as follows. Section 2 lays out the basic experimental design and data. We present our results in Section 3. Section 4 concludes with a discussion.

[11] This paper also adds to a niche literature about how cooperatives help farmers improve their incomes. The bulk of these papers are about agricultural marketing cooperatives [81, 166, 33], but there is also some evidence suggesting that farmers' cooperatives might be able to improve access to financial services and inputs [67]. The results from this paper suggest that the cooperative structure can be useful even in the absence of intermediation benefits that are central to marketing or input acquisition efforts. In the case of storage, collective action not only provides commitment benefits as described above, but can also help defray costs. Specifically, when asked about why the GSRA was helpful, 38 percent of the respondents reported the sharing of costs as a reason.

2.2 Experimental Design and Data

2.2.1 Background on seasonal price changes

This project took place in Busia District of Western Kenya. The staple crop in this area is maize and there are two main growing seasons: a longer, more productive "long rains" season with a harvest occurring around August; and a shorter season which harvests around December or January. Prices typically reach a peak around June, just before the long rains harvest, and fall to a low during the harvest period, increasing steadily thereafter.

Many previous papers have documented large seasonal price variations for grains in rural Africa. Price increases as high as 100 percent have been observed in some countries like Madagascar [143], Malawie [69], Southern Tanzania [163], and Zambia [148]. These cases are likely in the right tail of the seasonality distribution, however (for example, because road networks are very poor in these countries, limiting trade between rural locations with differing harvest schedules) [12] Price fluctuations in countries with somewhat better road networks are more modest, though still meaningful. For example, [47] document an average price increase of 25-50% in 5 countries in East Africa using data from RATIN; similarly, [85] document an average price increase of 33 percent for maize in 7 African countries.

[12] According to the CIA *World Factbook*, the density of roads in Madagascar, Malawi, Tanzania, and Zambia is 0.06, 0.13, and 0.05 kilometers per square kilometer of land area. Kenya, by contrast, has 0.28 kilometers of roads per square kilometer area. As benchmark, the United States has 0.67 kilometers of roads per square kilometer area.

We have two sources of data to document price increases: (1) reported prices from maize sales during the study period; and (2) responses to questions about month-by-month prices from retailers. Both sources show increases of about 30-40% (see Figure 4.5). Though we lack historical price data in Busia, we look at prices in the nearby city of Kisumu using several public data sources in Appendix Table A8. We find an average price increase of 46% in the 2006-16 period (33% if 2011, a major famine year, is removed).[13]

2.2.2 Experimental Design

Sampling and Randomization

In July 2015, we conducted a door-to-door census of 552 individuals in 17 villages spread across three counties in Western Kenya. The census asked people for ROSCAs in which they participated and collected basic identifying information about the ROSCA, as well as contact information for ROSCA officials. A total of 497 ROSCAs were identified in this way. After identifying this list, we randomly sampled 274 ROSCAs for project inclusion. Enumerators called the treasurers of selected ROSCAs to schedule an initial meeting (at one of the normally scheduled ROSCA meetings).

[13] A final point worth making regarding seasonality in this context is about price expectations. During our baseline survey, people reported expecting much larger price changes (the average expected price change was 100 percent – see Figure 1). Given the results in Table A8, we take this as suggestive that people overestimated increases in the survey. Interestingly, [47] also find that farmers expect a doubling of prices, compared to actual prices increase of 20 to 30 percent.

We randomized ROSCAs into 3 treatment groups: (1) the Group Savings and Reinvestment Account (GSRA), which is the focus of this paper; (2) control, and (3) an individual savings account group. The individual savings group was eventually de-emphasized; however, we include the individual savings group in our analysis for transparency. All regressions include a dummy for that treatment group, but we do not report this information in the tables since all coefficients are statistically indistinguishable from zero.[14]

Of the 274 sampled ROSCAs, 163 were successfully reached.[15] Since non-participation occurred before treatment was announced, it should not be possible that treatment affected project participation. However, due to random chance, more GSRA ROSCAs were reachable by phone than the other groups (of the 163 ROSCAs that were traced, 60 were GSRA, 52 were control, and 51 were ISRA). An additional 24 attrited before the intervention, leaving 139 ROSCAs.[16] Of these, 132 were traced for the endline.[17] For the reason listed above, there are therefore more GSRA ROSCAs (51) than control (38) and individual savings (43). Appendix Table A2, Column 1, shows compliance by

[14]The individual savings intervention was inspired by the fact that in this part of Western Kenya average plot sizes are small and many people who farm also do other small businesses on the side to earn cash. The savings intervention was an individual account labeled for agricultural input usage, held at the ROSCA. The accounts allowed deposits only of cash, not maize, and so provided no direct mechanism to allow arbitrage of harvested maize. Fifty-six percent of respondents took up these accounts and median/mean deposits were $2/$5.

[15]Ten ROSCAs were identified as duplicates. The remaining 101 were not reachable by phone, either because the treasurer did not pick up the phone when called (field staff called up to 4 times before stopping), or the phone number was wrong.

[16]The 24 ROSCAs who were not enrolled did not participate because they were unable to schedule a meeting time or because they were not interested in the project.

[17]Of the 7 that could not be traced, 4 had disbanded by midline and were not further contacted. No members could be traced in the other 3.

treatment status compliance is not differential by treatment.

Appendix Table A3 shows some statistics on ROSCAs. The average ROSCA has existed for about 6 years, has about 21 members, and the average round length is about 1 year. Nearly all ROSCA members farm, and many ROSCAs provide financial services aside from the pot, including credit (66%) and welfare insurance in case of emergencies (83%). ROSCAs also provide loans to members, at high interest rates (the average rate is approximately 13% per month). We find little difference across ROSCAs in these characteristics (Column 2) one of nine variables is significant at 10%.

GSRA Intervention

At the initial meeting, each ROSCA was read a script about the benefits of setting maize aside after the harvest, of using farming inputs such as chemical fertilizer, and of saving. This basic script was augmented for GSRA ROSCAs to also explain the group savings intervention. ROSCA members were encouraged to collectively set aside some portion of their harvest, and hold it to sell when prices had risen. ROSCAs were each given four hermetically sealed storage bags (called Purdue Improved Crop Storage, or PICS bags) [18] Hermetically sealed bags are likely a major technological improvement for farmers: several studies have compared the PICS bags to other techniques such as solarization, fumigation, metal drums, or storage with ash/mud (all of which are

[18]PICS bags are one of several types of hermetically sealed storage bag solutions that have been developed in recent years for the specific purpose of storing grain. Other examples include the IRRI superbag, the AgroZ bag, and the GrainPro SuperGrain bag.

likely superior to the technology our farmers use), and have found PICS bags to be more effective at preventing and arresting infestation (for instance, see Williams et al., 2017).[19] Moreover, PICS bags are also less labor intensive and more cost-effective. Specifically, the prevalent method of on-farm storage in gunny sacks requires pre-storage application of insecticide, with follow-up reapplications at every 3 months (Kimenju and DeGroote, 2010). PICS bags, on the other hand, work through cutting off oxygen which causes insects to suffocate, obviating the need for artificial insecticides.

In addition to the bags, ROSCAs were provided a heavily subsidized wooden stand to keep the maize elevated from the ground (and less susceptible to pests and water damage). Finally, ROSCAs were provided logbooks in which the treasurer could keep track of all deposits and withdrawals of maize by individual members. After describing the program, ROSCAs were given a month to think it over. Field staff emphasized that not all members of a participating ROSCA were required to contribute maize for their ROSCA to qualify for the program.

The GSRA could encourage savings through three main channels. First, the GSRA may be a technological improvement on the alternative of storing maize in burlap sacks at home. Second, the fact that the GSRA maize is held outside the home (for all but the treasurer) will limit access to the maize and may discourage withdrawals of maize for consumption or early sales. Third, the group nature of the intervention

[19] Also see https://www.entm.purdue.edu/PICS2/Abstracts.pdffor a summary of other studies on the efficacy of PICS bags.

may further encourage participation. The experiment was not designed to test between these pathways, but rather was designed to maximize the chances that the intervention might be effective.

Coupon Intervention

Though it is not the focus of this paper, we also report results from a coupon intervention we conducted for the 2016 long rains harvest. ROSCAs were randomly sampled to receive a discount on inputs at a local agricultural retailer on any input (including fertilizer, seeds, herbicide, and pesticide). The value of the coupon randomly varied from 10-90% off of the cost of inputs. The logic of this intervention was that farmers who stored maize in either the individual savings treatment or the GSRA might be more likely to redeem. Though we do find modest effects of the GSRA on redemption, in retrospect we realize the intervention was not well-timed because prices do not much increase between the long rains harvest (August) and the time inputs are needed for the next season (redemption was in February-March) this is because the smaller short rains occur in December or January, and thus prices only really rise starting in February. We include controls for the coupon in all regressions.

2.2.3 Data

We utilize four main data sources for this analysis. First, we conducted a baseline survey with all ROSCAs in August-September 2015. During the same time period, we also conducted a baseline survey with a randomly selected subset of respondents at each ROSCA meeting. We targeted 6 members per ROSCA. In addition to basic demographic questions, the survey included questions on harvest amounts, storage, and input usage. Second, we conducted an in-person midline survey in March 2016, in which we collected data on take-up of the GSRA, storage, sales, and other related outcomes. For this survey, we attempted to enroll 3 respondents per ROSCA. We initially attempted to enroll baseline respondents; if there were not 3 baseline respondents present at the meeting, a respondent would be replaced by another randomly selected ROSCA member who was present at that meeting. We enrolled a total of 529 respondents in this survey. Third, we conducted an endline survey over the phone from July-November 2016. We attempted to interview those respondents who had previously completed interviews and successfully interviewed 583 respondents. We use the endline as our primary measure of outcomes, since it is more comprehensive and had more refined modules to measure key outcomes of interest. Fourth, we asked all GSRA ROSCAs to keep logs of deposits, withdrawals, and sales. We visited ROSCAs at midline and endline to inspect these records.[20]

Attrition for the midline and endline is shown in Appendix Table A9. We find no evidence of differential attrition between the GSRA and control groups.

[20] We successfully collected logbooks with every GSRA ROSCA at midline, and with 47 out of 52 at endline. Of the 5 remaining ROSCAs, 4 were untraceable because the treasurer was out of town at endline and 1 ROSCA never kept records.

2.2.4 Summary Statistics and Balance Check

Table 4.9 presents summary statistics on our (post-attrition) sample, as well as a test for randomization balance. From Panel A, the average farmer is 39 years old, has close to 7 years of education, owns about $340 in durable good and animal assets, and owns 1.7 acres of land. Ninety-one percent of farmers live in homes with mud walls. Twenty-three percent of farmers have a bank account, though 64% have a mobile money account.

Panel B shows that farm productivity is very low: the average farmer reported a yield of just 480 kg, which is worth only about $135 at immediate post-harvest prices in 2015 ($180 if held until the peak price reached in 2015). Surprisingly, input usage (Panel C) is fairly high: 81% of farmers used fertilizer in the past year, and 75% used hybrid seeds.[21] Farmers use 52 kg of fertilizer per acre, close to recommended amounts.

Finally, Panel D presents some figures on maize storage. Virtually all households (89%) store some maize for some period of time (since the alternative is to sell the entire output immediately after harvest). However, as we show later, many farmers sell or consume much of this maize within a fairly short period of time. Nearly all households who store maize do so on a raised platform or table in the house, typically in a burlap sack. Storing in this way may be subject to pest and rodent infestation, which is borne

[21] This is much higher than previously reported in this part of Kenya, for example in [71]), suggesting that input usage has increased in Kenya over time.

out in reported losses: farmers report that at least some maize was lost in 30% of seasons and that these losses were substantial (1/3 of storage in those years). Another issue is that people may be tempted to consume the maize faster than if it were out of sight: a non-negligible minority of households (26%) report that they consume "too much" maize when maize is stored in the home. We find that most households are net buyers of maize: only 34% sell maize, while 78% buy.

We check for randomization in Column 2, which shows the coefficient from regressions of each of these variables on a GSRA indicator, with standard errors clustered by ROSCA. We find three significant differences at 10% out of 23 in this table: fertilizer usage, a measure of spoilage in the past 5 years, and whether a farmer sold maize in the last planting season. Though these are unfortunate outcomes to differ, we attempt to address this by controlling for each of these variables in our main specifications. Further, we do not think it is likely that these drive our treatment effects on sales, since the effect on sales is 3 times this baseline difference. Nevertheless, these baseline differences should be kept in mind.

2.2.5 Estimation Strategy

To estimate treatment effects, we rely primarily on the endline survey (we use the midline as supportive evidence). For each outcome for individual i in ROSCA r, we run the following Intent to Treat regression

$$Y_{ir} = \alpha_0 + \beta T_r + \theta X_{ir} + \epsilon_{ir} \tag{2.1}$$

where T_r is a dummy for receiving the GSRA. X_{ir} includes controls for the three variables that are significantly different in Table 4.9, as well as a control for harvest output in August 2015, which is exogenous to treatment since ROSCAs were visited either just before or slightly after harvest (and so there was no opportunity to change investment decisions). X_{ir} also includes indicators for the individual savings treatment and for the value of the coupon received, though coefficients are suppressed.[22] In all regressions, we include harvest output as a control to improve precision since it is the primary determinant of storage behavior. However, this control does not materially change results (see Panel A in Appendix Tables A5 and A6). We cluster standard errors at the ROSCA level.

While the ITT results are our primary focus, we also report Treatment on the Treated regressions in which the first stage is a regression of usage U_{ir} (ever having used the account) on treatment, and the second stage is as follows:

$$Y_{ir} = \alpha_0' + \gamma U_{ir} + \theta' X_{ir} + \epsilon_{ir} \tag{2.2}$$

[22]Removing the individual savings ROSCAs from the analysis does not materially change results (Panel B in Appendix Tables A5 and A6).

2.3 Results

2.3.1 Take up

Table 4.12 shows statistics on take-up of the GSRA, using data from the ROSCA logs and the endline. According to the logs, 57% of ROSCA members contributed to the GSRA. This percentage is higher (70%) among respondents who completed the endline survey. We conjecture that the main reason for this is that the respondents who were present at ROSCA meetings were likely to be the more active members of the ROSCA, and were therefore somewhat more likely to use the product than the average respondent. This should not affect the internal validity of our results, however, since the same types of respondents should have been present in treatment and control ROSCAs. Of those that used the GSRA, many used it quite a bit see Figure 4.6 for a CDF of total deposits into the GSRA. Among users, the average amount deposited was 44 kg on the logbooks (38 kg among endline respondents), equivalent to roughly 8-9% of harvest output. While this is a small amount in absolute terms (worth about $14-$17 at immediate post-harvest prices), it is a sizeable percentage of harvest income (since harvested output is very low). As a percentage, this effect size compares favorably to other papers in the savings literature, most of which are about cash savings. For example, recent studies have found treatment effects for deposits of 11% of income ([75] in Kenya), 6% ([147] in Nepal), 12% ([74] in Kenya), 8% ([73] in Malawi) and 18% ([73] in Uganda). The savings we document in the GSRA are noteworthy in that the return to storage is likely much higher than the return to saving cash in many of these previous studies (since many of the bank accounts offer little or no interest). As a development policy, maize storage thus offers an advantage over savings in financial institutions. Finally, we found somewhat higher take-up numbers on the surveys than on the ROSCA logs. This could be due to under-reporting on the logs or over-reporting on the surveys – we are not able to tease these apart. So long as any measurement error is uncorrelated with treatment status, our treatment effects should remain valid.

2.3.2 Storage

Table 4.13 shows results on storage of harvested maize, starting with the extensive margin in Column 1. To measure storage, we asked respondents the following question: "How much maize did you store which you intended to sale or consume more than a month after harvest?" Though the specific cutoff of one month is arbitrary, this question is meant to measure longer-term maize storage, rather than storage of just a few days or weeks. We observe a large, statistically significant treatment effect: while only 69% of control farmers reported yes to this question, this increased to 92% in the GSRA group.

Columns 2-4 show quantities. Column 2 shows all storage outside the home, pooling GSRA with any other storage outside the home. There is no storage at all outside the home among control group ROSCAs, which increase to 51 kg in the GSRA group. Column 3 shows home storage, which was slightly lower in the treatment group (by 18 kg). There is thus some evidence of crowd out, though far from complete.

Further, crowd-out from home storage is likely a desirable outcome due to the inefficient nature of home storage. Column 4 shows total storage, finding a 33 kg increase in the treatment group (Column 2 less Column 3), significant at 10%. The point estimate is quite large on the control base of only 185 kg – GSRA respondents increased storage by about 18% (26% for compliers). [23]

2.3.3 Sales

Table 4.14 shows effect on maize sales and farm cash income (all measures were only collected at endline). Column 1 shows that the GSRA had a large effect on the extensive margin of selling at least some maize: GSRA farmers were about twice as likely to sell maize in the year after the harvest as their control counterparts (74% vs. 36%). Though quantities and revenues are not significant, point estimates show increases in sales of about 20-25% on the control group. Of people who sold, Columns 4-5 show that GSRA farmers sold later (by about a month, on average, significant at 5%) and received higher prices for output (about 4% on average, significant at 10%).[24]

Figure 4.7 shows graphically the timing of maize sales in the GSRA and control groups. We calculate average maize sales per month by treatment group, and find that

[23] We perform several robustness checks in the Appendix. Appendix Table A10 shows 4 robustness checks: removing the harvest control (Panel A), dropping the individual savings group (Panel B), and either not winsorizing at all (Panel C) or at 1% (Panel D). Results are robust across all specifications and total storage is actually stronger with 5% trimming. Appendix Table A7 shows estimates using only the midline data, finding broadly similar effects. One difference here is that storage is higher in the control group in the midline this is due to differences in the wording of questions between midline and endline.

[24] Appendix Table A11 shows the same robustness checks as Appendix Table A10 results are not sensitive to these specification changes.

GSRA sales are shifted back in time conditional on selling, GSRA respondents are less likely to sell maize immediately, and more likely to hold onto maize until prices rise before the following year's harvest.

2.3.4 Other outcomes

We examine other outcomes in Table 4.15, including redemption of the experimental coupon (Columns 1-2), input usage (Columns 3-5), and food security (Columns 6-7). As discussed earlier, coupon redemption was before prices had much risen coupons were redeemable just before planting, in February/March, but prices do not reach a peak until June. Thus, any effect of the GSRA would likely be modest. That said, we do find a statistically significant higher redemption rate of 7 percentage points (significant at 10%) in the GSRA group. However, total input quantities do not differ (Columns 3-5), suggesting that much of this effect is crowding out market purchases. We also note that input usage was much higher in general than we had expected (fertilizer usage was 88%), so that there was comparatively little room to increase usage. Finally, we find no effect on food security.

2.3.5 Pathways

In designing the project, we anticipated at least three main reasons why the GSRA might be effective: (1) a reduction in losses due to pests or spoilage; (2) reducing demands on income from others; and (3) discouraging consumption of maize kept at home. In the endline, we included a number of questions to explore these possibilities, which we tabulate in Table 4.17. Starting with Panel A, we see descriptive evidence in favor of intra- and inter-household demands on income: 66 percent of respondents agree with the statement "If I have maize at home, my household is tempted to eat more than we need" while 50 percent agree with the statement "If a friend or relative comes to me to ask for maize, and if I have maize at home, I am obligated to give him/her some." We find limited evidence in favor of spoilage: in the season of the program, only 6 percent of maize stored at home was spoiled (conditional on spoilage, farmers lost 21 percent of their total maize). This is somewhat smaller than spoilage reported in Table 4.9, perhaps due to lower spoilage in the year of study than in previous years.

Panel B tabulates responses to a number of open-ended questions about the GSRA. Ninety-four percent of respondents reported that the GSRA was helpful (this number actually exceeds the number that took it up in the first place, perhaps because people expected to use it in future years). Those reporting yes were asked for reasons why they liked the GSRA: 53 percent reported lower spoilage, 39 percent reported that they used the GSRA to allocate money towards inputs, 38 percent reported the benefit of defraying costs of storage across members, 38 percent reported that they reduced consumption, and 24 percent reported giving away less maize to others. Forty percent agreed with the statement "The GSRA program prevented my household from eating more maize than needed" while 62 percent reported that they gave away less maize as a result of the GSRA. Of those who reported giving away less, 38 percent reported that they got fewer requests because less maize was in the house while 55 percent reported that it was easier to say no.

2.4 Discussion and Conclusion

This paper shows that a group-based savings scheme can increase storage among smallholder farmers providing savings clubs with a simple way to set aside maize increased the likelihood that a farmer stored maize by 23 percentage points, increased the amount stored by 17%, and doubled the likelihood of maize sales. Potentially this increase in storage could have a substantial effect on cash income from the farm: we find an increase in revenue of about 15% (though not statistically significant).

The effect sizes in this paper are similar to those in the savings literature (see [73] and [147] for a discussion of effect sizes in the previous literature), but are differentiated because they are based on storage of grain rather than cash savings. This type of storage departs from cash savings because the seasonality inherent in agricultural prices almost mechanically makes grain storage not just an act of saving, but also one of investment, with nearly guaranteed returns (so long as spoilage is limited). On the other hand, the real return to savings in the types of banks available in rural Africa often have negative real rates of return due to high fees and high inflation. This suggests that interventions to help farmers store maize could potentially have larger welfare effects on outcomes like real income than would encouraging savings in the banking options available to people currently.

An important caveat is that our experiment was not designed to test for pathways. The GSRA could have worked through the safe-keeping afforded by the bags, the impact of labeling that comes about due to segregating the grain for storage with the ROSCA, or the peer-effects generated by the communal storage. However, we do not think this diminishes the importance of our findings as in this case, we believe that the combination is the appropriate treatment. Specifically, no amount of mental accounting or social commitment will spur storage if farmers view it as fundamentally risky due to the potential for spoilage. Similarly, merely providing insulated bags that continue to locate grain in plain sight is unlikely to arrest intra and interpersonal issues.[25] Indeed, [26] who studied a similar question in Indonesia by providing storage supplies and lean season in-kind loans as two *separate* interventions, found that while storage in the absence of credit had a small positive effect on lean season consumption, credit in the absence of reliable storage had no effect. This point is of great importance even outside of the immediate context: the poor often operates under multiple binding constraints (for instance, a farmer's storage choices are guided by financial limitations as well as the lack of physical storage technology). Good policy will need to remove these constraints simultaneously in order to be effective.

Multilateral agencies and NGOs like Feed the Future, One Acre Fund, and USAID are currently working to commercialize PICS bags by building local capacity.[26]

[25]Our results on pathways show that the treatment effects are not explained by safe-keeping alone as people also report consuming and giving away less.

[26]Efforts are already underway in Burundi, DRC, and Kenya by USAID, in Tanzania and Sierra Leone by CRS, and in Ethiopia and Rwanda by the One Acre Fund.

There is ample entomological evidence to suggest that these bags could be helpful, for poor smallholder farmers whose current storage technology is inefficient. The basic social structure of the ROSCA, on which we layered the storage intervention, is widely prevalent in this part of the world, and comes about organically without outside intervention – suggesting that the GSRA could be easily scaleable. Even now, in Kenya PICS bags are commercially available in moderate-sized towns (like Busia), and usage of PICS bags has been expanding in recent years: the distribution and sale of PICS bags under the USAID's KAVES program went from 69,209 in 2014 to 215,248 in 2015 to over 300,000 by January 2016 (equivalent to more than 27,000 metric tonnes of maize in storage capacity).[27] Our results suggest that the effect of programs like USAID's might be larger if policy makers also encourage farmers to use their bags for setting aside a portion of their maize for communal storage in order to take advantage of seasonal fluctuations in maize prices.

An open question for future research concerns the general equilibrium effects of such an intervention. Bergquist et al. (2016) find a general equilibrium effect on prices from their credit intervention inducing people to hold maize will affect prices even for those who sell earlier. Analogously, returns will also be impacted for those who currently do benefit from seasonal arbitrage, notably large farmers and traders. Such general equilibrium effects will lessen incentives to hold maize in the first place. As the return to storage declines, people may find it less profitable to store maize then to invest

[27] Seehttps://picsnetwork.org/wp-content uploads/2016/04/Newsletter_2016_4-22-16.pdf.

elsewhere at potentially high returns [64]. Our paper suggests that at current prices, many farmers evidently find storage more profitable than the next-best alternative, but such storage would become less attractive as more people do it and seasonal price fluctuations diminish.

3

Digital Credit: A Snapshot of the Current Landscape and Open Research Questions

3.1 Introduction

Lack of access to finance is suspected to be an important impediment to development in low-income countries. Some symptoms consistent with binding liquidity constraints include high marginal returns to capital,[1] difficulty coping with unexpected income shocks such as household illness,[2] and a response of investment in durable goods such as bednets or water connections in response to credit [160, 68]. While these stylized facts suggest unmet demand for credit, take-up of microfinance has been rather low in

[1]Among others, see [64, 162, 22, **?**]

[2]See, for example, [**?**]. See [66] for a review.

experimental trials and impacts have been modest [20]. This has led some observers to question whether microfinance is a valuable development program, or whether resources should be put elsewhere.

A plausible reason that microcredit has been disappointing is that the existing set of credit products might not be appropriate for target customers. For example, many microcredit products still involve large transaction costs (such as travel costs to the nearest bank branch or time costs in regular group meetings), have imposing loan terms, or significantly restrict how loans can be used.

In the past few years, *digital credit* has emerged as an alternative mechanism for providing short-term loans. In a typical digital credit offering, a mobile phone operator will partner with a financial institution to provide small, short-term loans directly to customers over an existing mobile money ecosystem (we discuss other models of digital credit later). This approach offers several advantages to existing microcredit or bank credit. First, digital credit has the potential to dramatically lower transaction costs, since loans can be disbursed through mobile money, and converted to cash through existing agent networks (which are typically far more extensive than bank or ATM networks). Second, loans can be disbursed immediately, without requiring in-person vetting by a financial institutions. And third, digital credit providers use nontraditional data (in particular, mobile money and airtime usage) to develop alternative credit scores which make it possible to extend credit to large groups of individuals without collateral or traditional scores. The result is a product that has been very popular with consumers. For example, 1 in 5 Kenyans (4.5 million people) were using Safaricom's M-Shwari digital credit product as of 2015 [61].

At the same time, there are reasons to be concerned with the rapid expansion of digital credit in developing countries. In particular, the effective interest rates charged to consumers are typically quite high - for example, the "facilitation fee" for an M-Shwari loan is 7.5% per month (138% APR), and many products are much more expensive than this. Loans thus tend to look like payday loans in the developed world; while high-interest rate loans can in principle be helpful for liquidity constrained customers by providing cash in times of high need (i.e. [117, 142]), they may also be harmful, causing overindebetdness and bankruptcy [155], and making it hard to pay bills [138]. Moreover, consumer protections for these digital loans is still in its infancy there exist few protections for borrowers and anecdotal evidence suggests many borrowers do not fully understand loan terms [134]. Default is common enough that an estimated 2 million people have been reported to the Kenyan credit bureau for M-Shwari default, many for sums of a few dollars. It is an open question as to whether consumers are fully informed of the costs of credit, or whether providing more information may reduce demand for these high-interest rate loans (see [35] for evidence that information reduces payday loan demand in the US).

In this overview, we summarize the current state of digital credit, focusing primarily on the currently dominant form of credit consumer loans offered through mobile money systems, often backed by a financial institution. In Section 2, we summarize the current landscape. In Section 3, we discuss various ways in which digital credit will represent a change from previously available forms of credit, in particular microcredit or bank loans. Section 4 discusses some possible directions for further research.

3.2 Background

3.2.1 What is digital credit?

In 2007, the Kenyan telecom company Safaricom launched M-Pesa, a digital system which allows users to exchange cash for e-currency, which can be stored or sent to other users over the mobile phone network, and then withdrawn from the system through agents (these are often shopkeepers who work as M-Pesa agents in addition to their main business)[3] Since 2007, mobile money has rapidly proliferated in the developing world, and today there are more than half a billion registered mobile money accounts across 270 mobile money services in at least 90 countries [91].[4] While bank accounts are much more common than mobile money in most of the world, this is not true in Africa even by 2014, mobile money ownership exceeded bank account ownership in many African countries (and this gap has surely grown by now). The introduction of mobile money

[3]The first mobile money system - Smart Money - was launched in the Philippines by Smart Communications and Banco de Oro (BDO) in 2001.

[4]While mobile money account ownership has increased quite rapidly, it is important to note that transactions are still largely cash-based, even in countries with high mobile account penetration. In Tanzania, only 53 percent of registered mobile money users left the cash in their e-wallet for more than a few days; others cash out their account balance with mobile money agents quite frequently [140].

has been associated with important welfare effects: in Kenya, mobile money has been linked to improved risk-coping [104] and a reduction in poverty [159]. Consequently, many in the policy and aid communities view mobile financial services as the future to improving financial access in poor countries [91, 124].

Though mobile money could in principle have been used for other financial purposes such as savings, many people have primarily used mobile money for person-to-person transfers.[5] This was due in part to regulatory issues, since telecom providers were not registered as banks and therefore were prevented from earning interest on deposits.[6] Mobile money providers therefore did not market themselves as banks, and the products were not particularly well suited for saving since they featured withdrawal fees but no interest. In November 2012, Safaricom launched M-Shwari, a collaboration with the Commercial Bank of Africa (CBA), in which users can earn interest on savings and qualify for loans backed by CBA.

M-Shwari has taken off from there:[7] in the first two years of existence, Safaricom made over 20 million loans to 2.6 million borrowers [61].[8] In response to this success, similar products have now been launched in many other countries – see Table 4.20 for a partial listing of products. Though it is difficult to accurately measure global demand

[5]For example, see [72] for evidence that few people in Western Kenya used mobile money accounts to save in 2010-12.

[6]See [132] for a discussion of this in regards to M-Pesa.

[7]Safaricom operated two mobile loan platforms - M-Shwari in partnership with CBA, and KCB M-pesa in partnership with Kenya Commerical Bank.

[8]Safaricom reports that it currently makes two loans in the range of USD 15 to 25 every second across its two credit products . The Standard Digitalreports on borrowing across these two products.

for loans, existing evidence suggests substantial consumer interest (Table 4.20, Column 8 compiles statistics on demand, where available). For instance, M-Pawa in Tanzania reports making loans to 4.9 million borrowers during its first two years [6].

Relative to conventional credit, digital credit offers several key differences, of which CGAP (Consultative Group to Assist the Poor - a policy and research center housed at the World Bank) highlights three (see Figure 4.8). First, the process from loan application through approval is nearly instantaneous. Second, evaluation of loan applications is automated, since digital credit products leverage historical user data (often capturing mobile phone and mobile money use) to generate credit scores. Third, loans can be processed remotely, without requiring the customer to visit a store or agent in person.

A final distinguishing feature of digital credit is that loan decisions are frequently determined based on the analysis of unconventional sources of digital data, rather than the traditional credit scores calculated by a traditional credit bureau. This is particularly relevant in developing countries, where most households do not have credit scores, due both to the underdevelopment of credit bureaus and to the fact that many people do not have a history of financial transactions which can be verified by a lender.

3.2.2 Digital Credit Products

3.2.2.1 Consumer Credit Products

The currently dominant form of digital credit is short-term, high interest rate loans made directly to consumers. Table 4.20 shows some information on a sampling of digital credit products. In the most common scenario, which is a bank-telco partnership, the bank originates the loan, but customer interactions including loan disbursal and repayment are done via the mobile money platform. Loan amounts are not very large - the average M-Shwari loan is about USD 12 [61]. Loan terms are typically no longer than a month (e.g., M-Shwari) but may be as short as a week (e.g., Airtel Malawi). Though consumers are not usually officially charged an interest rate, they are instead charged a fixed "facilitation fee." As summarized in Table 4.20, these fees tend to be sizeable: ranging from 7.5% per month for M-Shwari (138% APR) to 10% per week for the Kutchova product from Airtel Malawi (over 1,000% APR). Late fees vary from provider to provider, and loans are not usually collateralized. While some companies automatically deduct mobile money balances in the case of late payment, companies are typically not able to deduct directly from airtime recharges (the mobile money and airtime systems are normally separate).

As in traditional models of lending, providers of digital credit employ dynamic incentives and punishment to reduce moral hazard and to incentivize repayment. Timely repayment of M-Shwari loans increases the probability of getting a larger loan in the future. Customers of Branch an app-based lender who repay their loans on time are more likely to qualify for larger loans (increasing from USD 2.50 to USD 500), with longer repayment periods (increasing from 2 weeks up to 1 year), and at lower interest rates (with APR ranging from 180 percent to 15 percent). Interest rates on many products, like Timiza Wakala loans and Tigo Nivushe loans provided by Airtel Tanzania and Tigo Pesa respectively, are determined largely by previous borrowing behavior. Further, many existing digital loan providers discourage default by one or more of these punishments: affecting access to future loans, automatic deduction of outstanding loan amount from linked mobile savings or mobile money accounts, or blacklisting defaulting borrowers with credit bureaus.

3.2.2.2 Other digital credit products

While bank-telco partnerships are currently dominant,[9] digital credit is a sector seeing rapid innovation. For instance, several financial technology ("fintech") companies provide intermediary credit scoring services, aggregating customer data and applying machine learning algorithms to convert the data into credit scores, which are then provided to banks and other loan originators.[10] Another set of companies directly originate loans to customers, but require applicants to install an app on their smartphone that tracks and analyzes phone usage (including phone and SMS activity, handset details, GPS data, and so forth) to determine loan eligibility.[11]

[9] As of December 2015, 85 percent of global digital credit services were partnerships between a mobile operator and a financial institution [90].

[10] Examples include Jumo and Cignifi.

[11] Examples include Branch and Tala.

There are several digital credit products that do not directly target micro-loans to consumers. For example, Grundfos Lifelink works with Safaricom to provide pay-as-you-go solutions for clean water distribution systems to rural Kenyan communities. Similarly, Safaricom partners with M-Kopa and MTN with Mobisol and Fenix International to sell solar home solutions on a down payment. Future payments are collected via regular mobile money transactions. Enforcement of repayment is accomplished through technology which allows the firm to turn off the solar panel remotely if the account is in default. Another Safaricom credit product Okoa Stima - allows customers to get cash advances to pay for electricity. Many telecom operators provide airtime advances using mobile loans. Examples include Safaricom's Okoa Jahazi and Airtel's Kutapa and Beerako in Malawi and Uganda respectively. Finally, some lenders provide digital credit to businesses, usually to business owners who use mobile payments platforms. Transactions on the payment platform is an important factor in determining creditworthiness. An example is Kopo Kopo's credit product (Grow) for businesses that use its payment platform.[12]

3.2.3 Competition among lenders

A competitive lending market can potentially lower the costs of scoring and disbursing loans to lenders, and help borrowers access more affordable credit. For

[12] Kopo Kopo's payment platform is designed to encourage business growth, without costly monitoring and unfair punishments. Businesses repay loans by automatically allocating a pre-determined percentage of their daily business revenue towards loan repayment. Thus, firms are not punished for being unable to repay in times of poor business. Kopo Kopo incentivizes borrowers to repay early by offering lower loan fees for higher daily deduction percentages.

instance, estimates from a joint CGAP-McKinsey exercise indicate that credit scoring based on nontraditional data reduces the cost of providing a USD 200 loan by 30 percent in Tanzania [53]. However, as we have highlighted, digital credit tends to be very expensive, in part because the telecom industry is very concentrated and lenders have considerable market power. A key feature of digital credit is generating credit scores from digitized financial transactions. Since credit bureaus are non-existent or poorly functioning in many settings, this may allow for credit scoring of people excluded from the normal financial system. A major downside of this, however, is that this information is proprietary and firms have little incentive to share, so that transactions on a mobile money network are only useful for scores on that network. This may tend to increase the market power of telecom companies.

3.3 What is new about digital credit?

Digital credit may offer several important advantages compared to microcredit or existing bank credit.

3.3.1 Credit scoring

Many developing countries either do not have credit bureaus or do not have very effective ones [89, 127, 63]. In addition, many low-income people in developing countries do not leave "financial footprints" (such as a history of usage of financial products and services) that can be incorporated into a credit score because their financial transactions are simply not recorded, which makes credit scoring difficult. By contrast, an estimated 80% of adults in emerging economies own a mobile phone [107], and recent evidence shows that mobile phone usage can be used to predict loan default [37, 38] as well as a broader range of socioeconomic characteristics of would-be borrowers [41]. In this environment, using mobile money to generate scores could expand credit access, especially in countries with high usage rates of mobile money accounts (see Table 4.18). To take one example, only 6.5% of adult Tanzanians appear in one of the country's private credit bureaus [89], while 32.4% have mobile money accounts [65].

The information leveraged by digital credit lenders to determine creditworthiness is varied. Most lenders from (or associated with) the telecom industry use the applicant's history of mobile phone usage, including phone calls, text messages, airtime purchases, data use, and mobile money transactions. When the applicant has an app installed on her smartphone, this app collects all of that information as well as GPS data, information on social media use, contacts lists, and the like. For example, Lenddo uses information about contacts, frequency of interaction, interests, messaging and browser history, apps, wifi network use, and even mobile phone battery levels, among other data points, to establish a "LenddoScore" as a measure of creditworthiness [120]. FirstAccess uses demographic, geographic, financial, and social data to determine creditworthiness. VisualDNA and Entrepreneurial Finance Labs (EFL) rely on psychometric analyses to determine creditworthiness. Revolution Credit provides online financial education videos and quizzes throughout the loan process to measure creditworthiness. Other information used to create non-traditional credit scores include histories of remittance transaction (Axis Bank, and Suvidha Infoserve) and usage of payment platforms (AMP Credit, Kopo Kopo).

3.3.2 Reduced Transaction Costs

Bank penetration in developing countries is still fairly limited, particularly in rural areas, and thus travel costs to bank branches can be substantial. Such transactions costs can be an impediment to bank usage (see [72] for evidence from Malawi and Uganda on the effect of distance on bank usage). Banking services are also often poor, featuring long wait times or limited operating hours, and many people may not fully trust banks [72, 18]. Group-based microcredit banks also tend to require regular repayment of loans and regular attendance at meetings, which increase transactions costs. To the poor, transaction costs can be formidable barrier to accessing financial services [112].

Digital credit can dramatically reduce these transactions costs, since e-cash can be transferred instantaneously and there is a much larger number of mobile money agents than bank branches (i.e. [104]). Table 3 reports the reach of commercial banks and active agent outlets in five countries where digital financial services are relatively more common (Bangladesh, Kenya, Pakistan, Tanzania, and Uganda). The number of agents is often an order of magnitude higher than bank branches. While these agents face other well-documented constraints (especially in the earlier stages of mobile money adoption), for example that they lack liquidity to allow people to cash out or that networks may be down, the sheer volume of agents suggests that a well-run network can lower transaction costs significantly relative to traditional bank-based credit.

3.3.3 Instantaneous loan approval and disbursement

A vast literature has shown that poor people are unable to effectively deal with income shocks (see [66] for a review). Digital credit might be very useful for shocks (just as mobile money transfers have been), since loans can be made remotely and instantaneously, with no need for human mediation. This is a particularly vivid contrast compared with the more traditional microcredit model in the spirit of the Grameen Bank, in which loans are typically geared towards productive investment and can usually be accessed only at pre-specified times. However, even for banks which allow loans for consumption, sending out loans instantly is a radical improvement.

Descriptive evidence is consistent with consumers often using loans for liquidity needs. The nationally representative FinAccess 2016 surveys in Kenya asked a question about what the main type of credit was that people accessed in times of need. People were much more likely to report digital credit (40.9%) or informal providers (40.9%) than traditional banks (6.7%) or microfinance 1.8%). In addition, credit to meet “day to day needs” is accessed most commonly from digital credit (46.2%) or informal providers (36%) than banks (5.9%) or microfinance institutions (3.6%) [52]. [62] discuss interviews conducted by the Omidyar Network with early adopters of digital credit in major cities of Kenya and Colombia nearly 60 percent of mobile borrowing is driven by unforeseen expenditures and debt repayment.

3.3.4 Product customization

Particularly among fintech firms, there is a culture of applying recent algorithmic developments many of which were first tested in the context of internet-based advertising to customize and optimize lending decisions and loan terms. While in theory such technology could also be utilized by traditional bank-based lenders, the data-rich environment of digital credit is particularly well-suited to such targeted customization. For instance, the supervised learning algorithms used to predict default risk can be updated frequently, quickly adapting to changing lending conditions and aggregate risk. It is also quite common that digital credit loans will employ dynamic incentives, such that borrowers become eligible for larger loans if they reliably repay smaller loans. More sophisticated systems offer different loan repayment periods. Given the near absence of regulation in this space (more on this below), lenders have considerable scope to develop proprietary and discriminatory pricing and lending systems.

3.3.5 Other possible differences

Trust in financial institutions is another factor impeding financial access [65, 72].[13] It is conceivable that digital credit would be relatively more trusted, since loans are provided by established telecom providers. These firms tend to be familiar and trusted, and their products (mobile phone services, mobile money) are used more regularly than those of microcredit institutions and banks. However, there are also

[13]Some reasons cited in the 2016 FinAccess Household Surveys for stopping usage of bank accounts in Kenya include banks not meeting needs of customers (19.7%), hidden charges (14.1%), money lost or taken by bank (12.7%), and people being dissatisfied with bank service (12%) [52].

anecdotes of people not trusting agents. Some agents have trouble holding enough liquidity to meet withdrawal requests, particularly in rural areas where many transactions are withdrawals of remittances sent from urban areas.[14] In some systems, agents have an incentive to strategically control their liquidity or to lie about liquidity to maximize revenue [110].[15] It thus remains to be seen whether digital credit will offer trust advantages over financial institutions.

3.4 Open questions

Over the course of just a few years, digital credit has proliferated rapidly in several developing countries, and demand for these products is accelerating across the globe. To our knowledge, however, not a single quantitative impact evaluation has rigorously measured the social and economic impacts of digital credit.[16] More broadly, there is a dearth of empirical evidence that can help development policymakers and regulators understand the implications of this financial transformation. Here, we briefly mention several questions that we believe deserve the attention of the research community.

[14] One policy to increase agent liquidity is for mobile money providers to provide credit to the agents. One example of a provider doing this is Airtel Tanzania, which launched Timiza Wakala loans in 2015. These digital loans, which range from USD 23 to USD 229, are provided to help qualifying Airtel mobile money agents meet their business needs.

[15] Anecdotal reports also suggest that customers often leave cash and PIN numbers with mobile money agents during network downtimes so that agents can carry out transactions on their behalf, and that this practice exposes mobile money users to fraud (McKee et al. 2015).

[16] The one ongoing evaluation we are aware of is being conducted by Prashant Bharadwaj, William Jack, and Tavneet Suri with M-Shwari in Kenya.

3.4.1 What is the impact of digital credit?

Digital credit is a very recent innovation, and represents a truly new way of accessing loans and thus impacts may differ from more traditional microcredit. While there is a lack of current research on the topic, there exists a time-limited window for conducting research in this space. Since products are just now being rolled out in new countries, there exist immediate opportunities to study these effects through randomized experiments (such as randomized offers or encouragement designs), natural experiments, as well as other non-experimental approaches (such as a regression discontinuity around an eligibility threshold).

In such studies, it is important to consider the possibility that digital credit may have negative as well as positive effects. One likely benefit of digital credit would be to help borrowers with short-term liquidity needs,[17] but a variety of plausible theories of change might be worthy of research.[18] At the same time, as we discuss in greater detail below, unsophisticated borrowers may borrow too much, may get shut out of the system through accidental default, or suffer in other unintended ways.

This is a context in which heterogeneity is certainly important. While some people will likely benefit from having easy access to cash in times of high liquidity needs,

[17]Thus researchers would likely need to focus on the responsiveness of households to shocks and other adverse events, and examine whether credit may help mitigate these shocks. Researchers may be able to anticipate likely effects simply from looking at loan uses.

[18]For instance, if consumers tend to use loans for other purposes, like business investment, loans will be unlikely to be effective unless available investment opportunities truly exceed 100% per year or more.

others may take out loans that they do not need. For example, time-inconsistent or less financially sophisticated borrowers may be tempted to take out high-interest loans because they are so easy to access (i.e. [137, 99]. Research should carefully consider heterogeneity in positive as well as negative impacts of digital credit.

It is also important to understand who are the winners and who are the losers in this ecosystem. Initial evidence indicates that early adopters of digital credit products are likely to be young, male, urban, educated, stably employed, bank account holders, and report being able to cover their basic expenses and save [61, 62]. It is not surprising that the tech-savvy with deeper digital footprints are the first to access digital credit. The demographics of users of digital credit is very likely to change over time: initial adopters of mobile money were more likely to be urban and wealthy, but the number of rural, and poor users of mobile money increased over time [104].

3.4.2 Consumer Protection

Digital credit brings financial services to many who have never before participated in a formal financial system. This can be a double-edged sword. On the one hand, this furthers efforts for financial inclusion. On the other, the target client base have little to no experience working with a financial institution, let alone through complicated user interfaces. For example, in Rwanda, only about half of borrowers report knowing their loan terms and the interest they pay on loans [102]. Focus groups run by CGAP and evidence from diary respondents indicate that customers have little awareness of the products, fees, and terms of the loan, and several respondents report taking their first loan without an intentional purpose for it (see [131, 134]. More broadly, less sophisticated borrowers may be especially susceptible to over-borrowing [137, 99], especially when a loan is accessible by dialing in a request on their mobile phones. And, conditional on borrowing, people with time-inconsistent preferences may find it more difficult to repay loans.

The procedure of obtaining informed consent with digital credit may be ineffective in really informing customers of their rights and the data that is being used. Most digital credit products direct customers to a website to understand the terms and conditions of the product it is unlikely that many have the resources (like internet connectivity) to access this information. Simply reading long loan descriptions is challenging on a feature phone. CGAP provides insights regarding how customers perceive the informed consent procedure from interviews and focus group discussion with 64 individuals in Tanzania. While their participants were willing to share data to access credit, they wanted more information about how their data is accessed and how it would be used than is currently provided by digital credit providers [130].

Digital credit products also raises a host of privacy issues. The data most commonly used on digital credit platforms are data that most people would consider private, and it is not clear that borrowers fully understand how such data is being used in determining loan eligibility. In more developed financial ecosystems, regulatory agencies (such as the Federal Trade Commission in the U.S.) oversee these institutions and determine how such data can be used, but such institutions are generally weak or nonexistent in the markets where digital credit is thriving.

Non-traditional scoring retains some trappings of traditional credit scoring models. Research shows that such models can acquire implicit biases based on gender and race (cf. [48]), and there is reason to think that such biases might be more severe in contexts where non-traditional data is used to predict default. In some cases, algorithms explicitly utilize information on borrower's social networks. For instance, Lenddo asks its borrowers to select a "Trusted Network" of at least three people. When a borrower defaults, this trusted network's Lenddo scores suffer and they become less likely to qualify for a loan with Lenddo [96]. It is also important to keep in mind that many who are financially excluded are likely to have shallow digital footprints. Scoring based on this data may need to be supplemented with other measures of creditworthiness, particularly when the consequences of default are so severe. While recent advances in machine learning provide options for "fair" predictive algorithms, a naive implementation could systematically exclude precisely those populations for whom digital credit might have the greatest positive impacts.

Separately, many lenders report concerns of fraud, from borrowers who register multiple accounts, to middlemen who resell SIM cards that have been approved for loans, to clients who deliberately manipulate their behavior to become eligible for larger loans.[19] If not contained, such behavior could threaten the broader ecosystem. Again, models and algorithms exist to detect and account for strategic and adversarial borrowers, but determining how to effectively integrate such insights into digital credit systems will require careful thought.

3.4.3 Product innovation and other lending models

Digital credit has been dominated by small, short-term, high interest rate loans. But can credit be delivered through alternative means, for example through supply chains? Should data analytics be complemented with information contained in value chains to increase effectiveness of credit? For example, [128] show that borrowers selected by traders increased production of cash crop and farm income more than farmers who were given microcredit. Or, what are the effects of credit being distributed through networks that restrict their usage? Tienda Pago pays distributors directly for inventory that is then delivered to the shop-owners; these shop owners repay Tienda Pago from sales revenue, via electronic mobile payment platform.

And while consumer loans are currently dominant and are the focus of this review, digital credit can be used with other lending models. For example, firms like M-Kopa and Fenix International sell solar panels to households on a down payment, and collect repayment via regular mobile money transactions. Enforcement of repayment is accomplished through technology which allows the firm to turn off the solar panel

[19] [144] discusses fraud in digital financial services. [134] provide a summary of key customer risk areas in digital credit.

remotely if the account is in default. The reduction in transaction costs from mobile money makes this type of model viable.

3.5 Conclusion

In the past several years, digital credit has rapidly proliferated in the developing world, particularly in Sub-Saharan Africa, yet there is virtually no quantitative research to examine its effects. Digital credit offers several substantial improvements relative to traditional credit, notably large reductions in transactions costs, near-instantaneous loan approval and disbursement, and an expansion in the consumer base resulting from using nontraditional data to generate credit scores. Yet the current products that are available are largely high interest rate, short-term loans that look very similar to payday loans in the developed world. In this environment, easy access to high interest rate loans is likely to have heterogeneous effects, potentially providing liquidity in times of need for some people while encouraging others to take out loans that they do not need (for example, less sophisticated or present-biased borrowers).

We have reviewed several open areas for research, starting with the most basic and important documenting the positive and negative impacts of digital credit on consumers, and examining how effects may vary with borrower characteristics. Another important research area is in consumer protection, since existing protections tend to be weak in many markets in which digital credit is dominant, and anecdotal evidence suggests some borrowers have limited knowledge about loan terms. More work can be done to understand and refine the algorithms used by lenders to determine creditworthiness. A final question we have highlighted is whether digital credit can be integrated into lending models other than consumer credit, for example into supply chains.

While there is virtually no quantitative evidence in the area, the policy implications of scholarship in this area are large, since so many people have either recently gotten access to digital loans or will be getting access in the coming years. And since digital credit is not yet scaled up, there is an opportunity to partner with lenders or telco companies during the expansion phase. For both reasons, we argue that the current moment offers a unique opportunity to do research in digital credit.

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4

Figures and Tables

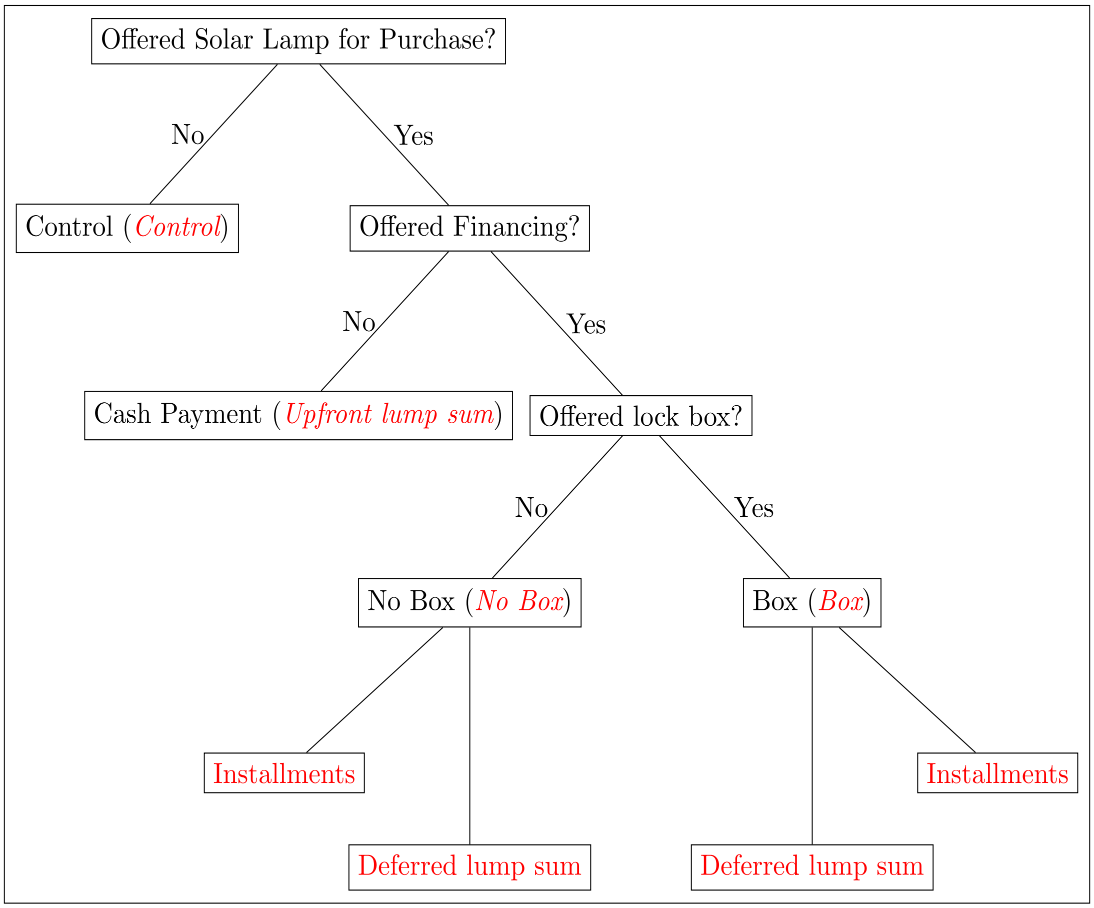


Figure 4.1: Treatment Design

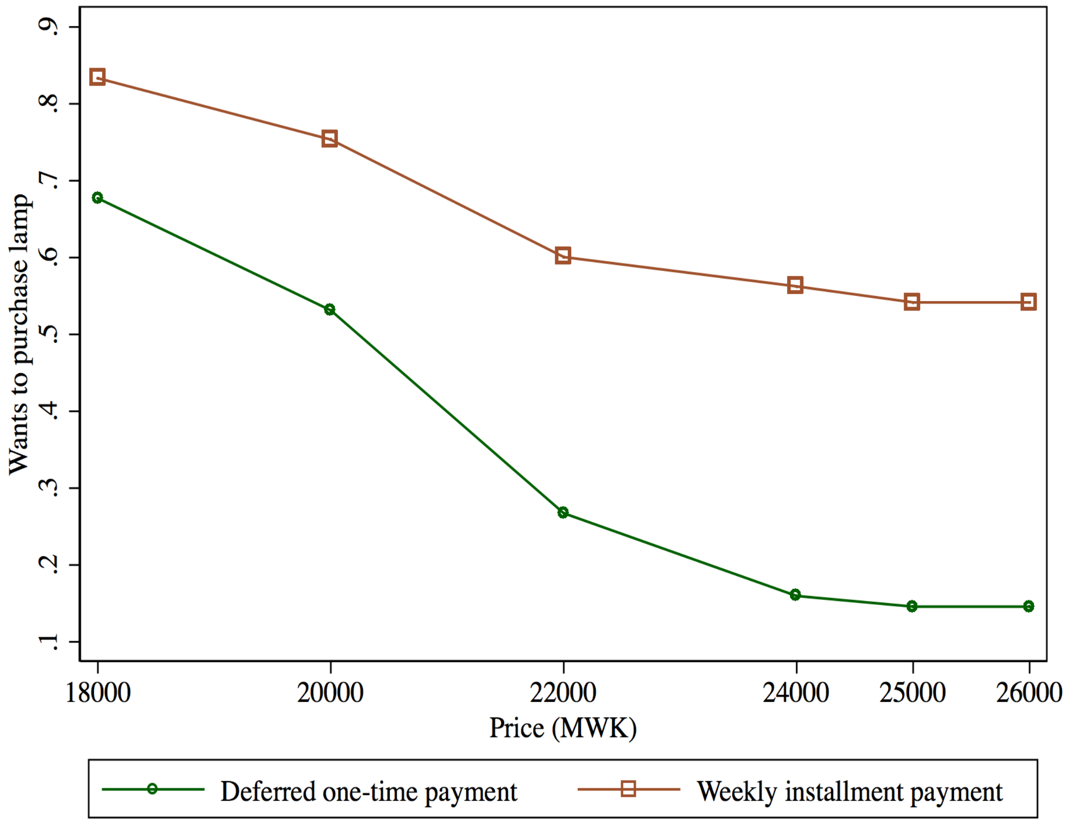
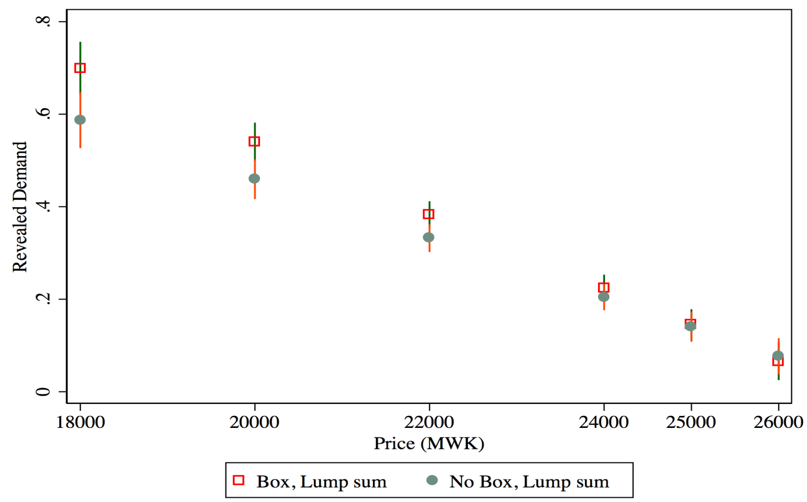
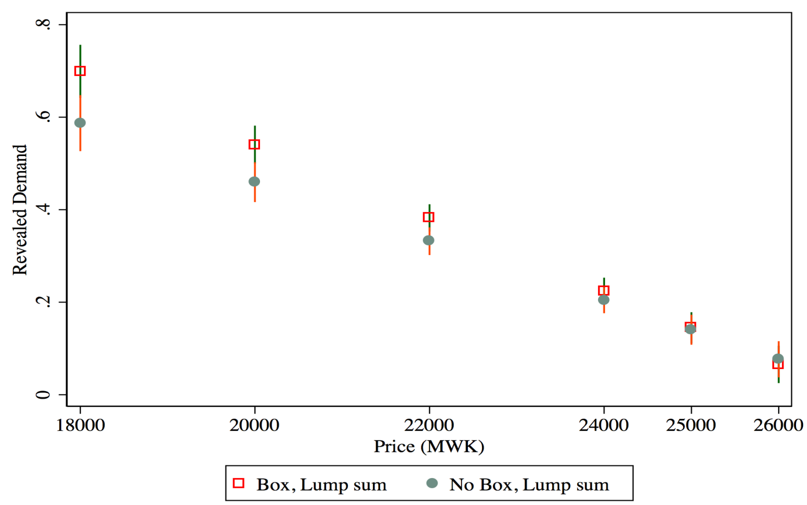


Figure 4.2: Repayment Frequency & Willingness to Pay

The figure plots demand curves using responses to willingness-to-pay exercises using linear probability model. Demand for the installment plan at $P_{ins} = 1$ if individual chooses to pay P_{ins} for the lamp in installments, instead of paying a lump sum price of MWK 20,000. At every price, demand is aggregated across all individuals in *Box* and *No Box* groups. All monetary values are reported in Malawian Kwacha (MWK). At the time of the study, the exchange rate was roughly MWK 720/ 1 USD. Observations = 1,728.



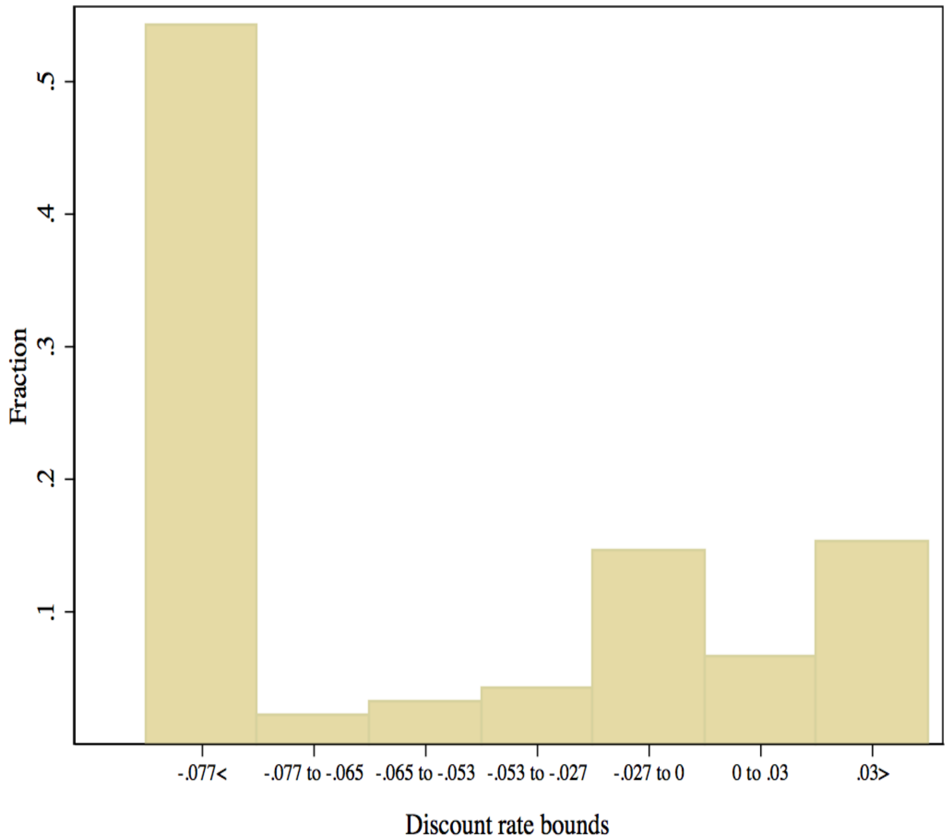
Willingness to Pay with Installments Plan



Willingness to Pay with Lump Sum Plan

The figures plot demand curves using responses to willingness-to-pay exercises using linear probability models. At every price, demand is aggregated across all individuals in *Box* and *No Box* groups. Robust standard errors reported. All monetary values are reported in Malawian Kwacha (MWK). At the time of the study, the exchange rate was roughly MWK 720/ 1 USD.

Figure 4.3: Willingness to Pay



The price at which respondents choose to switch from paying in installments to paying a deferred lump sum is used to construct bounds on respondents' "implied discount rates." The most and least negative discount rate windows pertain to respondents who never choose to pay in lump sum and installments, respectively.

Figure 4.4: Implied Discount Rates

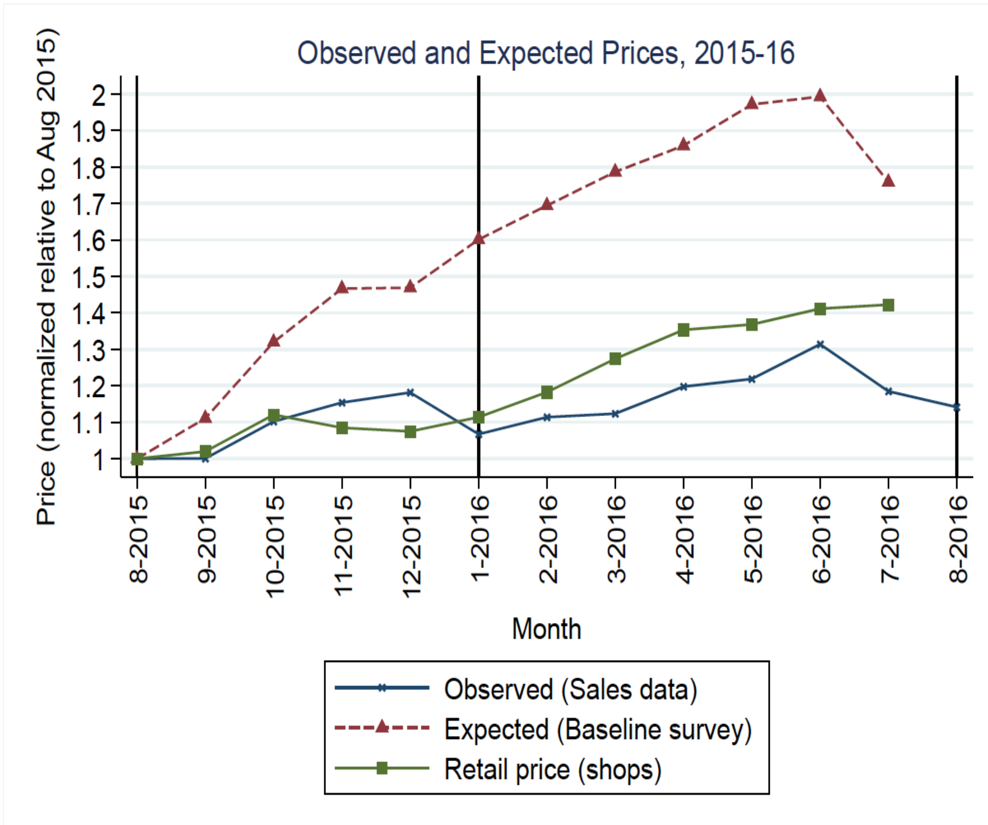


Figure 4.5: Prices Over Season

The vertical axis shows the price, normalized to August 2015. Vertical loans show the long rains harvest (around August) and the short rain harvest (around January). Expectations data comes from the baseline survey; observed sales data comes from sales data collected from respondents during surveys; data for shops comes from interviews with shop-owners conducted in the primary markets for our respondent farmers (10 markets in all).

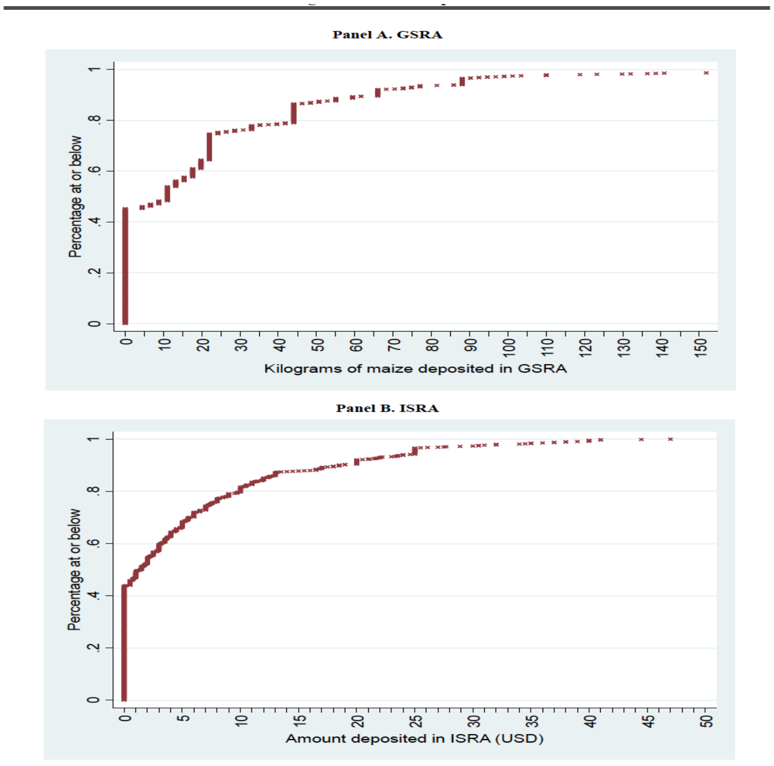


Figure 4.6: CDFs of deposits

For readability, CDF in Panel A shows values below the 99th percentile. A kilogram of maize was worth about USD 0.27 in August 2015, rising to USD 0.36 by June 2016. Average total harvest was approximately 480 kilograms. The exchange rate at the time was approximately 1 dollar to 100 Ksh.

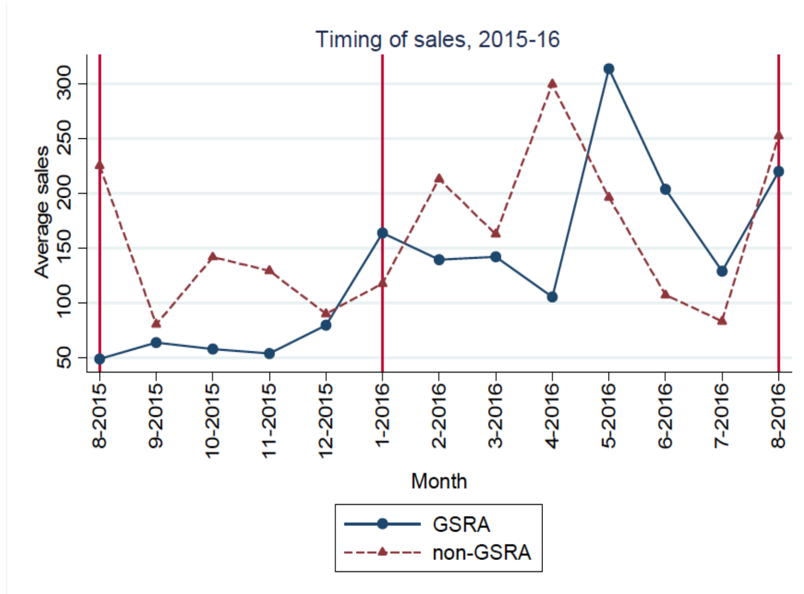
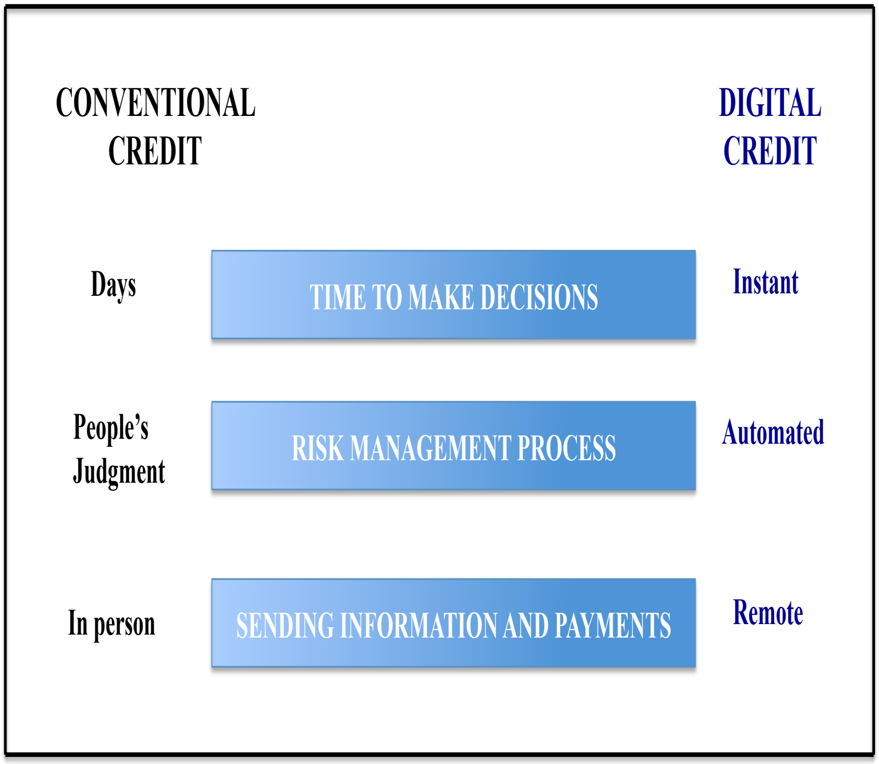


Figure 4.7: CDFs of deposits

Y-axis shows average sales (in kilograms), by month. The long rains harvest was in August 2015. The unit of analysis is the average monthly sales by treatment group, where ISRA and Control are pooled. This figure is based on the endline survey (sales were not recorded in the GSRA logbooks).



Source: Chen and Mazer (2016).

Figure 4.8: Features of Digital Credit

4.1 Tables

Table 4.1: Baseline Statistics and Randomization Check

	Box	Deferred lump sum	Upfront lump sum	Control	Joint test 1[a]	Joint test 2[b]	Joint test 3[c]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Demographic & Household characteristics							
Female	.29	.35	.3	.33	.29	.65	.52
	(.46)	(.48)	(.46)	(.47)			
Age	35.94	33.64	34.85	35.23	.08	.96	.22
	(11.16)	(11.17)	(11.09)	(11.64)			
Education (years)	9.0	9.19	8.68	8.28	.59	.25	.43
	(3.04)	(2.79)	(2.85)	(3.02)			
Married	.78	.71	.9	.81	.2	0	0
	(.42)	(.46)	(.30)	(.39)			
Head of household	.78	.74	.77	.77	.53	.93	.82
	(.42)	(.44)	(.43)	(.42)			
Household size	4.53	4.32	4.67	4.48	.38	.34	.45
	(1.92)	(2.1)	(1.98)	(1.66)			
Children (count)	2.28	2.03	2.27	2.19	.17	.54	.33
	(1.53)	(1.58)	(1.52)	(1.35)			
Burnt brick walls	.65	.66	.63	.69	.93	.7	.93
	(.48)	(.48)	(.49)	(.46)			
Iron sheets roof	.94	.87	.85	.87	.03	.21	.03
	(.23)	(.34)	(.36)	(.34)			
Cement floor	.77	.66	.8	.69	.03	.08	.03
	(.42)	(.48)	(.40)	(.46)			

Financial characteristics							
Interest rate on	.23	.23	.23	.26	.95	.92	.99
one-month loan[e]	(.20)	(.22)	(.18)	(.20)			
Has a bank account	.30	.23	.38	.2	.16	.05	.05
	(.46)	(.42)	(.49)	(.40)			
Participates in ROSCA	.23	.2	.32	.17	.53	.07	.15
	(.42)	(.40)	(.47)	(.38)			
Participates in VSLA	.15	.23	.25	.19	.11	.3	.15
	(.36)	(.42)	(.43)	(.39)			
Has own mobile money	.66	.51	.53	.45	.01	.4	.03
account	(.48)	(.50)	(.50)	(.50)			
Mobile money account	.38	.17	.27	.21	0	.92	0
with spouse	(.49)	(.38)	(.45)	(.41)			
Business characteristics							
Owned this shop (years)	5.96	5.37	6.54	5.89	.41	.31	.41
	(6.18)	(5.67)	(7.1)	(6.4)			
Open air shop	.11	.08	.15	.12	.41	.24	.34
	(.32)	(.28)	(.36)	.33			
Daily hours worked	10.81	10.95	11.1	10.77	.61	.46	.67
	(2.36)	(2.31)	(2.34)	(2.45)			
Business profit (good week)	25.5	16.9	21.8	21.4	.16	.88	.18
	(68.13)	(19.18)	(20.05)	(28.80)			

Business profit (bad week)	13.35	12.33	11.48	10.67	.84	.67	.83
	(28.80)	(51.80)	(16.21)	(19.46)			
Lighting expenditure & solar technology awareness							
Monthly grid exp (home)	2.31	3.07	1.47	2.38	.49	.08	.22
	(5.28)	(11.99)	(4.04)	(8.33)			
Monthly grid exp (shop)	1.10	0.88	0.45	2.57	.61	.08	.22
	(4.46)	(2.93)	(1.94)	(10.92)			
Monthly off-grid exp[f]	5.38	5.08	5.42	59.63	.68	.8	.89
	5.73	6.61	6.23	7.53			
Know of solar lights	.65	.64	.65	.63	.87	.89	.98
	(.48)	(.48)	(.48)	(.49)			
Has solar light(s)	.03	.06	.07	.03	.25	.3	.26
	(.17)	(.23)	(.26)	(.16)			

Notes: [a]Test of equality of means across *Box* and *No Box* groups. [b]Test of equality of means across Upfront lump sum, Installments, and Deferred lump sum groups. [c]Test of equality of means across groups offered lamp for purchase and group not offered the lamp for purchase. [d]Columns 1-4 report means and standard deviations in parentheses. Column 4 reports p-value of test of difference in means across groups 1 and 2. Column 5 reports p-values from a test of equality of means across all four groups.

[e]This is the interest rate paid on loan from most commonly used lender (formal or informal).

[f]Sources of non-electric lighting are candles, kerosene lamps, battery-operated lights and generator (runs on diesel).

All monetary values are reported in USD. At the time of the study, the exchange rate was roughly 1 USD/ MWK 720

Table 4.2: Preference for Installments & Purchase Decision

	Prefer Installments		Prefer Installments at Higher Effective Price		Premium (Installments)	
	(1)	(2)	(3)	(4)	(5)	(6)
Box	0.08*	0.06	-0.04	-0.06	-644.46*	-617.23*
	(0.042)	(0.044)	(0.057)	(0.058)	(367.727)	(372.147)
Mean dep. variable	0.81	0.81	0.66	0.66	4384.62	4384.62
Observations	288	288	288	288	244	244
Adjusted R-squared	0.009	0.015	-0.002	0.020	0.008	0.035
Individual Controls	No	Yes	No	Yes	No	Yes

This table shows the impact of the *Box* treatment on revealed preference for the installments plan. Each respondent reveals whether she prefers to pay P_L as a deferred lump sum or $P_{ins} = P_L(1+r)$ in weekly installments for the solar lamp for six different values of r. The dependent variable in columns 1 and 2 is 1 if the respondent ever chose to pay in installments over paying the lamp's price as a deferred lump sum. The dependent variable in columns 3 and 4 is equal to 1 for those respondents who chose to pay in installments when $r > 1$. The dependent variable in columns 5 and 6 is the difference between the highest price that an individual is willing to pay for the installments plan and the deferred lump sum price of MWK 20,000. Even columns control for baseline measures of age, gender, marital status, mobile money account ownership, control over own income, interest paid on an informal loan, household wealth indicator and ownership of other solar technology. All monetary values are reported in Malawian Kwacha (MWK). At the time of the study, the exchange rate was roughly MWK 720/ 1 USD.

Robust standard errors are in parentheses. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Source: WTP exercise administered at baseline survey.

Table 4.3: Solar Light Take-Up Across Treatment Groups

	Decides to try out solar lamp							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Deferred payment	0.47***	0.48***						
	(0.038)	(0.041)						
Box			0.19***	0.13**			0.20**	0.17**
			(0.061)	(0.063)			(0.087)	(0.086)
Installments					0.08	0.04	0.10	0.07
					(0.062)	(0.063)	(0.087)	(0.088)
Installments & Box							-0.03	-0.07
							(0.123)	(0.123)
Individual Controls	No	Yes	No	Yes	No	Yes	No	Yes

Mean dep. variable	0.04	0.04	0.28	0.28	0.47	0.47	0.37	0.37
Sample	All groups offered lamp		Installments & Deferred lump sum only					
Observations	339	339	258	258	258	258	258	258

Notes: This table reports linear probability model estimates of the decision to purchase the solar lamp. The dependent variable indicates whether the individual bought the solar lamp (for the upfront lump sum payment group)/ decided to try out the solar lamp (in the installments, and deferred lump sum groups). The independent variable in the first two columns indicates whether the respondent was offered the lamp on a deferred payment plan (either Installments or Deferred lump sum). The dependent variable in columns 3 through 8 indicates whether an individual decides to try out the lamp on the deferred payment plan. The regressions in these columns are estimated for the sub-sample that received the deferred payment plan. Even columns control for baseline measures of age, gender, education, household size, martial status, whether respondent is household head, measure of control over own income, experimentally measured marginal rate of substitution, hours and days worked, ownership of financial accounts and solar devices, and expenditure on lighting. Robust standard errors are in parentheses. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.
Source: Purchase decision measured at baseline survey.

Table 4.4: Completing Solar Lamp Payment

	Has active lamp					
	(1)	(2)	(3)	(4)	(5)	(6)
Box	0.14**	0.12**			0.13*	0.14*
	(0.057)	(0.056)			(0.075)	(0.077)
Installments			0.13**	0.10*	0.12*	0.12
			(0.057)	(0.057)	(0.074)	(0.075)
Installments & Box					0.01	-0.04
					(0.113)	(0.113)
Mean dep. variable	0.16		0.24		0.17	
Observations	258	258	258	258	258	258
Individual Controls	No	Yes	No	Yes	No	Yes

Notes: All columns report linear probability model estimates. The dependent variable indicate whether respondent has a solar lamp that is completed paid for at the end of 8 weeks. Even columns control for baseline measures of age, gender, education, household size, martial status, whether respondent is household head, measure of control over own income, hours and days worked, ownership of financial accounts, and implied discount rate from willingness-to-pay exercise administered at baseline.

Robust standard errors are in parentheses. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 4.5: Repayment Choices and Lamp Ownership

	Has a working lamp		Bought lamp	
	(1)	(2)	(3)	(4)
Random offer matches	0.02	0.02	0.04	0.04
elicitation exercise				
	(0.152)	(0.159)	(0.183)	(0.191)
Installment	-0.14*	-0.15	-0.28**	-0.29**
	(0.085)	(0.096)	(0.110)	(0.117)
Random offer matches	0.30*	0.31*	0.46**	0.45**
elicitation exercise				
& Installments	(0.177)	(0.187)	(0.212)	(0.222)
Box	0.12	0.11	0.17*	0.16
	(0.087)	(0.088)	(0.098)	(0.098)
Box & Random offer	-0.10	-0.10	-0.03	-0.01
matches				
elicitation exercise	(0.208)	(0.211)	(0.243)	(0.251)
Box & Installments	-0.19*	-0.16	-0.08	-0.08
	(0.106)	(0.121)	(0.191)	(0.196)
Box & Random offer	0.29	0.26	0.03	-0.01
matches				
elicitation exercise &	(0.237)	(0.249)	(0.306)	(0.316)
Installments				
Observations	263	263	263	263
Individual Controls	No	Yes	No	Yes

This table reports effect of the random repayment plan matching what the respondent's choice in the elicitation exercise. The variable "Random offer matches elicitation exercise" is 1 of individuals who, by chance, were offered the installment (lump sum) plan as the experimental repayment plan and also chose installment (lump sum) plan in the WTP exercise. The variable "Installment" is 1 for individuals who were offered the installments repayment plan, and "Box" is 1 for individual randomized into the *Box* group.

*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Source: Baseline survey.

Table 4.6: Impact of Solar Lamps : Lighting Expenditure

	Off-grid expenditure (home)		Grid expenditure (home)		Off-grid expenditure (shop)		Grid expenditure (shop)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bought lamp	-137.97***	-135.92***	37.22	23.33	-127.75***	-132.44***	30.34	34.65
	(28.717)	(29.323)	(44.177)	(44.293)	(32.249)	(34.748)	(55.311)	(54.299)
Control mean	158.8	158.8	47.05	47.05	133.6	133.6	50.43	50.43
Observations	8,763	8,763	8,762	8,762	8,763	8,763	8,762	8,762
Individual Controls	No	Yes	No	Yes	No	Yes	No	Yes

This table reports average daily effects of using the lamp on lighting expenditure. The results are from instrumental variable regressions where“Bought lamp” is instrumented with each of the treatment groups. Regressions are at the respondent-day level. Standard errors are in parentheses, clustered at both the individual and day level. Even columns control for baseline measures of gender, education, number of children, self reported control over own income, and measured time preference indicator.

*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Source: Daily logbook records.

Table 4.7: Impact of Solar Lamps : Mobile Phone outcomes & Savings

	Phone out of power		Phone recharge expenditure		Savings (lighting & mobile)	
	(1)	(2)	(3)	(4)	(5)	(6)
Bought lamp	-0.93***	-0.91***	-43.45***	-43.21***	-241.67**	-262.55***
	(0.292)	(0.293)	(8.039)	(7.819)	(99.087)	(98.787)
Control mean	1.54	1.54	45.05	45.05	434.85	434.85
Observations	8,763	8,763	8,763	8,763	8,763	8,763
Individual Controls	No	Yes	No	Yes	No	Yes

This table reports average daily effects of using the lamp on mobile phone outcomes (columns 1-4) and total savings in energy expenditure (columns 5 and 6). The results are from instrumental variable regressions where"Bought lamp" is instrumented with each of the treatment groups. Regressions are at the respondent-day level. Standard errors are in parentheses, clustered at both the individual and day level. Even columns control for baseline measures of gender, education, number of children, self reported control over own income, and measured time preference indicator.

*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Source: Daily logbook records.

Table 4.8: Impact of Solar Lamps : Business & Home Outcomes

	Hours worked		Sales revenue		Children study hours	
	(1)	(2)	(3)	(4)	(5)	(6)
Bought lamp	-0.28	-0.25	-390.78	-727.52	-0.08	-0.09
	(0.409)	(0.411)	(2,110.652)	(2,134.594)	(0.103)	(0.110)
Control mean	12.07		9894	9894	0.270	0.270
Observations	8,762	8,762	8,763	8,763	8,762	8,762
Individual Controls	No	Yes	No	Yes	Yes	Yes

This table reports average daily effects of using the lamp on business outcomes and hours spent on study by children. The results are from instrumental variable regressions where"Bought lamp" is instrumented with each of the treatment groups. Regressions are at the respondent-day level. Standard errors are in parentheses, clustered at both the individual and day level. Even columns control for baseline measures of gender, education, number of children, self reported control over own income, and measured time preference indicator.

*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Source: Daily logbook records.

Table 4.9: Baseline characteristics and randomization check

	Control Mean	Difference between GSRA and control
	(1)	(2)
Panel A. Demographics and asset ownership		
Age	39.22	-0.50
	(13.45)	(1.50)
Years of education	6.77	0.35
	(3.41)	(0.38)
Home has a thatch roof	0.15	-0.03
	(0.35)	(0.04)
Home has mud walls	0.90	-0.01
	(0.30)	(0.04)
Value of durable goods owned (USD)	130.90	1.00
	(72.36)	(8.84)
Value of animals owned (USD)	212.50	19.55
	(258.50)	(27.30)
Has a mobile phone	0.80	0.04
	(0.40)	(0.04)
Has a bank account	0.22	0.04
	(0.42)	(0.05)
Has a mobile money account	0.65	0.05
	(0.48)	(0.05)

Owns land	0.99	-0.01
	(0.10)	(0.01)
Acres of land owned	1.76	0.29
	(1.94)	(0.26)
Panel B. Harvest output		
Harvest output from 2015 long rains	480.60	7.62
(kilograms)	(341.50)	(42.37)
Value of harvest output at	131.1	2.08
post-harvest prices (60 Ksh / gg)	(93.13)	(11.56)
Panel C. Input usage		
Used fertilizer (2015 long rains)	0.81	0.05
	(0.39)	(0.04)
Used hybrid seeds (2015 long rains)	0.75	0.01
	(0.43)	(0.05)
Kilograms of fertilizer per acre planted	51.92	11.14*
	(53.93)	(6.44)
Panel D. Maize storage and sales		
Do you ever store maize?	0.89	0.03
	(0.31)	(0.03)
If stores: store on platform or table in	0.98	-0.02
house	(0.13)	(0.01)

Percentage of seasons in which some maize was spoiled (past 5 years)	0.31 (0.32)	0.06* (0.03)
In those seasons, average percentage of maize lost	0.32 (0.21)	0.04 (0.02)
Did you sell maize in the 2014 long rains?	0.33 (0.47)	0.12** (0.05)
Do you buy maize?	0.77 (0.42)	-0.07 (0.05)
Do you ever feel that you consume "too much" maize when you have bags in the house?	0.26 (0.44)	-0.01 (0.04)
Number of observations	752	
Number of ROSCAs	132	

In Column 1, standard deviations in parentheses; in Column 2, standard errors (clustered by ROSCA) in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%.

[1] Panel D is from the endline survey. However, output for the 2015 long rains should be exogenous to the treatment since the intervention began only just before harvest. There are 511 observations for this variable.

Table 4.12: Take-up (GSRA respondents only)

	All respondents	Respondents in endline survey sample
	(1)	(2)
Panel A. ROSCA Logbooks (N=1,105)		
Contributed maize to GSRA	0.57	0.70
If yes, kilograms	44.45	37.95
	(73.03)	(32.93)
Panel B. Endline survey (N=221)		
Contributed maize to GSRA	-	0.84
If yes, kilograms	-	63.43
		(66.52)

Notes: Panel A is from logbooks kept by treasurers. Panel B is from endline survey. Monetary values are winsorized at 1%. Standard deviations in parentheses.

Table 4.13: Effects on storage

	Stored maize to consume/ sell at least 1 month after harvest	Quantities stored		
		Outside home (including GSRA)	At home	Total stored
	(1)	(2)	(3)	(4)
Panel A. Intent to Treat				
GSRA	0.24***	50.97***	-17.53	32.93*
	(0.05)	(3.78)	(18.87)	(19.05)
2015 Long Rains Harvest	0.06	0.87	35	33.91
	(0.05)	(2.54)	(24.97)	(24.51)
Control mean	0.69	0.00	185.20	185.20
Control sd	-	0.00	196.70	196.70
Number of respondents	583	581	583	581
Number of ROSCAs	132	132	132	132
Panel B. Treatment on the Treated				
Used GSRA	0.33***	69.98***	-24.25	45.21*
	(0.07)	(6.34)	(26.12)	(26.25)
2015 Long Rains Harvest	0.41***	0.38	33.8	37.33*
	(0.08)	(3.05)	(22.01)	(21.06)
Control complier mean	0.62	-17.01	189.20	172.70
Control sd	-	28.36	229.10	232.10
Number of respondents	583	581	583	581
Number of ROSCAs	132	132	132	132

All variables measured from the 2015 long rains harvest, from the endline survey. Quantities are winsorized at 1%. All weights in kilograms. Regressions in Panel B are IV regressions where using the GSRA is instrumented with GSRA treatment. Standard errors clustered by ROSCA in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively. [1]Harvest is measured in 1,000 kilograms in Columns 1, and in kilograms in the remaining Columns.

Table 4.14: Effects on maize sales, prices received, and farm revenue

	Sales between Aug 2015 and Aug 2016			For those who sold	
	Indicator for selling any maize	Quantity sold	Total Revenue	Days between sale and 2015 harvest	Log (average sales price)
	(1)	(2)	(3)	(4)	(5)
Panel A. Intent to Treat					
GSRA	0.38***	24.95	6.94	35.80**	0.04*
	(0.06)	(21.10)	(6.89)	(14.07)	(0.03)
2015 Long Rains Harvest[1]	0.07	43.87	10.44	2.49	-0.05
	(0.06)	(29.38)	(7.72)	(15.13)	(0.03)
Control mean	0.36	103.30	33.62	169.80	-1.19
Control sd	-	196.70	66.78	91.60	0.19
Number of respondents	583	583	583	294	294
Number of ROSCAs	132	132	132	106	106

Panel B. Treatment on the Treated

GSRA	0.52***	34.52	9.6	44.20**	0.05*
	(0.08)	(28.96)	(9.47)	(17.70)	(0.03)
2015 Long Rains Harvest[1]	-0.27**	33.02	0.74	8.92	-0.01
	(0.13)	(23.22)	(22.15)	(13.58)	(0.05)
Control complier mean	0.29	106.70	35.44	156.80	-1.19
Control sd	-	215.00	71.04	92.34	0.27
Number of respondents	583	583	583	294	294
Number of ROSCAs	132	132	132	106	106

All data is from endline survey. All variables measured from the 2015 long rains harvest. Monetary values in USD. All weights in kilograms. Standard errors clustered by ROSCA in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively. [1]Harvest is measured in 1,000 kilograms in Columns 1 and 3, and in kilograms in the other columns. [2]Harvest occurs around August. For people with multiple sales, average is weighted by the quantity of maize sold per transaction. [3]Average is weighted by quantity.

Table 4.15: Other outcomes

	Input coupon experiment[1]		Agricultural Inputs			Food security	
	Redeemed Coupon	Quantity spent on inputs	Used chemical fertilizer	Used hybrid seeds	Total input expenditures (USD)	Ran out of maize & couldn't afford more	Reduced food intake around planting for inputs
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. Intent to Treat							
GSRA	0.07*	194.93	-0.01	0.02	-0.91	0.02	0.02
	(0.04)	(156.43)	(0.04)	(0.03)	(3.61)	(0.07)	(0.07)
Control mean	0.31	998.40	0.88	0.90	56.58	0.45	0.45
Control sd	-	-	-	-	36.98	-	-
Number of respondents	2966	2966	577	577	483	583	583
Number of ROSCAs	141	141	132	132	130	132	132

Panel B. Treatment on the Treated

GSRA	0.13*	365.17	-0.01	0.03	-119.58	0.03	0.03
	(0.07)	(271.48)	(0.05)	(0.04)	(475.70)	(0.10)	(0.10)
Control complier mean	0.28	988.20	0.90	0.95	5764	0.41	0.41
Control sd	-	-	-	-	3913	-	-
Number of respondents	2941	2941	577	577	483	583	583
Number of ROSCAs	141	141	132	132	130	132	132

All data is from endline survey. Farming questions are in relation to the 2016 long rains season. Regressions include controls for Long Rains harvest output. Standard errors clustered by ROSCA in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively. [1]Regressions in Columns 8-9 are from experimental coupon intervention, and include all members of ROSCAs (2,966 respondents). There are no other controls in these regressions, since a baseline was conducted with only a subset of respondents. See text for details.

Table 4.16: Pathways

	GSRA only	All respondents
	(1)	(2)
Panel A. Barriers to home storage		
Agrees with statement: "If I have maize at home, my household is tempted to eat more than we need"	0.50	0.42
Agrees with statement "If a friend or relative comes to me to ask for maize, and if I have maize at home, I am obligated to give him/her some."	0.66	0.59
Agrees with statement: "If I refuse requests when people ask me for maize, they are going to be less likely to help me out in the future."	0.61	0.67
Some maize stored at home after 2015 harvest was spoiled	0.06	0.05
If yes, percentage spoiled	0.21	0.22
Consumed maize stocks earlier than had planned and/or consumed maize intended for sale	0.11	0.08
If yes, percentage	0.24	0.25
Panel B. GSRA respondents		
Do you think the GSRA was helpful?	0.94	
If yes, why?		
Less spoilage	0.53	
Allocated money for inputs	0.39	

Shared costs	0.38	
Consumed less	0.38	
Gave away less	0.24	
Agrees with statement: "The GSRA program prevented my household from eating more maize than needed."	0.40	
Do you think you gave away less maize because of GSRA?	0.62	
If yes, why do you think you gave away less?		
Fewer people asked for maize because I had less in house	0.38	
It was easier to say no because I had less maize in the house	0.55	
Some maize stored in the GSRA in 2015 was spoiled	0.06	
If yes, percentage spoiled	0.02	
Do you plan to participate in the program next year?		
Number if respondents	208	537

Data from midline and endline surveys.

Table 4.18: Global account ownership

	Has an account at a financial institution[1] (%)	Has a mobile money account[2] (%)
	(1)	(2)
Argentina	50.2	0.4
Bangladesh	29.1	2.7
Botswana	49.2	20.8
Burkina Faso	13.4	3.1
Cambodia	12.6	13.3
Chile	63.2	3.8
China	78.9	–
Congo, Dem Rep.	10.9	9.2
Cote d'Ivoire	15.1	24.3
Dominican Republic	54.0	2.3
Ecuador	46.2	–
Egypt	13.7	1.1
Ethiopia	21.8	0.0
El Salvador	34.6	4.6
Gabon	30.2	6.6
Ghana	34.6	13.0
India	52.8	2.4
Indonesia	35.9	0.4
Kenya	55.2	58.4
Madagascar	5.7	4.4
Malawi	16.1	3.8
Mali	13.3	11.6

Mexico	38.7	3.4
Namibia	58.1	10.4
Nigeria	44.2	2.3
Pakistan	8.7	5.8
Philippines	28.1	4.2
Rwanda	38.1	18.1
South Africa	68.8	14.4
Tanzania	19.0	32.4
Uganda	27.8	35.1
Vietnam	30.9	0.5
Zambia	31.3	12.1
Zimbabwe	17.2	21.6

Source: Global Financial Inclusion (Global Findex) Database 2014, World Bank Group [1]Percentage of respondents who report having an account (by themselves or together with someone else) at a bank or another type of financial institution; having a debit card in their own name; receiving wages, government transfers, or payments for agricultural products into an account at a financial institution in the past 12 months; paying utility bills or school fees from an account at a financial institution in the past 12 months; or receiving wages or government transfers into a card in the past 12 months (% age 15+). [2]Percentage of respondents who report personally using a mobile phone to pay bills or to send or receive money through a GSM Association (GSMA) Mobile Money for the Unbanked (MMU) service in the past 12 months; or receiving wages, government transfers, or payments for agricultural products through a mobile phone in the past 12 months (% age 15+).

Table 4.20: Sample of Digital Credit Products

Product	Country	Start Year	Provider	Qualifying requirements	Fees	Maturity	Customer base[1]
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
M-Shwari	Kenya	2012	Safaricom & Commercial Bank of Africa	Active user of M-Shwari savings, and other Safaricom products	Faciliation fee: 7.5%	1 month	3.9m active 30 day users (Mar, 2016)
KCB M-Pesa	Kenya	2015	Safaricom & Kenya Commerical Bank	Active M-pesa account	Faciliation fee of 2.5% + monthly interest of 1.16%	1 month	0.73m active 30 day users (Mar, 2016)
Branch	Kenya	2015	Branch	Registered M-pesa user, active social media (e.g. Facebook) user	1%-14% pm	2 weeks-1 year	100,000 borrowers (Sep, 2016)
Equitel Eazzy Loan	Kenya	2015	Equity Bank Group	Registered Equitel user; active account with Equity Bank	14%	1 month	3.5 million loans worth Sh30 billion issued in year ending 9/16
Tala	Multiple	2014	Tala	Registered Tala users	11%-15%	1 month	100,000 borrowers in July, 2016
Grow	Kenya	2016	Kopo Kopo	Merchant credit for Kopo Kopo's payments platform users	Fixed fee: 1%	Until repaid	-
Timiza Loans	Tanzania	2014	Airtel Tanzania & Jumo	Active Airtel money user	Varying	7-28 days	-
Timiza Wakala Loans	Tanzania	2015	Airtel Tanzania & Jumo	Airtel mobile money agents	Varying	7-28 days	-

M-Pawa	Tanzania	2014	Vodacom Tanzania & Commercial Bank of Africa	Active m-Pesa user	Faciliation fee: 9%	1 month	4.9 million borrowers during first two years[2]
Tigo Nuvushe		2016	Tigo Pesa, Jumo	Active Tigo pesa users	Faciliation fee based on length of tenure	1-3 weeks	-
MoKash	Uganda	2016	MTN Uganda & Commercial Bank of Africa	MTN mobile money subscriber , save on MoKash and actively use other MTN services	Faciliation fee: 9%	1 month	1 million registered users within 3 months of launch.[3]
Airtel Money Bosea	Ghana	2016	Airtel Ghana, Fidelty Bank Ghana, Tiaxa	Active Airtel users	10%-20%4	1 month	-
Airtel Money Kutchova	Malawi	2016	Airtel, FDH Bank	Airtel money subscriber	10%	7 days	-

[1]Unless otherwise noted, all information is from official lender sources. [2]Aglionby, 2016. [3]Reported in PC Tech Magazine http://pctechmag.com/2016/10/mtn-mokash-reach-one-million-subscribers-milestone-after-3-months/ [4]Reported in Ghana News Agency http://www.ghananewsagency.org/economics/airtel-launches-airtel-money-bosea–103765"

Table 4.21: Bank & Agent Pentration

Commercial bank branches (per 100,000 adults)		Active agents (per 100,000 adults)	
	(1)		(2)
Bangladesh	8.4		111.0
Kenya	5.9		272.9
Pakistan	10.0		52.4
Tanzaia	2.5		236.0
Uganda	3.0		175.4

"Notes: Indicator for Commercial bank branches (per 100,000 adults) is from the World Bank World Development Indicators Database. All measures are from 2015. Active agents (per 100,000 adults) is calculated using Helix Institute's count of active agent outlets, and adult populations reported in Bersudskaya and McCaffrey (2017). Data for Kenya and Pakistan is from 2014, and for Bangladesh, Tanzania and Uganda, it is from 2015.

5

Appendix

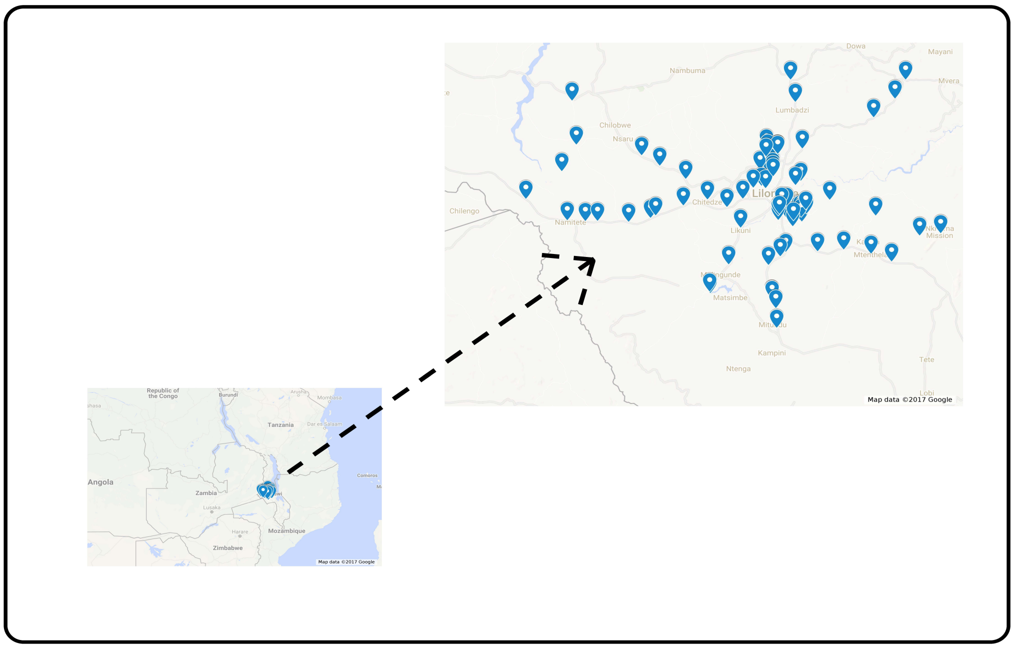


Figure A1: Markets where the experiment was implemented.

Thanks to Google Maps.

Figure A2: Omnivoltaic Pilot X PAYG light.

Source: Omnivoltaic website.

Figure A3: Lockboxes used in the study

Source: Author's collection.

This is round 3 of prices. In round 3 there are two ways to pay for the solar lamp.

Option 1: pay MWK 20,000 after 8 weeks.
So, if you pick option 1 you would pay MWK 20,000 for the solar lamp + charger.

Option 2: pay MWK 3,250 every week for 8 weeks.
So, if you pick option 2 you would pay MWK 26,000 in total for the solar lamp + charger.

Option 3: Don't want to buy the solar lamp.

Figure A4: Example of question in WTP exercise

Table A1: Self-reported Reason for Preference for Repayment Plan

	Mean	Observations
	(1)	(2)
Panel A: Why do you prefer to pay in installments		
I may be tempted to spend the money before 8 weeks	0.705	156
The money may get stolen before 8 weeks	0.122	156
Family/ friends will ask for money	0.039	156
Other[a]	0.135	156
Panel B: Why do you prefer to pay as a deferred lump sum		
I want to use money for my business	0.64	25
I want to use my money for home needs	0.12	25
I want to keep my money with me in case of an emergency	0.20	25
Other	0.16	25

Notes: The data is collected at baseline survey. The summary statistics in Panel A are from the sub-sample who demonstrated the strongest desire for the installments plan by reporting that they would rather pay the highest installment price (MWK 26,000) over the deferred lump sum price (MWK 20,000) for the solar lamp. The summary statistics in Panel B are from the sub-sample who demonstrated the strongest desire for the lump sum plan by reporting that they would rather pay the lump sum price of MWK 20,000 over the lowest installment price of MWK 18,000 (MWK 18,000) for the solar lamp. [a]Commonly cited other reason include "the payment frequency matches income frequency," and "it is easy [to remember]." A small fraction (0.045) thought the installment plan was cheaper

Table A2: Amount paid for the solar lamp

	Mean	Std. dev	Obs.
	(1)	(2)	(3)
Completed payment on time			
Installment	0.68	0.47	72
Deferred lump sum	0.52	0.50	60
Amount paid for the solar lamp			
Installment	15660	7494	72
if did not finish repayment at 8 weeks	5795	6564	22
Deferred lump sum	11333	9994	60
if did not finish repayment at 8 weeks	–		
Box	13974	8804	78
No box	13287	9225	54

Notes: This table presents summary statistics on amount paid for the solar lamp. The installment group was scheduled to complete payment in eight weekly installments of MWK 2500 each. The deferred lump sum group pays MWK 20,000 at the end of eight weeks. The box-treatment was crosscut with the repayment frequency treatment.
Source: Angaza Energy Hub, through SunnyMoney Malawi.

Table A3: Days Device Shut Off for Incomplete Payment

	Mean	Std. dev	Obs.
	(1)	(2)	(3)
Installment	12.33	17.25	72
if did not finish repayment at 8 weeks	20.23	19.61	22
Deferred lump sum	–		
Box	8.09	15.49	78
No box	6.65	14.36	54

Notes: The solar lamp is set up to provide energy until a payment is due. It shuts off when a payment has to be made and does not provide energy until the payment is completed. During the experimental period, the solar lamp could have turned off eight times for the installment group, at each of the scheduled installment dates. The deferred lump sum group, on the other hand, does not experience any shut of days during this period.This table presents summary statistics on the number of days that the solar lamp was shut off for the installments group, and also variation from the box-treatment. Arrears are usually, but not always, settled when project staff visit respondents a week later to collect the next installment after a week.
Source: Angaza Energy Hub, through SunnyMoney Malawi.

Table A4: Correlates of Willingness to Pay, Purchase Decision

	WTP > 0	Bought light
	(1)	(2)
Group 1 (Box + deferred)	0.06***	0.13***
	(0.033)	(0.063)
Group 3 (Payment at purchase)	-0.08	-0.42***
	(0.050)	(0.056)
Age	0.00	0.01***
	(0.002)	(0.002)
Married	0.03	-0.02
	(0.043)	(0.063)
Female	0.06	-0.01
	(0.043)	(0.066)
Education (years)	0.01	-0.01
	(0.007)	(0.009)
Household size	0.02	-0.03
	(0.018)	(0.022)
Children (count)	-0.01	0.05***
	(0.024)	(0.029)
Head of household, proportion	0.01	0.08
	(0.047)	(0.075)
Has a bank account	-0.06	0.03
	(0.040)	(0.057)
Has own mobile money account	0.08***	0.11***
	(0.032)	(0.050)
Participates in informal financial group	0.01	0.11***
	(0.037)	(0.054)

Food insecure in the past month	0.01	-0.03
	(0.046)	(0.071)
Monthly non-grid lighting cost (log)	0.01	0.02***
	(0.009)	(0.012)
Daily hours worked	0.01	0.01
	(0.009)	(0.011)
Business revenue in a good week (log)	0.01	0.05
	(0.024)	(0.038)
Business revenue in a bad week (log)	-0.02	-0.05***
	(0.018)	(0.033)
Home has cement floor	-0.02	-0.02
	(0.045)	(0.071)
Home has iron sheets roof	-0.03	-0.04
	(0.062)	(0.092)
Know of solar lights	0.04	0.02
	(0.040)	(0.055)
Has solar light(s)	-0.00	-0.13
	(0.097)	(0.095)
Mean dep variable	0.89	0.41
Std. dev. dep variable	0.21	0.49
Observations	369	339
Adjusted R-squared	0.031	0.239
P-value of F model	0.111	0.000

Notes: Data collected during baseline survey. The dependent variables are indicators for whether respondent wanted to purchase the solar lamp at some positive price (column 1), and whether respondent prefers to pay for the solar light in installments for at least one of the experimental prices (columns 2). Preference for installments plans is measured only for groups 1 and 2. Groups 1 and 2 were unaware of their randomly assigned price when reporting WTP for solar lamp, but knew whether they received a box as part of the study and that they qualified for deferred payment plan. Robust standard errors in parentheses. *** p<0.1, ** p<0.05, * p<0.01

Table A5: Reported Preferences & Purchase Behavior

	Actual Purchase Decision	
	Did not buy lamp	Bought lamp
	(1)	(2)
Reported preference with installments		
Will not buy lamp	0.897	0.103
Will buy lamp	0.291	0.709
Reported preference with lump sum		
Will not buy lamp	0.906	0.094
Will buy lamp	0.293	0.707

Data collected at endline survey administered to a random sub-sample of lamp users. All monetary values are reported in Malawian Kwacha (MWK). At the time of the study, the exchange rate was roughly MWK 720/ 1 USD.

Table A6: Descriptive Statistics: Lamp Usage

Uses the lamp at:	
Home	0.308
Business	0.168
Home & Business	0.523
Largest Impact of lamp:	
Children study more	0.178
Less smoke inside house	0.037
Work longer at business	0.439
Feel safe in the dark	0.047
Mobile phone always charged	0.299
Box respondents only	
Used box	0.967
Saved more money than needed for the lamp in the box	0.067
If used box, money saved:	
Mean	15396.67
Median	20000
Standard Deviation	7360.49

Data collected at endline survey administered to a random sub-sample of lamp users. All monetary values are reported in Malawian Kwacha (MWK). At the time of the study, the exchange rate was roughly MWK 720/ 1 USD.

Table A7: First Stage: Effect of Lamp Usage

Treatment	
Box & Installment	0.230***
	(0.0153)
No Box & Installment	0.166***
	(0.0154)
Box & Deferred lump sum	0.059***
	(0.015)
Upfront lump sum	-0.387***
	(0.0145)
Control	-0.432***
	(0.015)
Constant	0.432***
	(0.011)
F-Stat	754.28
Observations	8762

Here I report coefficients on the first-stage regression of trying out the lamp on treatment indicators. The omitted group is "No Box & Deferred lump sum." All errors are clustered at the day-individual level.
Source: Logbook records.

Table A8: Peak-trough variation in maize prices in Kisumu, 2006-2016

Year	Dataset			Average across datasets
	FAO	RATIN	WFP	
(1)	(2)	(3)	(4)	(5)
Panel A. Year by year				
2006	1.42	1.48	1.40	1.43
2007	1.17	1.18	1.15	1.17
2008	1.50	1.44	2.07	1.67
2009	1.22	1.21	1.18	1.20
2010	1.61	1.62	1.54	1.59
2011	2.81	2.88	2.36	2.69
2012	1.40	1.44	1.45	1.43
2013	1.14	1.16	1.13	1.14
2014	1.30	1.44	1.38	1.37
2015	1.28	1.16	1.15	1.20
2016	1.20		1.04	1.12
Panel B. Average, 2006-16				
Mean peak/trough ratio	1.46			
Standard deviation	0.45			

All data is from endline survey. Farming questions are in relation to the 2016 long rains season. Regressions include controls for Long Rains harvest output. Standard errors clustered by ROSCA in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively. [1]Regressions in Columns 8-9 are from experimental coupon intervention, and include all members of ROSCAs (2,966 respondents). There are no other controls in these regressions, since a baseline was conducted with only a subset of respondents. See text for details.

Table A9: Compliance and attrition

Panel A:ROSCA-level	ROSCA could be traced	If traced: ROSCA completed baseline visit	If completed baseline: ROSCA completed midline visit	If completed baseline: ROSCA completed endline visit
GSRA	0.08	0.06	0.05	0.04
	(0.07)	(0.06)	(0.04)	(0.05)
Control mean	0.53	0.87	0.93	0.93
Number of ROSCAs	264	153	139	139
Sample	All	Sample traced for intervention	Sample traced for intervention	Sample traced for intervention

Duplicate ROSCAs removed. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Panel B:Individual-level attrition

	Has midline survey		Has endline survey
GSRA	0.05	0.00	0.04
	(0.04)	(0.02)	(0.06)
Did baseline survey?	Y	N	Y
Control mean	0.44	0.07	0.62
Number of respondents	795	2267	795
Number of ROSCAs	141	141	141

Standard errors clustered at the ROSCA level in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Table A10: Robustness checks for storage regressions

	Stored maize to be consumed or sold at least 1 month after harvest[1]	Quantities stored		
		Outside home (including GSRA)	At home	Total stored
	(1)	(2)	(3)	(4)
Panel A. ITT, dropping harvest control				
GSRA	0.23***	50.74***	-23.14	27.64
	(0.05)	(3.89)	(23.32)	(24.27)
Control mean	0.69	0.00	185.20	185.20
Control sd	-	0.00	196.70	196.70
Number of respondents	583	527	583	581
Number of ROSCAs	132	135	132	132

Panel B. ITT, dropping ISRA group				
GSRA	0.24***	50.94***	-19.92	30.79
	(0.05)	(3.80)	(18.51)	(18.80)
Control mean	0.69	0.00	185.20	185.20
Control sd	-	0.00	196.70	196.70
Number of respondents	389	387	389	387
Number of ROSCAs	89	89	89	89
Panel C. No Winsorizing				
GSRA	-	64.48***	-1.20	56.84*
	-	(12.11)	(24.70)	(33.17)
Control mean	-	0.00	187.30	222.90
Control sd	-	0.00	205.40	298.40
Number of respondents	-	581	583	583
Number of ROSCAs	-	132	132	132

Panel D. 1% Winsorizing

GSRA	-	55.23***	-12.06	42.62**
	-	(5.21)	(20.64)	(20.82)
Control mean	-	0.00	187.30	187.30
Control sd	-	0.00	205.40	205.40
Number of respondents	-	581	583	581
Number of ROSCAs	-	132	132	132

Notes: All variables measured from the 2015 long rains harvest. All weights in kilograms. Standard errors clustered by ROSCA in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Table A11: Robustness checks for sales regressions

	Sales between Aug 2015 and Aug 2016			For those who sold	
	Indicator for selling any maize	Quantity sold	Total Revenue	Days between sale and 2015 harvest	Log (average sales price)
	(1)	(2)	(3)	(4)	(5)
Panel A: ITT, dropping harvest control					
GSRA	0.37***	20.99	5.65	34.90**	0.05*
	(0.06)	(24.02)	(7.91)	(14.06)	(0.03)
Control mean	0.36	103.30	33.62	169.80	-1.19
Control sd	-	196.70	66.78	91.60	0.19
Number of respondents	583	583	583	294	294
Number of ROSCAs	132	132	132	106	106

Panel B. ITT, dropping ISRA group					
GSRA	0.37***	26.54	7.67	36.45**	0.05**
	(0.06)	(21.07)	(6.86)	(14.30)	(0.03)
Control mean	0.36	103.30	33.62	169.80	-1.19
Control sd	-	196.70	66.78	91.60	0.19
Number of respondents	389	389	389	224	224
Number of ROSCAs	89	89	89	76	76
Panel C. No Winsorizing					
GSRA	-	-3.29	2.75	-	-
	-	(74.17)	(23.24)	-	-
Control mean	-	177.50	53.86	-	-
Control sd	-	639.10	188.80	-	-
Number of respondents	-	583	583	-	-
Number of ROSCAs	-	132	132	-	-

Panel D. 1% Winsorizing

GSRA	-	-14.05	-1.66	-	-
	-	(68.87)	(20.64)	-	-
Control mean	-	177.00	53.38	-	-
Control sd	-	635.40	185.20	-	-
Number of respondents	-	583	583	-	-
Number of ROSCAs	-	132	132	-	-

All data is from endline survey. All variables measured from the 2015 long rains harvest. All weights in kilograms. Standard errors clustered by ROSCA in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.