Two Sides of the Same Rupee? Comparing Demand for Microcredit and Microsaving in a Framed Field Experiment in Rural Pakistan*

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Abstract

Following recent literature, we hypothesise that saving and borrowing among microfinance clients are substitutes, satisfying the same underlying demand for a regular deposit schedule and a lump-sum withdrawal. We test this using a framed field experiment among women participating in group lending in rural Pakistan. The experiment — inspired by the rotating structure of a ROSCA and implemented with daily repayments — involves randomly offering credit products and savings products to the same subject pool. We find high demand both for credit products and for savings products, with the same individuals often accepting both a credit product and a savings product over the three experiment waves. This behaviour can be rationalised by a model in which individuals prefer lump-sum payments (for example, to finance a lumpy expenditure), and in which individuals struggle to hold savings over time. We complement our experimental estimates with a structural analysis, in which different types of participants face different kinds of constraints. Our structural framework rationalises the behaviour of 75% of participants; of these 'rationalised' participants, we estimate that two-thirds have high demand for lump-sum payments coupled with savings difficulties. These results imply that the distinction between microlending and microsaving is largely illusory; participants value a mechanism for regular deposits and lump-sum payments, whether that is structured as a credit or debt contract.

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1 Introduction

1.1 Saving and borrowing: An illusory distinction?

Saving and borrowing are often considered to be diametrically different behaviours: the former is a means to defer consumption; the latter, a means to expedite it. However, this distinction collapses under two important conditions that are common in developing countries. First, many in poor communities struggle to hold savings over time, *e.g.*, because of external sharing norms (Anderson and Baland, 2002; Platteau, 2000) or internal lack of self-control (Ashraf, Karlan, and Yin, 2006). Second, the poor sometimes wish to incur lumpy expenditures — for instance, to purchase an 'indivisible durable consumption good' (Besley, Coate, and Loury, 1993) or take advantage of a 'high-return but lumpy and illiquid investment opportunity' (Field, Pande, Papp, and Rigol, 2013).

If these two conditions hold — as they clearly do in many poor communities — then the same individual may prefer to take up a saving product than to refuse it *and*, simultaneously, prefer to accept a loan product than to refuse it. This demand has nothing to do with deferring or expediting consumption. Rather, both products provide a valuable mechanism by which a lump-sum expenditure can be implemented at *some* point in time. In doing so, each product meets the same demand for a regular schedule of deposits and a lump-sum withdrawal. No longer do saving products and borrowing products stand in stark juxtaposition to each other; they are, rather, two sides of the same coin. Several authors have suggested this kind of motivation for the adoption of microlending contracts in developing countries. Rutherford (2000) contrasts 'saving up' (setting aside funds to receive a lump sum) and 'saving down' (receiving a lump sum that is repaid in regular installments). Bauer, Chytilová, and Morduch (2012) support this 'alternative view of microcredit', showing 'a robust positive correlation between having present-biased preferences and selecting microcredit as the vehicle for borrowing'.

In this paper, we run a framed field experiment in rural Pakistan to test directly whether microlending serves a microsaving objective. We take a simple repayment structure — loosely modeled on the idea of a ROSCA — and offer it as an individual microfinance product. We repeat the exercise three times. In each repetition, we randomly vary the time of repayment: thus, within the same structure and the same respondent pool, we randomly offer some participants a microsaving contract and others a microcredit contract. We also randomly vary the repayment amount: some respondents receive a payment equal to their total contribution, some receive a payment 10% larger, and some receive a payment 10% smaller. Together, these two sources of variation allow us to test between a 'traditional' model of microfinance in which participants prefer *either* to borrow *or* to save, and an alternative model in which participants welcome *both* borrowing and savings contracts as opportunities for lump-sum payments.

We find that the same pool of respondents simultaneously have a demand *both* for microcredit and for microsaving. Indeed, over the course of the three experiment waves, 277 of our 709 respondents were offered both a credit contract and a savings contract; of these, 148 (53%) accepted both forms of contract. Demand for our microfinance product is generally high, with approximately 65% take-up. Sensitivity to interest rate and day of payment is statistically significant but not large in magnitude.

We extend this analysis using a structural estimation to quantify the heterogeneity in clients' deep preferences. Specifically, we build competing structural models of demand for microfinance products, and we develop a Non-Parametric Maximum Likelihood method to estimate the proportion of respondents adhering to each model. Our structural framework rationalises the behaviour of 75% of the participants. Of these 'rationalised' participants, two-thirds behave as if they have high demand for lump-sum payments coupled with savings difficulties. Together, the results imply that the distinction between microlending and microsaving is largely illusory. Rather, many people welcome microcredit and microsavings products for the same reason: that each provides a mechanism for regular deposits and a lump-sum payment.

1.2 Daily deposits and the context of our experiment

We implement our experiment using a fixed schedule of daily deposits. We do this to ensure that our product has a regular and frequent commitment component. We also do this so that our experiment can speak directly to a practice that is widespread in developing economies. Daily deposit schedules are a relatively common feature of microfinance products in many countries — particularly those targeted at clients who are self-employed. In particular, they are the defining feature of 'daily collectors' — informal mobile bankers who allow daily deposits and withdrawals in many countries, particularly in West Africa.[1] These mobile bankers provide a critically important financial service for many poor households. For example, in a sample drawn from the outskirts of Cotonou, Somville (2011) finds that approximately one third of positive income-earners make such payments (see also Aryeetey and Steel (1995) and Aryeetey and Udry (1997)). Similarly, Ananth, Karlan, and Mullainathan (2007) describe a small survey of vegetable vendors in Chennai. They find that approximately 50% of respondents had engaged in very short-term borrowing for at least a decade, including the use of daily repayment products to support working capital; this can even involve taking a loan in the morning to purchase vegetables from a wholesaler, then repaying the loan on the same afternoon from daily sales.[2]

[1] Such collectors are also known as '*tontinier*' in Benin, '*susu*' in Ghana, '*esusu*' in Nigeria and '*deposit collectors*' in parts of India (Somville, 2011).

[2] See also Rutherford (2000), who discusses the same practice in Andhra Pradesh.

Formal organisations sometimes play the same role. Most prominently, the NGO *Safe*Save provides 'passbook savings' accounts, in which clients may make deposits and withdrawals at their house when a collector calls each day (Armendáriz de Aghion and Morduch, 2005; Dehejia, Montgomery, and Morduch, 2012; Islam, Takanashi, and Natori, 2013).[3] Similarly, Ashraf, Gons, Karlan, and Yin (2003) document Jigsaw Development's 'Gold Savings' account, in which daily installments were used to repay purchases of gold; the authors also describe the 'Daily Deposit Plan', the most popular account of Vivekananda Sevakendra O Sishu Uddyon, an NGO operating in West Bengal.[4]

Daily deposit schedules are also facilitated by many ROSCAs. For example, Rutherford (1997) studied 95 *loteri samities* in the slums of Dhaka, finding that approximately two-thirds collected payments daily.[5] Work in other contexts finds the proportion to be much smaller, but certainly not to be negligible. For example, Adams and Canavesi de Sahonero (1989) find that 15% of sampled *pasankus* in Bolivia used daily repayments (particularly those used by self-employed women), Aliber (2001) reports that 10% of *stockvels* in Northern Province used daily payments (again, particularly those used by the self-employed), Tanaka and Nguyen (2010) report a figure of 8.8% of *huis* in South Vietnam, and Kedir and Ibrahim (2011) report 2.8% for Ethiopian *equbs*.[6]

[3] See also `http://www.safesave.org/products`.

[4] Of course, even banks without formal daily payment products may still facilitate daily deposits. For example, Steel, Aryeetey, Hettige, and Nissanke (1997) describe a savings and loan company in Ghana that would encourage self-employed women to deposit proceeds each evening and then withdraw as necessary the following morning.

[5] Rutherford's impression from those *loteri samities* matches closely the key hypothesis that we test in this paper. Rutherford writes (page 367): "The most common answer to the question 'why did you join this *samity*?' was 'to save, because it is almost impossible to save at home'. Follow-up questions showed that the intermediation of those savings into a usefully large lump sum is also important. But it is not true that most members want to take that lump sum as a *loan*. . . . There is little doubt in my mind that our respondents understand these *samities* as being, primarily, about savings rather than about loans."

[6] See also Handa and Kirton (1999), who report that 6% of Jamaican ROSCAs — known as 'partners' — meet more frequently than once per week.

In our sample, approximately 80% of respondents are familiar with the concept of a ROSCA (known in Pakistan as a 'savings committee'); of these, about two-thirds have ever participated in one. This is important for ensuring that our repayment structure resonates with a well-understood local financial product. Of our respondents who had ever participated in a committee, 90% report that the committee required payments on a monthly basis; only 4% of respondents reported a committee with daily deposits. Anecdotal evidence suggests that daily installment structures are nonetheless quite common in Pakistan Punjab through informal providers, including in the locations of our study. Often, this involves 'commission agents' (*arthis*), who can offer short-term loans to retailers to enable the purchase of stock; for small shopkeepers and street vendors, this can involve a daily loan to be paid back at the close of business (sometimes as a percentage of daily sales).[7]

In sum, commitment products with daily repayments are common in many developing countries. In Pakistan, such products are hardly ever offered as ROSCAs, and appear to have fallen beneath the radar of microfinance institutions. Nonetheless, the demand for daily borrowing through informal providers indicates that there are many Pakistanis with extremely short-term cash flow management needs. In this paper, we offer an original solution to these problems; this is the ideal way to test for the value of having regular deposits towards an achievable goal.

Similarly, we deliberately run our experiment using clients of a microcredit programme: a subject population with a demonstrated demand for credit. If this population displays as much interest in a commitment saving device as in borrowing, this will suggest that their demand for credit should be reinterpreted as a demand for commitment saving. Finally, to

[7] See Haq, Aslam, Chaudhry, Naseer, Muhammad, Mushtaq, and Saleem (2013), who describe the role of *arthis* in longer-term lending for agricultural commodity markets.

make the demonstration even more salient, we choose a short credit and saving duration — *i.e.*, one week — in order to reduce the attractiveness of credit as an intertemporal smoothing device: if borrowing only serves to accelerate consumption or investment, we expect few takers for credit contracts with a one week maturation period and a high interest rate.

1.3 Recent research on microfinance

Our key empirical result — that a high proportion of microfinance clients demand *both* credit *and* savings — is useful for understanding recent research on microfinance. Growing empirical evidence suggests that savings products can be valuable for generating income and for reducing poverty (Burgess and Pande, 2005; Dupas and Robinson, 2013; Brune, Giné, Goldberg, and Yang, 2014). Standard microcredit products — with high interest rates and immediate repayments — increasingly seem unable to generate enterprise growth (Karlan and Zinman, 2011; Banerjee, Duflo, Glennerster, and Kinnan, 2015). In contrast, recent evidence shows that an initial repayment grace period increases long-run profits by facilitating lumpy investments (Field, Pande, Papp, and Rigol, 2013). This is consistent with estimates of high and sustained returns to capital in at least some kinds of microenterprise (De Mel, McKenzie, and Woodruff, 2008, 2012; Fafchamps, McKenzie, Quinn, and Woodruff, 2014).

A growing literature suggests that part of the attraction of microcredit is as a mechanism to save — whether to meet short-term liquidity needs (Kast and Pomeranz, 2013), to resist social or familial pressure (Baland, Guirkinger, and Mali, 2011), or as a commitment device against self-control problems (Bauer, Chytilová, and Morduch, 2012; Collins, Morduch, Rutherford, and Ruthven, 2009).[8] We make several contributions to this literature. *First*, we introduce a new experimental design which, to our knowledge, is the first to allow a direct test between demand for microsaving and demand for microcredit. This design can easily be replicated in a wide variety of field contexts. Further, since it is based on the structure of a ROSCA, it is easily understood in most developing economies. *Second*, our design generates new empirical results in which we find, for the first time, that the same respondent population has high demand for both microcredit and microsaving. Indeed, the same individuals often take up either contracts within the span of a couple weeks. *Third*, we make a methodological contribution through our structural framework. Specifically, we parameterise a Besley, Coate, and Loury (1993) model to test the demand for (latent) lumpy purchases. We show how to nest this model in a discrete finite mixture framework to allow for maximal heterogeneity in individual preferences.

The paper proceeds as follows. In section 2, we provide a conceptual framework. This motivates our experimental design, which we describe in section 3. We report regression results in section 4. Section 5 parameterises our conceptual framework for structural analysis and presents our Non-Parametric Maximum Likelihood estimator. We discuss identification and show structural results. Section 6 concludes.

2 Conceptual framework

This section develops a theoretical framework to motivate our experiment. We use a dynamic model in which we introduce a preference for infrequent lump-sum payments. We begin with a standard approach, in which individuals may either demand a savings product

8 Mullainathan and Shafir (2009) discuss the role of lottery tickets as commitment savings devices – analogously to random ROSCAs. See also Basu (2008), who provides a theoretical model in which sophisticated time-inconsistent agents find it welfare-enhancing both to borrow and to save simultaneously.

or demand a loan product, but not both. We then show how this prediction changes when we impose that people cannot hold cash balances. This theoretical framework provides the conceptual motivation — and the key stylised predictions — for our experimental design. It also provides the foundation for the structural analysis, which follows in Section 5.

We are interested in understanding the demand for individual financial products by the poor. We start by noting that the simple credit and savings products used by the poor can be nested into a generalised ROSCA contract. ROSCAs are common across the developing world; they are used by consumers to purchase durables, and by small entrepreneurs to save for recurrent business expenditures, such as paying suppliers: Besley, Coate, and Loury (1993). In some countries, agents have begun offering ROSCA-like contracts to individuals, but without the need to form a group. These agents — known as 'susu collectors' in Ghana, for instance — operate de facto as small financial intermediaries, albeit largely outside the formal financial sector.

We build on these observations to derive a model of demand for generalised ROSCA contract with a single payout period and a fixed series of installments. The contract involves periods $t \in \{1, \ldots, T\}$, and a single payout period, $p \in \{1, \ldots, T\}$. In periods $t \neq p$, the participant pays an installment of s; in period $t = p$, the participant receives a lump-sum equal to $(T-1) \cdot s \cdot (1+r)$. Parameter r represents the interest rate of the contract, which can be positive or negative. In a standard ROSCA contract, $r = 0$ and p is determined through random selection. In a typical (micro)credit contract with no grace period, $r < 0$, the lump-sum is paid in period $p = 1$, and installments s are made in each of the remaining $T - 1$ periods. A typical set-aside savings contract (*e.g.*, retirement contribution) is when $r > 0$, the lump-sum is paid in the last period ($p = T$), and installments s are made from period 1 to period $(T - 1)$.

We begin by considering a standard utility maximizing framework; we begin by assuming (i) that there is no particular demand for lumpy consumption, and (ii) that individuals may hold balances effectively between time periods. To illustrate the predictions this framework makes about the demand for generalised ROSCA contracts, we consider a short-term T-period model with cash balances $m_t \geq 0$. Each individual is offered a contract with an installment level s, a payment date p, and an interest rate r; we can therefore completely characterise a contract by the triple (s, p, r). The individual chooses whether or not to take up the contract, which is then binding.

Let y be the individual's cash flow from period 1 to T.[9] The value from *refusing* a contract (s, p, r) is:

$$V_r = \max_{\{m_t \geq 0\}} \sum_{t=1}^{T} \beta^t \cdot u_t(y_t + m_{t-1} - m_t), \tag{1}$$

where $u_t(.)$ is an instantaneous concave utility function (which may be time-varying), $\beta \leq 1$ is the discount factor, and $m_0 \geq 0$ represents initial cash balances. Given the short time interval in our experiment, β is approximately 1. Hence if $u_t(.) = u(.)$, the optimal plan is approximately to spend the same on consumption in every period. In this case, demand for credit or saving only serves to smooth out fluctuations in income.[10]

The more interesting case is when the individual wishes to finance a lumpy expenditure

[9] We could make y_t variable over time, but doing so adds nothing to the discussion that is not already well known. Hence we ignore it here.

[10] When $u_t(.)$ is constant over time but y_t variable, people can in principle use saving or credit contracts to smooth consumption. However, in our experimental setting, any contract (s, t, r) with a fixed installment schedule is unlikely to fit a particular individual's cash flow $\{y_t\}$, especially if the time interval is short. Hence we would expect little take-up if this were the only reason for take-up. We do not focus on this case here.

(*e.g.*, consumer durable, school fee, or business investment). We treat the purchase of a lumpy good as a binary decision taken in each period ($L_t \in \{0, 1\}$), and we use α to denote the cost of the lumpy good. We consider a lumpy purchase roughly commensurate to the lump-sum payment: $\alpha \approx (T - 1) \cdot s \cdot (1 + r)$. Following Besley, Coate, and Loury (1993), we model the utility from lumpy consumption $L = 1$ and continuous consumption c as $u(c, 1) > u(c, 0)$. Without the generalised ROSCA contract, the decision problem becomes:

$$V_r = \max_{\{m_t \geq 0, L_t = \{0,1\}\}} \sum_{t=1}^{T} \beta^t \cdot u(y_t + m_{t-1} - m_t - \alpha \cdot L_t, L_t). \tag{2}$$

With the ROSCA contract, the value from taking the contract (s, p, r) is:

$$V_c = \max_{\{m_t \geq 0, L_t = \{0,1\}\}} \left\{ \sum_{t \neq p} \left[\beta^t \cdot u\left(y_t - s + m_{t-1} - m_t, L_t\right)\right] \right. \\ \left. + \quad \beta^p \cdot u\left[y_p + (T-1) \cdot s \cdot (1 + r) + m_{p-1} - m_p - \alpha, L_p\right] \right\}. \tag{3}$$

If α is not too large relative to the individual's cash flow y_t, it is individually optimal to accumulate cash balances to incur the lumpy expenditure, typically in the last period T. Otherwise, the individual gets discouraged and the lumpy expenditure is either not made, or delayed to a time after T. Taking up the contract increases utility if it enables consumers to finance the lumpy expenditure α. For individuals who would have saved on their own to finance α, a savings contract with $r > 0$ may facilitate savings by reducing the time needed to accumulate α. Offering a positive return on savings may even induce saving by individuals who otherwise find it optimal not to save (McKinnon, 1973). Hence we expect some take-up of savings contracts with a positive return.

A credit contract allows paying for lumpy consumption right away and saving later. Hence, for a credit contract with a positive interest charge to be attractive, the timing of $L_t = 1$ must be crucial for the decision maker. Otherwise the individual is better off avoiding the interest charge by saving in cash and delaying expenditure L by a few days. This is the reason that — as discussed earlier — we do not expect an individual to be willing to take up *both* a credit and a savings contract at the same time: either the timing of $L_t = 1$ is crucial or it is not.

In addition to the above observations, the presence of cash balances also generates standard arbitrage results. The predictions from this standard model can thus be summarised as follows:

(i) Individuals always refuse savings contracts ($p = T$) with $r < 0$ (*i.e.*, a negative return). This is because accepting the contract reduces consumption by $T \cdot s \cdot r$. Irrespective of their smoothing needs, individuals can achieve a higher consumption by saving through cash balances.

(ii) Individuals always accept credit contracts ($p = 1$) with $r > 0$ (*i.e.*, a negative interest charge). This is because, irrespective of their smoothing needs, they can hold onto $T \cdot s$ to repay the loan in installments, and consume $T \cdot s \cdot r > 0$.

(iii) Individuals refuse credit contracts ($p = 1$) with a large enough cost of credit $r < 0$. This follows from the concavity of $u(.)$: there is a cost of borrowing so high that individuals prefer not to incur expenditure L.

(iv) Individuals accept savings contracts ($p = T$) with a high enough return $r \geq 0$. This too follows from the concavity of $u(.)$.

(v) The same individual will not demand *both* a savings contract (with a positive return $r > 0$) and a credit contract (with a non-negative interest cost $r \leq 0$).

Things are different when people use credit or ROSCAs as a commitment device to save. Within our framework this is most easily captured by assuming that people cannot hold cash balances (that is, $m_t = 0$). This could arise for a variety of reasons that we do not model explicitly — for example, because people succumb to impulse buying, because they are subject to pressure from spouse and relatives, or for any other reason (Gugerty, 2007). Since accumulating in cash balances is now impossible, the only way to take the lumpy purchase is to take the (s, p, r) contract. This creates a wedge between V_r and V_c that increases the likelihood of take-up: the contract enables the individual to incur the lumpy expenditure, something they could not do on their own. If the utility gain from buying the lumpy good is high, individuals are predicted to accept even contracts that would always be refused by someone who can hold cash balances — such as savings contracts with a negative return or credit contracts with a high interest charge.

Take-up predictions under the commitment model can thus be summarised as follows:

(i) Time of payment (p) is irrelevant: if an individual accepts a credit contract with s and r , (s)he also accepts a savings contract with the same s and r.

(ii) Individuals may accept savings contracts ($p = T$) with $r < 0$ (*i.e.*, a negative return); the arbitrage argument no longer applies. Individuals refuse savings contracts ($p = T$) with a low enough return r. This again follows from the concavity of $u(.)$: the only difference is that now the threshold interest rate r may be negative.

(iii) Individuals do not always accept credit contracts $(p = 1)$ with $r > 0$ (*i.e.*, a negative interest charge). This is because they cannot hold onto $(T - 1) \cdot s$ to repay the loan in installments. Individuals refuse credit contracts ($p = 1$) with a large enough cost of credit $r < 0$. This prediction still holds since it follows from the concavity of $u(.)$.

3 Experiment

3.1 Experimental design

We implement a stylised version of this theoretical model as a field experiment. At the beginning of each week, on day 0, each participant is offered one of 12 different generalised ROSCA contracts, where the type of contract offered is determined by the random draw of cards.[11] The 12 contracts differ by (i) timing of lump sum payment p and (ii) interest rate r but all share the same installment size s. All disbursements start the next day, on day 1. This short delay serves to mitigate against distortions in take-up arising from differences in the credibility of lumpsum payment between contracts (Coller and Williams, 1999; Dohmen, Falk, Huffman, and Sunde, 2013). Lump sum payments are either made on Day 1, Day 3, Day 4 or Day 6. On any day that the lump sum is not paid, the participant is required to pay $s = 200$ Pakistani rupees (PKR). The base lump sum payment is either 900 PKR (that is, $r = -10\%$), 1000 PKR ($r = 0$) or 1100 PKR ($r = +10\%$). At the time of the experiment, 200 Pakistani rupees was worth approximately US\$1.90; 1000 rupees was therefore approximately US\$9.50. (As we explain in more detail shortly, the average daily household income for Sargodha district is approximately 1000 rupees.)

The following table illustrates the payment schedule for a contract with lumpsum payment on day $p = 3$ and interest rate $r = +10\%$:

	DAY 0	DAY 1	DAY 2	DAY 3	DAY 4	DAY 5	DAY 6
Participant pays	*take up*	200	200		200	200	200
Bank pays	*decision*			1100			

[11] This is equivalent to exploiting the structure of a one-off lottery random ROSCA (Kovsted and Lyk-Jensen, 1999) implemented on an individual basis.

Since there are three possible interest rate values and four possible days for the lumpsum payment, 12 different contracts are used in the experiment to represent each combination of p and r. At the beginning of the week each participant in the experiment is offered one of these contracts, and must make a take-it-or-leave-it decision whether to accept it. We are interested to test (i) whether there is demand for this generalised ROSCA contract, and (ii) if so, how demand varies with the terms of the contract.

3.2 Experimental implementation

We ran this experiment over September and October 2013 in Sargodha, Pakistan Punjab. Our sample comprises female members of the National Rural Support Programme (NRSP) who are currently, or have in the past, been clients of microfinance products being offered by the NRSP. The experiment was conducted through four NRSP offices in the Sargodha district.[12] Female members of these four branches were invited to attend meetings set in locations near their residences. Members who stayed for the first meeting were offered a generalised ROSCA contract randomly selected from the 12 possible contracts described above. Participants were free to take up or reject the contract offered in that week. Even if they refused the contract offered to them in that week, participants were still required to participate in the meeting held the following week, when they were again offered a contract randomly selected from the list of 12. In total, there were three weekly meetings. Those who attended all three weekly meetings (whether choosing to accept or reject the product for that week) received a show-up fee of 1100 PKR at the end of the trial. Once a subject had accepted a contract, they were expected to abide by the terms of that contract. Failure to do so resulted in exclusion from the rest of the experiment – and from receiving the show-up fee. NRSP ensured that subjects did not benefit or suffer financially from dropping out (apart from losing the show-up fee). In practice, this meant reimbursing subjects

[12] The Sargodha office is also the NRSP regional head office for South Punjab.

for partial contributions, and recouping amount received but not fully repaid.

We implemented the experiment in NRSP branches located within a 30 km radius around Sargodha. We implemented the experiment in 32 microfinance groups. In three of these groups, there were breaches of experiment protocol.[13] We drop these three groups from the analysis, a decision taken before we began any of the analysis. This means that we have a total of 29 microfinance groups/clusters in the following analysis.[14]

In these 29 groups, we collected baseline data from 955 respondents. Of these, 889 decided to participate in the experiment, and made a decision on the first offered contract. Of the 66 women who left before the experiment began, 41 stated that they did not have time to attend each day; six said that they did not understand the product. Table 1 describes the sample of women who participated in the first meeting and made a decision on an offered contract. The sample ranges in age from 18 to 70, with a median age of 38. 90% of our participants are married, and only 30% have any education (that is, have completed at least one year of schooling). By design, our respondents live close to the meeting place (the median is four minutes' walking time). This is important for ensuring that take-up decisions are based primarily on the financial costs and benefits of the products offered, rather than on the time and effort of commuting to the place of payment.

< Table 1 here. >

For each respondent characteristic, Table 1 also shows the p-value for a test of balance in

[13] These breaches were through no fault of our research team or our implementing partner, NRSP. This is discussed in more detail in the appendix.

[14] Our results are robust to the use of Moulton-corrected standard errors (results available on request). This is not surprising given that most of our regression results of interest are highly significant.

randomisation.[15] This shows that two of the 17 variables are mismatched at the 90% confidence level: the number of years as an NRSP client; and a dummy variable for whether the respondent makes the final decision on household spending (either individually or jointly with her husband or others). As a robustness check we control for these two variables in the subsequent analysis, but doing so does not affect our results.

Attrition from the experiment comes from two sources: 80 subjects defaulted on a contract, and another 97 simply stopped coming.[16] The large majority of defaults and exits occur within or at the end of the first round. Most exiting subjects answered an exit questionnaire, stating the reason for leaving. Defaulting subjects list shocks (e.g., illness, travel), inability to pay, and unwillingness to come to daily meetings as their main reasons for leaving. Non-defaulting leavers list unwillingness to come to daily meetings as main reason. There is a small but significant effect of contract terms on the probability of default: women offered $p = 1$ were about 2.7 percentage points less likely to default than women drawing $p = 3$, $p = 4$ or $p = 6$. In Section 4.4 and Appendix 4, we show that attrition does not affect our other results.

It is worth nothing that subjects who attrite forfeit the show-up fee of 1100 PKR. Participants should therefore refuse a contract that they do not expect to fulfill: by defaulting they lose a show-up fee of 1100 PKR compared with a maximum material gain of 100 PKR on a contract. If they had refused the contract instead of defaulting, they would have avoided a loss $\geq$ 1000 PKR. Individuals who default can thus be seen as misjudging their future ability to fulfill a commitment contract. This behavior is akin to the type of 'naive sophisticates' studied by John (2015), namely, individuals with a mistaken anticipation about their

[15] This is generated by estimating equation 8, treating each covariate in turn as an outcome variable, and running a joint test that all parameters other than the intercept are zero.
[16] Five subjects are recorded as having defaulted but remained in the experiment.

future ability to comply with an incentivized commitment contract.[17]

Of the 709 respondents participating in all three experiment rounds, 92% said afterwards that they understood the product, 96% said that they were glad to have participated, and 87% said that they would recommend the product to a friend. 82% said that the product helped them to commit to saving, and 64% said that the product helped them to resist pressure from friends and family to share money. At baseline, we asked respondents to imagine that NRSP were to loan them 1000 rupees and asked them an open-ended question about how they would use the money. Approximately half gave a non-committal response (*e.g.*, domestic needs or something similar). Of those who gave a specific answers, a majority listed a lumpy purchase, that is, an expenditure not easily made in small increments. Of the lumpy purchases described, the most common are sewing equipment, chickens or goats, and school materials (particularly school uniforms).

4 Regression results

In this section we present linear regression results.[18] To contextualise our regression results, we start by presenting stylised facts about take-up.

4.1 Stylised facts about take-up

Table 2 shows average take-up across the 12 different types of contract offered. The table shows the first two important stylised facts. *First*, overall take-up is very high (approximately 65%, on average). *Second*, take-up varies with contractual terms – respondents

[17] A standard example of naive sophisticates concerns individuals who take a membership to a gym as a commitment to exercise, but fail to use it: DellaVigna and Malmendier (2006).

[18] We use the identification strategy outlined in our Pre-Analysis Plan, which was submitted and registered with 3ie's Registry for International Development Impact Evaluations before we began our analysis.

are more likely to take a contract when $p = 1$ than when $p = 6$. But the variation is not large, and certainly not nearly as stark as the variation predicted by the standard model with $m_t \geq 0$.

< Table 2 here. >

Table 3 shows an important *third stylised fact*: there appears to be important heterogeneity across individuals. Of the 709 individuals completing all three experiment waves, 319 (45%) accepted all three contracts offered, and 121 (17%) accepted none of the contracts offered. This was despite the vast majority of respondents having been offered three different contracts.

< Table 3 here. >

The implication of this is clear, and is a *fourth stylised fact*: many individuals accepted both a credit contract and a savings contract, even over the very short duration of the experiment. Of the 709 respondents completing all waves, 277 were offered both a savings contract ($p = 6$) and a credit contract ($p = 1$). Of these, 148 accepted at least one savings contract and at least one credit contract.

< Table 4 here. >

This fact already challenges the standard model. Recall Prediction 5 of that model: the same individual will not demand both a savings contract with $r > 0$ and a credit contract with $r \leq 0$. Table 5 considers those respondents who were both offered a savings contract with $r > 0$ and a credit contract with $r \leq 0$. There were 87 such respondents; of these, 44 (51%) accepted both a savings contract with $r > 0$ and a credit contract with $r \leq 0$.

< Table 5 here. >

Similarly, the standard model predicts that individuals always refuse savings contracts ($p = T$) with $r < 0$, and always accept credit contracts ($p = 1$) with $r > 0$. In our experiment, 184 respondents were offered at least one savings contract with $r < 0$; of these 86 accepted at least one (47%).[19] 230 respondents were offered at least one credit contract with $r > 0$; of these, 29 rejected at least one (13%).

Together, these stylised facts suggest strongly that saving and borrowing among microfinance clients are substitutes, satisfying the same underlying demand: for a regular schedule of deposits and a lump-sum withdrawal. Indeed, as Table 6 summarises, our experiment provided 439 of our 709 respondents an opportunity to violate at least one of the specific predictions of the standard model: 155 of them did so.

< Table 6 here. >

4.2 Product take-up and contract terms

We begin by testing sensitivity of take-up to interest rates, and to the day of lump sum payment. Define y_{iw} as a dummy variable for whether individual i agreed to the offered contract in experiment wave $w \in \{1, 2, 3\}$, and define $r_{iw} \in \{-0.1, 0, 0.1\}$ as the interest rate offered. We estimate the following linear probability model:

$$y_{iw} = \beta_0 + \beta_r \cdot r_{iw} + \mu_{iw}. \tag{4}$$

Define $rneg_{iw}$ as a dummy for $r_{iw} = -0.1$ and $rpos_{iw}$ as a dummy for $r_{iw} = 0.1$. We also

[19] Indeed, 84 of these 86 accepted all such contracts that they were offered: 163 respondents were offered one such contract, of whom 72 accepted it, 19 were offered two such contracts, of whom 11 accepted both, and two were offered three such contracts, of whom one accepted.

estimate allowing for asymmetric interest rate effects:

$$y_{iw} = \beta_0 + \beta_{neg} \cdot rneg_{iw} + \beta_{pos} \cdot rpos_{iw} + \mu_{iw}, \tag{5}$$

where zero interest rate is the omitted category.

Symmetrically, we estimate the following regression to test sensitivity to the day of lump sum payment p. Define $p_{iw} \in \{1, 3, 4, 6\}$ as the day of payment, and $p1_{iw}$ and $p6_{iw}$ as corresponding dummy variables (leaving days 3 and 4 as the joint omitted category). Then we estimate:

$$y_{iw} = \beta_0 + \beta_d \cdot p_{iw} + \mu_{iw} \tag{6}$$

$$y_{iw} = \beta_0 + \beta_1 \cdot p1_{iw} + \beta_6 \cdot p6_{iw} + \mu_{iw}. \tag{7}$$

Finally, we estimate a saturated specification (leaving as the base category an offer of a zero interest rate with lump sum payment on either day 3 or day 4):

$$\begin{aligned} y_{iw} = \beta_0 + \beta_{neg} \cdot rneg_{iw} + \beta_{pos} \cdot rpos_{iw} + \beta_1 \cdot p1_{iw} + \beta_6 \cdot p6_{iw} + \gamma_{neg,1} \cdot rneg_{iw} \cdot p1_{iw} \\ + \gamma_{neg,6} \cdot rneg_{iw} \cdot p6_{iw} + \gamma_{pos,1} \cdot rpos_{iw} \cdot p1_{iw} + \gamma_{pos,6} \cdot rpos_{iw} \cdot p6_{iw} + \mu_{iw}. \end{aligned} \tag{8}$$

Table 7 shows the results. We observe a significant response to the interest rate (column 1): relative to a zero interest rate, we find a significant negative effect of a negative interest rate, and a significant positive effect of a positive interest rate (column 2). Similarly, we find a significant effect of the day of payment (column 3); a significant positive effect of receiving payment on day 1, and a significant negative effect of receiving payment on day 6 (column 4). Column 5 shows the saturated specification: the coefficients on day of payment and interest rate barely change from columns 3 and 4, and the interaction effects are not significant.

However, crucially, none of the estimated effects are particularly large. For example, column 2 shows an average take-up of about 67% for clients with $r = 0$; this falls only to 54% for clients offered $r = -0.1$, and rises to 73% for clients offered $r = 0.1$. Similarly, column 4 shows an average take-up of 63% for clients with $d = 3$ or $d = 4$, which rises to 75% for clients offered $d = 1$ and falls to 57% for $d = 6$.

< Table 7 here. >

4.3 Product take-up and heterogeneous effects

We now disaggregate by key participant characteristics to test for heterogeneous product demand. Appendix 3 discusses subgroup variation in detail, and shows regression results for all subgroups. Table 8 summarises these results: the table reports the intercept terms from estimations of equation 8, with tests for (i) intercept equality between subgroups and (ii) equality of all other parameters. We find significant heterogeneity by the distance the respondent lives from the meeting place (respondents living further away being significantly and substantially less likely to agree to a contract offering payment on day 1) and respondent occupation (though this result may be driven by the very small proportion of respondents not earning income from agriculture, self-employment or salaried or casual labour).

< Table 8 here. >

Particularly important are significant differences in terms of measures of demand for lump-sum payments. Respondents who described saving or investing a hypothetical loan have a significantly and substantially larger intercept term than those who did not, and are significantly less responsive to contractual terms (in particular, less responsive to being offered a positive interest rate and to having payment on day 1). Similarly, respondents who report pressure from family and friends are significantly less responsive to contractual terms — again, less responsive to being offered a positive interest rate and to having payment on day 1. We interpret these results as suggestive evidence that these respondents value the product — whether offered in the credit or the savings domain — as a means to insulate income in return for a lump-sum payment.

4.4 Extensions and Robustness

Appendix 4 reports several tests of time effects. First, we test for the effect of lagged acceptance (which we instrument using the lagged contractual offer). We find that lagged acceptance has a large and highly significant effect: accepting in period t causes a respondent to be about 30 percentage points more likely to accept in period $t + 1$. This speaks to possible 'familiarity' or 'reassurance' effects: it suggests that trying the product improves respondents' future perceptions of the offer. Appendix 4 also reports a further test of parameter stability across experiment waves. The appendix shows a large and significant decline in willingness to adopt (that is, the intercept term is significantly smaller in the third experiment wave); this is in addition to a significant increase in sensitivity to a positive interest rate, and to receiving a negative interest rate on the first payment day. This could be due to a variety of causes, including respondent fatigue. This, however, does not affect our main results of interest.

We run several other robustness checks. Appendix 4 reports a battery of estimations on attrition. We find that respondents are more likely to attrit having just been offered a contract with payment on day 6 (regardless of whether the interest rate was positive, negative or zero). We find no other significant effect of contractual terms on attrition. A separate estimation (omitted for brevity) tests attrition as a function of a large number of baseline characteristics; none of the characteristics significantly predicts attrition. Further, Appendix 4 compares the saturated estimations from Table 7 with a saturated estimation using only those respondents who remained in the experiment for all three rounds: we find that this attrition has no significant effect on our parameter estimates ($p = 0.334$).[20]

5 Structural analysis

The regression results show (i) a high take-up in general, (ii) a small but statistically significant sensitivity to the terms of the contract, and (iii) some interesting heterogeneity on baseline observable characteristics — particularly on whether respondents would save/invest a hypothetical loan, and whether respondents report pressure from friends or family to share cash on hand. Together, these results cast doubt on the standard model and on the sharp contrast traditionally drawn between microsaving and microcredit contracts.

However, the regression analysis does not tell the full story: it documents the general pattern of take-up, but does not identify the kind of heterogeneity that can account for this pattern. Put differently, the regressions identify Average Treatment Effects — but they do not identify the underlying distribution of behavioural types among participants. Yet this underlying distribution is a critical object of interest for our study: we want to know what proportion of participants behave as the standard model predicts, what proportion follow the alternative model presented in the conceptual section, and what proportion follow neither of the two.

To recover that underlying distribution, we need a structural framework. In this section,

[20] Further, we have confirmed that our results are not being driven by 'day of week' effects. We have also re-run the estimations including the two covariates for which the randomisation was unbalanced (namely, years as a microfinance client, and whether the respondent makes the final decision on spending). Our conclusions are robust to these further checks; results are available on request.

we parameterise the models developed in section 2 and use numerical methods to obtain predictions about the take-up behaviour of different types of decision-makers. We then nest those predictions in a discrete finite mixture model. Our results show that approximately 75% of participants can have their decisions rationalised by at least one of the scenarios considered by our model; of these scenarios, the largest share comprises women who value lump-sum payments and who struggle to hold cash over time.

5.1 A structural model

We begin by parameterising the conceptual framework of Section 2. First, we parameterise respondents as having log utility in smooth consumption, and receiving an additively separable utility gain from consuming the lumpy good: $u(c, L; \gamma) = \ln c + \gamma \cdot L$, where $L \in \{0, 1\}$. The parameter γ is thus fundamental to our structural estimation. If $\gamma = 0$, respondents behave as if they have no preference for lumpy consumption; as γ increases, the importance of lumpy consumption increases relative to the importance of smooth consumption.[21]

To give a meaningful interpretation to the magnitudes of c and γ, we need a normalisation for income. We use $y_{iw} = 1039$ Pakistani rupees. This value is drawn as the average daily household income across the district of Sargodha from the 2010-11 PSLM survey

[21] The assumption of log utility could readily be changed — for example, by using a CRRA utility. However, the curvature of that function (*i.e.* reflecting the intertemporal elasticity of substitution) is not separately identified since there is nothing in our experimental design to shed light on individuals' intertemporal substitution preferences. We therefore use log utility for convenience. We could vary this assumption; doing so would not change any of the predictions of our model, and would therefore not change any of our structural estimates. It would, of course, require a reparameterisation of the critical values of γ in Table 9 — but these values serve simply as an expositional device for the preference for lumpy consumption.

(corrected for CPI inflation since 2011).[22] We set $\alpha = (T-1) \cdot s \cdot (1-0.1) = 900$, as a description of the kind of lumpy expenditure that we are considering — namely, lumpy expenditures made possible by the kind of ROSCAs found in our study area. For simplicity — and given the short time-frame of our experiment — we assume that respondents do not discount future periods ($\beta = 1$).[23]

We solve the problem numerically, by a series of nested optimisations: see Appendix 5. Table 9 shows the consequent take-up predictions. Note the close congruence to the predictions in section 2; the structural specification is a parameterised version of the earlier model, so all of the general predictions in Section 2 hold in Table 9. To understand the magnitude of our estimates of γ, we report using a stylised measure of equivalent variation, γ_{ev}. This is defined through a simple thought experiment. We imagine, in a static setting, a respondent holding the daily wage, y; we imagine giving her the cost of lumpy consumption (α), and allow her to spend this either by purchasing the lumpy consumption good or by augmenting the continuous consumption good. We define γ_{ev} as the additional currency payment required to persuade her not to consume the lumpy good — that is, $\ln(y) + \gamma \equiv \ln(y + \alpha + \gamma_{ev})$.

< Table 9 here. >

[22] In our original Pre-Analysis Plan, we had specified a simpler structural model that we intended to estimate; this was the method that we specified for constructing the daily income flow without the contract.That structural model said nothing about consumption of lumpy goods. We have abandoned that model in favour of the current model. Results from that model are available on request — but they add nothing of substance to the current structural results.

[23] This assumption, too, could be changed by setting another value for β. Since our experiment is not designed to identify intertemporal preferences, it is convenient to set $\beta = 1$ given that the time horizon of the experiment is very short (*i.e.*, 6 days) and that sensitivity to present preference is mitigated by separating take-up decisions (taken on day 0) from payments, which taken place on the other six days of the week.

5.2 A discrete finite mixture estimator

How, then, should our model be estimated? We want to estimate our model with maximal heterogeneity: we want to allow different respondents to have different values of γ, and to differ in terms of whether constrained to $m_t = 0$. To do this, we use a discrete finite mixture model. This follows a body of recent literature — led by Glenn Harrison, Elisabet Rutström and co-authors — showing empirically that laboratory behaviour can be rationalised by allowing for a mixture of different behaviour types in a population: Andersen, Harrison, Lau, and Rutström (2008); Harrison and Rutström (2009); Harrison, Humphrey, and Verschoor (2010); Harrison, Lau, and Rutström (2010); Andersen, Harrison, Lau, and Rutström (2014); Coller, Harrison, and Rutström (2012). Our specific approach is similar in spirit to Stahl and Wilson (1995): our model implies a number of different types of potential respondent, and we want to estimate the proportion of each type in the population.[24] Mixture models for experimental analysis typically require the estimation *both* of mixing proportions *and* of other parameters — typically, parameters characterising the shape of participants' utility functions. In our context, Table 9 makes discrete predictions — so, in contrast to previous experimental analysis, we develop a simple Non-Parametric Maximum Likelihood estimator to recover our mixture distribution.

We take the predictions in Table 9 as the foundation for our estimation. We define this model over combinations of three offered contracts — that is, the contract offered in the first wave, the contract offered in the second period and the contract offered in the third period. We index all such offered contract combinations by $k \in \{1, \ldots, K\}$, where K

[24] Von Gaudecker, Van Soest, and Wengström (2011) use an alternative approach with a continuous distribution of the parameters of interest, on the basis that 'finite mixture models have difficulty handling a large number of potential values for the parameters and a small set of values seems insufficient to explain the very heterogeneous choice behaviour illustrated…' (page 677). The finite mixture model is appropriate for our case, however, given that our model only predicts a relatively small number of distinct forms of behaviour (namely, the behaviour shown in the rows of Table 9.

is the total number of contract combinations offered.[25] For each contract combination, a respondent can make eight possible choices for (y_{i1}, y_{i2}, y_{i3}). We index these eight possible choices by $c \in \{1, \ldots, C\}$.

Table 9 shows that we can identify six distinct types; we index these types as $t \in \{1, \ldots, T\}$.[26] Define a matrix $\boldsymbol{X}$ of dimensions $(KC) \times T$, such that element $\boldsymbol{X}_{C\cdot(k-1)+c,t}$ records the probability that type t will make choice c when faced with contract combination k. To illustrate, consider 'Type A' from Table 9. Suppose that someone of this type is offered the following three contracts: $(r, p) = (0.1, 1)$, then $(r, p) = (0, 3)$, then $(r, p) = (-0.1, 4)$. Table 9 shows that this person should accept the first of these, but not the second or third; thus, with probability 1, someone of Type A should respond to this contract combination by choosing $(1, 0, 0)$.

Define a (KC)-dimensional vector $\boldsymbol{y}$, such that element $\boldsymbol{y}_{C\cdot(k-1)+c}$ is the sample probability of a respondent choosing choice combination c, conditional on having been offered contract combination k. Define $\boldsymbol{\beta}$ as a T-dimensional vector for the proportions of each type in the population (such that $\sum_t \boldsymbol{\beta}_t = 1$). Then, straightforwardly, $\boldsymbol{y} = \boldsymbol{X} \cdot \boldsymbol{\beta}$. $\boldsymbol{\beta}$ is the key structural parameter of interest. By standard properties of the Moore-Penrose pseudoinverse, $\boldsymbol{\beta}$ is identified if and only if rank$(\boldsymbol{X}) = T; T \leq KC$. (In the current application, rank$(\boldsymbol{X}) = T = 6$ and $K \times C = 4288$; $\boldsymbol{\beta}$ is therefore identified.) Given that $\boldsymbol{\beta}$ is identified, we can estimate efficiently by Non-Parametric Maximum Likelihood. Let the sample size be N, and let the number facing contract combination k be n_k. Then the

[25] There are $12^3 = 1728$ possible contract combinations that could have been offered; in practice, only 536 of these possible combinations were actually offered.

[26] Note that the model makes identical predictions for 'Type B' and 'Type D'; we therefore cannot separately identify these types, so we combine them into a single 'Type B/D'. The same applies for Types C and E. This will not change any of our empirical conclusions.

log-likelihood for the sample is:

$$\ell(\boldsymbol{\beta}) = \sum_{k=1}^{K} n_k \cdot \sum_{c=1}^{C} \boldsymbol{y}_{[C\cdot(k-1)+c]} \cdot \ln \left(\sum_{t=1}^{T} \boldsymbol{\beta}_t \cdot \boldsymbol{x}_{[C\cdot(k-1)+c],t} \right). \tag{9}$$

5.3 Structural results

The structural estimates are reported in Table 10 (where we include 95% confidence intervals from a bootstrap with 1000 replications). The results are stark: we estimate that about 60% of respondents are constrained in holding cash between periods (namely, Types F, G and H). For about 50% of respondents (*i.e.* Types G and H), this is coupled with a large value on lumpy consumption purchases (in the sense of $\gamma > 0.98$). These proportions dwarf those of respondents who adhere to a standard model, in which $m_t \geq 0$: the total mass on such respondents is only about 12% (Types A, B, C and D).

< Table 10 here. >

In Table 11, we estimate our mixture model separately for different subsets. We disaggregate by (i) whether the respondent is literate, (ii) whether the respondent faces pressure from family members to share available funds, (iii) whether the respondent reports difficulty in saving, (iv) whether the respondent describes a lumpy purchase at baseline, and (v) whether the respondent indicates a desire to save/invest a hypothetical loans of 1000 PRK.

In the final case, we strongly reject a null hypothesis that the model proportions are equal across the two sub-populations. Among those who would save or invest, we find a substantially lower preference for lumpy purchases among those with $m_t \geq 0$, and a substantially higher preference for lumpy purchases among those constrained to $m_t = 0$. In each of the other four cases, we fail to reject a null hypothesis that the proportion of types is equal across the respective subsamples. Nonetheless, there are two differences in these other cases that are interesting. First, among respondents who report that they do not face pressure from family members, we estimate a higher proportion having $m_t \geq 0$: specifically, we estimate about 16% in Types A through E as against about 10% for those who do report such pressure. Similarly, for those who do not report difficulties saving, we estimate about 14% having $m_t \geq 0$, as against about 11% for those who do. In each case, much of the difference appears to be explained by variation in the proportion of respondents whose behaviour can be rationalised by the model.

< Table 11 here. >

5.4 Structural results: Robustness

We run two robustness checks using the structural model. First, we consider the possibility that — in anticipation of receiving the 1100 PKR show-up fee — respondents may deviate from their usual strategy to refuse offers in the third period. (Table 23, for example, shows that general take-up declined in the final wave; we may be concerned about the implications of such behaviour for our structural results.) To test this, we add additional types: we take each of the types in Table 9 and add a 'star' to denote a variation in which the respondent refuses all contracts offered in the final period.[27] Thus, for example, Type A accepts if and only if $r = 0.1$ and $p \in \{1, 3\}$; Type A$\star$ accepts if and only if $r = 0.1$ and $p \in \{1, 3\}$, but always rejects in the final wave.

Table 12 shows the results. The key conclusions do not change: indeed, allowing for this kind of deviation only strengthens our earlier conclusions. We now find that almost 75% of respondents act as if they are constrained in holding cash between periods, and over 60% of respondents also have a preference for lumpy consumption (that is, types G, G$\star$, H and H$\star$).

[27] The model remains identified under this extension: $\text{rank}(\boldsymbol{X}) = T = 11$.

< Table 12 here. >

Second, we consider the possibility that some respondents are simply playing randomly — as if tossing a coin to decide whether to accept, rather than behaving for any the purposive reasons that we have modelled. To test this, we allow an additional type, whose respondents accept every offer with 50% probability.[28] Table 13 shows the results. By allowing for this additional type, we can now rationalise all of the observed play. Previously, we were unable to rationalise the behaviour of 24% of respondents; we now estimate that 40% of respondents are playing randomly. This is an interesting result in its own right — it suggests, for example, that many respondents may not have understood well the potential costs and benefits of the product (despite self reports to the contrary). However, the result does not change the substantive conclusions from the main structural estimates: we still estimate that almost 55% of respondents act as if constrained in holding cash (Types F, G and H), and that about 45% of respondents also have a preference for lumpy consumption (types G and H).

< Table 13 here. >

6 Conclusions

In this paper, we have introduced a new design for a framed field experiment, which has allowed us to test directly between demand for microcredit and demand for microsaving. Standard models predict that people should either demand to save or demand to borrow. This, however, is emphatically not what we find. Rather, we find a high demand both for saving and for credit — even among the same respondents at the same time. We hypothesise that saving and borrowing are substitutes for many microfinance clients, satisfying the same

[28] The model remains identified under this extension, too: $\text{rank}(\boldsymbol{X}) = T = 7$.

underlying demand for lump-sum payments and regular deposits. We have tested this using a new structural methodology with maximal heterogeneity; our results confirm that a clear majority of respondents have high demand for lump-sum payments while also struggling to hold cash over time. This result has potential implications both for future academic research and for the design of more effective microfinance products.

Table 1: **Description of sample**

	N	Mean	S.Dev.	1st Q.	Median	3rd Q.	Min.	Max.	Balance (p-values)
Age (years)	888	38.6	10.4	30.0	38.0	46.0	18.0	70.0	0.842
Dummy: Any education	889	0.3	0.5	0.0	0.0	1.0	0.0	1.0	0.760
Dummy: Literate	889	0.3	0.5	0.0	0.0	1.0	0.0	1.0	0.408
Distance (minutes)	887	4.5	3.8	2.0	4.0	5.0	1.0	30.0	0.313
Log (distance (minutes))	887	1.2	0.8	0.7	1.4	1.6	0.0	3.4	0.363
Years as a client	889	2.7	1.6	1.0	2.0	3.0	1.0	10.0	0.039**
Dummy: Owes more than 20,000 PKR	889	0.4	0.5	0.0	0.0	1.0	0.0	1.0	0.381
Dummy: Household larger than 6	889	0.4	0.5	0.0	0.0	1.0	0.0	1.0	0.997
Dummy: Respondent makes final decision on spending	889	0.3	0.5	0.0	0.0	1.0	0.0	1.0	0.048**
Dummy: Family members request money	889	0.7	0.5	0.0	1.0	1.0	0.0	1.0	0.660
Dummy: Respondent finds it hard to save	889	0.4	0.5	0.0	0.0	1.0	0.0	1.0	0.308
Dummy: Respondent or family owns livestock	889	0.5	0.5	0.0	0.0	1.0	0.0	1.0	0.238
Dummy: Respondent or family grows crops for sale	889	0.2	0.4	0.0	0.0	0.0	0.0	1.0	0.717
Dummy: Respondent or family runs a business	889	0.3	0.5	0.0	0.0	1.0	0.0	1.0	0.454
Dummy: Respondent or spouse earns from salaried/casual labour	889	0.7	0.5	0.0	1.0	1.0	0.0	1.0	0.816
Dummy: Respondent married	889	0.9	0.3	1.0	1.0	1.0	0.0	1.0	0.438
Dummy: Respondent would save/invest a 1000 PKR loan	888	0.3	0.4	0.0	0.0	1.0	0.0	1.0	0.415

This table describes the key covariates for our sample, recorded at baseline. The p-values for randomisation balance were generated by regressing each covariate on dummy variables for the contractual terms offered (in a saturated specification), and running a joint test that all parameters other than the intercept are zero.

Table 2: **Product take-up by contract type**

PAYMENT DAY	INTEREST RATE		
	$r = -0.1$	$r = 0$	$r = 0.1$
$p = 1$	**60.0%** of 215 offers	**78.2%** of 239 offers	**86.6%** of 262 offers
$p = 3$	**51.9%** of 131 offers	**64.6%** of 127 offers	**68.4%** of 133 offers
$p = 4$	**52.6%** of 116 offers	**61.9%** of 113 offers	**72.7%** of 154 offers
$p = 6$	**47.8%** of 207 offers	**57.2%** of 187 offers	**64.2%** of 243 offers

This table shows average take-up across the 12 different types of contract offered.

Table 3: **Individual heterogeneity**

ACCEPTANCES	UNIQUE CONTRACTS OFFERED			TOTAL	
	3	2	1		
0	94	26	1	121	(17%)
1	88	17	1	106	(15%)
2	135	24	4	163	(23%)
3	241	73	5	319	(45%)
	558	140	11	709	(100%)

This table shows the total number of contract acceptances by individual respondents, against the total number of different types of contract offered to those individuals. It highlights that almost half the respondents accepted all contracts offered.

Table 4: **Acceptance of both credit and savings contracts**

	accepted a savings contract?		
accepted a credit contract?	NO	YES	TOTAL
NO	45	19	64
YES	65	148	213
TOTAL	110	167	277

This table shows the number of respondents accepting a savings contract and the number of respondents accepting a credit contract. As a cross-tabulation, it highlights that 277 respondents were offered both a savings and a credit contract, of which 148 accepted at least one contract of each type.

Table 5: **Acceptance of savings contracts with $r \geq 0$ and credit contracts with $r \leq 0$**

accepted a credit contract with $r \leq 0$?	*accepted a savings contract with $r > 0$?* NO	YES	TOTAL
NO	15	11	26
YES	17	44	61
TOTAL	32	55	87

This table is motivated by Prediction 5 of the standard model. It shows that 87 respondents were offered a savings contract with $r > 0$ and a credit contract with $r \leq 0$; of these 44, accepted at least one contract of each type.

Table 6: **Violations of the standard model**

PREDICTION	OPPORTUNITY TO VIOLATE PREDICTION	PREDICTION VIOLATED
will not accept savings with $r > 0$ and credit with $r \leq 0$	87	44 (51%)
always refuse savings with $r < 0$	184	86 (47%)
always accept credit with $r > 0$	230	29 (13%)
any prediction	439	155 (35%)

This table summarises the predictions of the standard model; it shows the number of respondents violating such predictions, compared to the number being offered the opportunity to do so.

Table 7: **Determinants of take-up: Interest rate and payment day**

	(1)	(2)	(3)	(4)	(5)
***Dependent variable:* Whether the respondent accepted the offer**					
Interest rate	0.929				
	(0.142)***				
Payment day			-0.036		
			(0.005)***		
Dummy: Negative interest		-0.125			-0.099
		(0.030)***			(0.048)**
Dummy: Positive interest		0.063			0.082
		(0.024)**			(0.045)*
Dummy: Payment day is 1				0.126	0.152
				(0.030)***	(0.052)***
Dummy: Payment day is 6				-0.055	-0.042
				(0.025)**	(0.056)
Dummy: Negative interest and payment day is 1					-0.077
					(0.073)
Dummy: Negative interest and payment day is 6					0.011
					(0.071)
Dummy: Positive interest and payment day is 1					-0.010
					(0.054)
Dummy: Positive interest and payment day is 6					-0.042
					(0.060)
Constant	0.646	0.668	0.776	0.627	0.628
	(0.039)***	(0.045)***	(0.040)***	(0.044)***	(0.056)***
Obs.	2347	2347	2347	2347	2347
R^2	0.026	0.027	0.023	0.025	0.053

This table reports LPM estimates for take-up as a function of contract terms.
Parentheses show standard errors, which allow for clustering by microfinance group.
Significance: $* \Leftrightarrow p < 0.1$, $** \Leftrightarrow p < 0.05$, $*** \Leftrightarrow p < 0.01$.

Table 8: **Summary of sub-group analysis**

INTERACTION	INTERCEPT TERMS		EQUALITY TESTS (p-values)	
	'YES'	'NO'	INTERCEPT	OTHER
Literate?	0.548	0.667	0.125	0.148
Distance > 4 minutes?	0.637	0.624	0.890	0.022**
Self-employed / wage?	0.634	0.533	0.484	0.000***
Would save/invest a loan for 1000 PKR?	0.726	0.598	0.083*	0.006***
Family members request money whenever it is on hand?	0.661	0.570	0.316	0.021**
Has difficulty saving?	0.618	0.635	0.844	0.802
Described a lumpy purchase at baseline?	0.667	0.612	0.508	0.513

This table summarises results from a series of estimations; all are shown in the appendix. Note that 'self-employed / wage' refers to whether the respondent or her spouse grows crops for sale, runs a business or earns from salaried or causal labour.

Table 9: **Definition of possible respondent types**

		CONTRACT OFFERED											
	r	-0.1				0				0.1			
	p	1	3	4	6	1	3	4	6	1	3	4	6
TYPE	**DEFINITION**	**DECISION** ($1 =$ **ACCEPT**)											
'A'	$m_t \geq 0$ and $\gamma_{ev} \in [-900, 490)$	0	0	0	0	0	0	0	0	1	1	0	0
'B'	$m_t \geq 0$ and $\gamma_{ev} \in [490, 620)$	0	0	0	0	0	0	0	0	1	1	1	0
'C'	$m_t \geq 0$ and $\gamma_{ev} \in [620, 1310)$	0	0	0	0	0	0	0	0	1	1	1	1
'D'	$m_t \geq 0$ and $\gamma_{ev} \geq 1310$	0	0	0	0	0	0	0	0	1	1	1	0
'E'	$m_t = 0$ and $\gamma_{ev} \in [-900, 620)$	0	0	0	0	0	0	0	0	0	0	0	0
'F'	$m_t = 0$ and $\gamma_{ev} \in [620, 830)$	0	0	0	0	0	0	0	0	1	1	1	1
'G'	$m_t = 0$ and $\gamma_{ev} \in [830, 1120)$	0	0	0	0	1	1	1	1	1	1	1	1
'H'	$m_t = 0$ and $\gamma_{ev} \geq 1120$	1	1	1	1	1	1	1	1	1	1	1	1

This table records the predictions of our structural model for different types of contract offered. (Note that we rule out any cases where $\gamma > \log(1039) - \log(139) \approx 2.01$ *(implying* $\gamma_{ev} \approx 5827$*). Once* γ *becomes so large, the respondent will purchase the lumpy good in every period without the contract and without saving. This is not a meaningful case to consider in this context.)*

Table 10: **Structural estimates**

TYPE	ESTIMATED PROPORTION	95% CONFIDENCE	
		LOWER	UPPER
'TYPE A'	3.7%	1.1%	6.3%
'TYPE B/D'	5.0%	1.9%	8.4%
'TYPE C/F'	3.2%	1.0%	5.7%
'TYPE E'	11.8%	8.9%	14.7%
'TYPE G'	11.7%	8.4%	14.9%
'TYPE H'	40.5%	36.6%	44.5%
NOT RATIONALISED	24.1%	21.0%	27.4%
N	709		
log-likelihood	-529.291		

This table reports Non-Parametric Maximum Likelihood estimates from our mixture model. 'Types' refer to Table 9. 'Not rationalised' means that an individual did not behave as any of the types predict. 95% confidence intervals are obtained from a bootstrap with 1000 replications.

Table 11: **Structural estimates: Disaggregating by baseline characteristics**

	ESTIMATED PROPORTIONS									
	LITERATE?		FAMILY MEMBERS REQUEST MONEY?		DIFFICULTY SAVING?		LUMPY PURCHASE?		WOULD SAVE/INVEST?	
	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO
'TYPE A'	8.0%	2.6%	4.2%	2.2%	3.8%	3.7%	2.7%	4.2%	5.9%	2.5%
'TYPE B/D'	3.3%	4.6%	4.9%	5.9%	3.4%	5.8%	6.4%	4.7%	4.3%	5.9%
'TYPE C/F'	6.7%	2.5%	1.0%	8.3%	3.7%	3.2%	0.0%	4.0%	0.0%	4.1%
'TYPE E'	9.6%	12.4%	11.4%	12.0%	15.6%	9.2%	9.6%	12.6%	3.6%	14.8%
'TYPE G'	14.2%	10.7%	11.4%	12.7%	8.7%	13.6%	14.3%	10.9%	13.5%	11.1%
'TYPE H'	35.2%	42.7%	41.0%	39.3%	36.5%	43.6%	42.8%	40.0%	47.0%	38.1%
NOT RATIONALISED	23.1%	24.6%	26.1%	19.5%	28.3%	20.9%	24.2%	24.1%	25.7%	23.6%
N	229	480	494	215	307	402	198	511	189	522
log-likelihood	-172.2	-353.1	-351.3	-173.6	-213.2	-312.0	-137.4	-389.6	-112.9	-406.6
H_0 : Same proportions (p)	0.24		0.19		0.23		0.60		0.003***	

This table reports Non-Parametric Maximum Likelihood estimates from our mixture model, disaggregated by binary baseline covariates. 'Types' refer to Table 9. 'Not rationalised' means that an individual did not behave as any of the types predict. The last line of the table tests for whether the estimated proportions are the same between 'yes' and 'no' columns; this is implemented as a Likelihood Ratio test with six degrees of freedom (where Table 10 provides the restricted model).

Table 12: **Structural estimates: Allowing automatic refusal in wave 3**

TYPE	ESTIMATED PROPORTION	95% CONFIDENCE	
		LOWER	UPPER
‘TYPE A’	3.8%	0.0%	6.3%
‘TYPE A⋆’	0.0%	0.0%	4.7%
‘TYPE B/D’	2.6%	0.0%	5.8%
‘TYPE B⋆/D⋆’	1.3%	0.0%	4.9%
‘TYPE C/F’	2.5%	0.6%	4.8%
‘TYPE C⋆/F⋆’	0.9%	0.0%	2.6%
‘TYPE E/E⋆’	11.1%	7.6%	14.1%
‘TYPE G’	8.7%	5.7%	12.0%
‘TYPE G⋆’	4.6%	2.2%	7.0%
‘TYPE H’	41.5%	37.7%	45.4%
‘TYPE H⋆’	9.0%	6.6%	11.5%
NOT RATIONALISED	14.1%	11.4%	16.9%
N	709		
log-likelihood	-749.686		

This table reports Non-Parametric Maximum Likelihood estimates from our mixture model. This augments the estimates in Table 10 by allowing some respondents to behave according to the structural model in waves 1 and 2, then refuse automatically in wave 3; this is denoted by the addition of ‘⋆’. ‘Types’ refer to Table 9. ‘Not rationalised’ means that an individual did not behave as any of the types predict. 95% confidence intervals are obtained from a bootstrap with 1000 replications.

Table 13: **Structural estimates: Allowing a type with random play**

TYPE	ESTIMATED PROPORTION	95% CONFIDENCE	
		LOWER	UPPER
'TYPE A'	1.2%	0.0%	4.8%
'TYPE B/D'	4.6%	0.2%	7.7%
'TYPE C/F'	0.0%	0.0%	3.2%
'TYPE E'	8.7%	5.3%	11.8%
'TYPE G'	8.5%	4.9%	11.8%
'TYPE H'	36.6%	32.5%	41.0%
RANDOM PLAY	40.4%	35.0%	45.5%
NOT RATIONALISED	0.0%	0.0%	0.0%
N	709		
log-likelihood	-1183.8		

This table reports Non-Parametric Maximum Likelihood estimates from our mixture model. This augments the estimates in Table 10 by introducing a type that decides to accept or reject by tossing a fair coin in each wave. 'Types' refer to Table 9. 'Not rationalised' means that an individual did not behave as any of the types predict. 95% confidence intervals are obtained from a bootstrap with 1000 replications.

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Appendices for Online Publication

Appendix 1: Construction of the variables

The following table — taken from the Pre-Analysis Plan — describes how each variable was constructed.

VARIABLE	DEFINITION	SOURCE
	DATA ON CONTRACTS OFFERED:	
y_{it}	A dummy variable for whether individual i accepts the contract in period t.	Individual contract offers.
r_{it}	The interest rate offered in period t, such that $r = 10\%$, $r = 0\%$ or $r = -10\%$.	Individual contract offers.
d_{it}	The day payment is received by individual i in period t, such that $d = 1$, $d = 3$, $d = 4$ or $d = 6$.	Individual contract offers.
$rneg_{it}$	A dummy variable equal to 1 when the interest rate in period t is -0.1; 0 otherwise.	Individual contract offers.
$rpos_{it}$	A dummy variable equal to 1 when the interest rate in period t is 0.1; 0 otherwise.	Individual contract offers.
$d1_{it}$	A dummy variable equal to 1 when the payment is received by individual i on the first day of the product cycle in period t; 0 otherwise.	Individual contract offers.
$d6_{it}$	A dummy variable equal to 1 when payment is received on the sixth day of the cycle in period t; 0 otherwise.	Individual contract offers.
	DATA ON INDIVIDUALS:	
Age	The age of individual i.	Baseline questionnaire (Q.10).
Education	A dummy variable for whether individual i has 1 or more years of schooling.	Baseline questionnaire (Q.11).
Literate	A dummy variable for whether individual i assesses that she can read and write.	Baseline questionnaire (Q.12).
Distance	A continuous variable for the number of minutes i reports that she takes to walk from her home to the meeting place.	Baseline questionnaire (Q.13).
Log(Distance)	The natural log of the ‘distance’ variable.	Baseline questionnaire (Q.13).

Years as a client	The number of years that individual i has been a client of NRSP.	Baseline questionnaire (Q.14).
Money owed	A dummy variable for whether individual i owes money above the median level of money owed by the sample.	Baseline questionnaire (Q.15).
Household size	A dummy variable for whether individual i has a household size above the median household size of the sample.	Baseline questionnaire (Q.16).
Final decision	A dummy variable for whether individual i makes the final decision about spending money in the household (either alone or jointly).	Baseline questionnaire (Q.17).
Family pressure	A dummy variable for whether family members request money whenever individual i has money on hand.	Baseline questionnaire (Q.18).
Difficult to save	A dummy variable for whether individual i finds it hard to save money.	Baseline questionnaire (Q.19).
Owns livestock	A dummy variable for whether individual i or her family owns livestock.	Baseline questionnaire (Q.20).
Grows crops for sale	A dummy variable for whether individual i or her family grow crops for sale.	Baseline questionnaire (Q.23).
Runs a business	A dummy variable for whether individual i or her family run a business.	Baseline questionnaire (Q.26).
Income from salaried work or casual labour	A dummy variable for whether individual i or her spouse earns income from salaried work or from casual labour.	Baseline questionnaire (Q.30 and 32).
Save or invest	A dummy variable for a hypothetical situation in which NRSP loans Rs 1000 to individual i, and individual i chooses to save or invest it (0 if the individual lists other purposes).	Baseline questionnaire (Q.34); to be coded by Uzma Afzal and Farah Said, based on individual responses.
`group`	An index for the individual's experiment group.	Baseline questionnaire (ID control section).

Appendix 2: Breach of experimental protocol

In three of the 32 groups, our research assistants observed serious breaches of the experiment protocol. In summary:

(i) In one group, one woman (who was not supposed to be present) pressured the others into a mass walk-out; as a result, only six out of 45 women agreed to participate in the research.

(ii) In a second group, one man gathered all the participants and spoke to them before the ballots at the second meeting. He also told research assistants that participants in the area are 'too busy' for this kind of scheme. When drawing the contracts, it seemed that at least some of the participants exchanged glances with this gentleman when prompted for a decision. At this group's first meeting, 24 of the 27 participants accepted the contract offer; whereas at the second meeting, 0 of the 16 remaining participants accepted the contract offer.

(iii) In a third group, all women declined the offer in the third meeting, because the owner of the host house was ill and she apparently instructed everyone to decline so that she would not have to host the daily payment meetings. The week 2 ballot may also have been affected by these considerations, since she was apparently already ill in week 2.

Appendix 3: Subgroup variation

Table 15 shows that literate respondents were about 10 percentage points less likely to take up the product than illiterate respondents, and were significantly more responsive to the interest rate (in particular, they were substantially more likely to react positively to a positive interest rate).

< Table 15 here. >

Table 16 considers heterogeneity by the distance that the respondent lives from the meeting place. We bifurcate the sample into those respondents living more than four minutes' walk away and those living less (four minutes' walk being the median distance in the sample). We find generally similar responses to the contracts offered, with the notable exception of being offered payment on day 1: respondents living further away were significantly and substantially less likely to agree to a contract offering payment on day 1.

< Table 16 here. >

Table 17 disaggregates by occupation — that is, by whether the respondent (or her spouse) receives income from growing crops for sale, runs a business, or earns income from salaried work or casual labour. (That is, we compare women meeting *any* of these categories with women who meet *none*. Relatively few women — only 58 — fall into the latter category.) Responses are generally homogenous between these two groups. (Columns (5) and (6) imply that women without income are sensitive to negative interest rates only when they are offered on day 6 — but it seems likely that this result is driven by the small number of women not earning income in this way.)

< Table 17 here. >

Finally, we consider various measures of respondents' demand for lump-sum payments, and for their ability to hold cash balances; we test heterogeneity by whether the respondent reported that she would save/invest a hypothetical loan of 1000 rupees (Table 18), whether family members request money whenever the respondent has it on hand (Table 19), whether the respondent reports difficulty in saving (Table 20) and whether the respondent described a lumpy purchase with a hypothetical loan of 1000 rupees (Table 21).

There are several significant differences among the first two of these four comparisons. First, take-up is generally higher among those who described saving or investing a hypothetical loan than those who did not (see particularly columns 1 and 2 of Table 18). Similarly, those who did not describe saving or investing such a loan were significantly more likely to accept a contract with a negative interest rate than those who did (columns 1 and 2, Table 18). Similarly, respondents who did not face family pressure were significantly more responsive to the interest rate (in particular, the offer of a positive interest rate) than those who do face such pressure (columns 1 and 2, Table 19).

< Table 18 here. >

< Table 19 here. >

< Table 20 here. >

< Table 21 here. >

Table 15: **Heterogeneity by literacy**

	(1)	(2)	(3)	(4)	(5)	(6)
Literate?	**YES**	**NO**	**YES**	**NO**	**YES**	**NO**
***Dependent variable:* Whether the respondent accepted the offer**						
Dummy: Negative interest	-0.092	-0.143			-0.023	-0.135
	(0.055)	(0.037)***			(0.099)	(0.060)**
Dummy: Positive interest	0.147	0.022			0.144	0.054
	(0.045)***	(0.027)			(0.076)*	(0.059)
Dummy: Payment day is 1			0.171	0.106	0.196	0.131
			(0.040)***	(0.035)***	(0.070)***	(0.054)**
Dummy: Payment day is 6			-0.070	-0.047	-0.048	-0.038
			(0.037)*	(0.029)	(0.086)	(0.066)
Dummy: Negative interest and payment day is 1					-0.125	-0.055
					(0.155)	(0.069)
Dummy: Negative interest and payment day is 6					-0.069	0.043
					(0.119)	(0.088)
Dummy: Positive interest and payment day is 1					0.016	-0.024
					(0.072)	(0.069)
Dummy: Positive interest and payment day is 6					0.000	-0.066
					(0.100)	(0.088)
Constant	0.599	0.701	0.598	0.641	0.548	0.667
	(0.062)***	(0.043)***	(0.057)***	(0.043)***	(0.083)***	(0.054)***
Obs.	746	1601	746	1601	746	1601
R^2	0.042	0.024	0.042	0.018	0.085	0.044
Parameter equality: Intercept (p-value)	0.057*		0.300		0.125	
Parameter equality: All other parameters (p-value)	0.051*		0.185		0.148	

Parentheses show standard errors, which allow for clustering by microfinance group.
Significance: $* \Leftrightarrow p < 0.1$, $** \Leftrightarrow p < 0.05$, $*** \Leftrightarrow p < 0.01$.

Table 16: **Heterogeneity by distance**

	(1)	(2)	(3)	(4)	(5)	(6)
Distance > 4 minutes?	**YES**	**NO**	**YES**	**NO**	**YES**	**NO**
***Dependent variable:* Whether the respondent accepted the offer**						
Dummy: Negative interest	-0.121	-0.133			-0.110	-0.093
	(0.045)**	(0.037)***			(0.071)	(0.070)
Dummy: Positive interest	0.072	0.053			0.081	0.083
	(0.035)**	(0.035)			(0.072)	(0.073)
Dummy: Payment day is 1			0.063	0.173	0.057	0.223
			(0.039)	(0.034)***	(0.069)	(0.060)***
Dummy: Payment day is 6			-0.061	-0.051	-0.037	-0.048
			(0.036)*	(0.033)	(0.068)	(0.075)
Dummy: Negative interest and payment day is 1					-0.078	-0.085
					(0.112)	(0.075)
Dummy: Negative interest and payment day is 6					0.049	-0.018
					(0.097)	(0.099)
Dummy: Positive interest and payment day is 1					0.068	-0.068
					(0.084)	(0.075)
Dummy: Positive interest and payment day is 6					-0.098	0.001
					(0.099)	(0.085)
Constant	0.645	0.688	0.635	0.623	0.637	0.624
	(0.059)***	(0.054)***	(0.050)***	(0.060)***	(0.067)***	(0.080)***
Obs.	1039	1302	1039	1302	1039	1302
R^2	0.027	0.028	0.010	0.041	0.046	0.070
Parameter equality: Intercept (p-value)	0.516		0.858		0.890	
Parameter equality: All other parameters (p-value)	0.932		0.012**		0.022**	

Parentheses show standard errors, which allow for clustering by microfinance group.
Significance: $* \Leftrightarrow p < 0.1$, $** \Leftrightarrow p < 0.05$, $*** \Leftrightarrow p < 0.01$.

Table 17: **Heterogeneity by economic activity**

Respondent or spouse grows crops for sale, runs a business or earns from salaried/casual labour?	(1) **YES**	(2) **NO**	(3) **YES**	(4) **NO**	(5) **YES**	(6) **NO**
Dependent variable: **Whether the respondent accepted the offer**						
Dummy: Negative interest	-0.125	-0.108			-0.111	0.133
	(0.031)***	(0.146)			(0.052)**	(0.237)
Dummy: Positive interest	0.070	-0.064			0.082	0.067
	(0.024)***	(0.104)			(0.044)*	(0.151)
Dummy: Payment day is 1			0.119	0.258	0.143	0.290
			(0.031)***	(0.095)**	(0.053)**	(0.152)*
Dummy: Payment day is 6			-0.059	0.015	-0.066	0.324
			(0.026)**	(0.112)	(0.055)	(0.156)*
Dummy: Negative interest and payment day is 1					-0.076	-0.111
					(0.078)	(0.220)
Dummy: Negative interest and payment day is 6					0.047	-0.606
					(0.072)	(0.283)**
Dummy: Positive interest and payment day is 1					-0.009	0.019
					(0.056)	(0.195)
Dummy: Positive interest and payment day is 6					-0.021	-0.352
					(0.059)	(0.213)
Constant	0.663	0.739	0.629	0.595	0.634	0.533
	(0.045)***	(0.107)***	(0.044)***	(0.093)***	(0.054)***	(0.167)***
Obs.	2223	124	2223	124	2223	124
R^2	0.029	0.009	0.023	0.065	0.054	0.129
Parameter equality: Intercept (p-value)	0.424		0.682		0.484	
Parameter equality: All other parameters (p-value)	0.319		0.301		0.000***	

Parentheses show standard errors, which allow for clustering by microfinance group.
Significance: $* \Leftrightarrow p < 0.1$, $** \Leftrightarrow p < 0.05$, $*** \Leftrightarrow p < 0.01$.

Table 18: **Heterogeneity by whether or not the respondent would save/invest a hypothetical loan of 1000 PKR**

	(1)	(2)	(3)	(4)	(5)	(6)
Respondent would save/invest a loan for 1000 PKR?	**YES**	**NO**	**YES**	**NO**	**YES**	**NO**
Dependent variable: **Whether the respondent accepted the offer**						
Dummy: Negative interest	-0.186	-0.102			-0.132	-0.091
	(0.060)***	(0.033)***			(0.084)	(0.052)*
Dummy: Positive interest	0.009	0.085			0.007	0.105
	(0.039)	(0.028)***			(0.068)	(0.047)**
Dummy: Payment day is 1			0.124	0.126	0.114	0.158
			(0.042)***	(0.035)***	(0.073)	(0.051)***
Dummy: Payment day is 6			0.027	-0.093	0.077	-0.101
			(0.033)	(0.032)***	(0.089)	(0.063)
Dummy: Negative interest and payment day is 1					-0.085	-0.067
					(0.124)	(0.071)
Dummy: Negative interest and payment day is 6					-0.066	0.040
					(0.130)	(0.081)
Dummy: Positive interest and payment day is 1					0.107	-0.039
					(0.088)	(0.049)
Dummy: Positive interest and payment day is 6					-0.063	-0.019
					(0.101)	(0.071)
Constant	0.793	0.620	0.687	0.607	0.726	0.598
	(0.033)***	(0.057)***	(0.039)***	(0.053)***	(0.057)***	(0.064)***
Obs.	631	1715	631	1715	631	1715
R^2	0.041	0.025	0.014	0.032	0.062	0.059
Parameter equality: Intercept (p-value)	0.007***		0.129		0.083*	
Parameter equality: All other parameters (p-value)	0.220		0.005***		0.006***	

Parentheses show standard errors, which allow for clustering by microfinance group.
Significance: $* \Leftrightarrow p < 0.1$, $** \Leftrightarrow p < 0.05$, $*** \Leftrightarrow p < 0.01$.

Table 19: **Heterogeneity by whether family members request money whenever the respondent has money on hand**

	(1)	(2)	(3)	(4)	(5)	(6)
Family members request money whenever it is on hand?	**YES**	**NO**	**YES**	**NO**	**YES**	**NO**
***Dependent variable:* Whether the respondent accepted the offer**						
Dummy: Negative interest	-0.122	-0.132			-0.092	-0.129
	(0.037)***	(0.046)***			(0.055)	(0.080)
Dummy: Positive interest	0.037	0.121			0.034	0.177
	(0.031)	(0.038)***			(0.057)	(0.063)***
Dummy: Payment day is 1			0.109	0.165	0.122	0.205
			(0.037)***	(0.040)***	(0.066)*	(0.065)***
Dummy: Payment day is 6			-0.080	-0.001	-0.081	0.030
			(0.030)**	(0.040)	(0.069)	(0.076)
Dummy: Negative interest and payment day is 1					-0.092	-0.029
					(0.087)	(0.100)
Dummy: Negative interest and payment day is 6					0.018	0.007
					(0.087)	(0.119)
Dummy: Positive interest and payment day is 1					0.031	-0.086
					(0.072)	(0.075)
Dummy: Positive interest and payment day is 6					-0.010	-0.103
					(0.076)	(0.095)
Constant	0.680	0.641	0.644	0.592	0.661	0.570
	(0.050)***	(0.076)***	(0.042)***	(0.083)***	(0.060)***	(0.084)***
Obs.	1629	718	1629	718	1629	718
R^2	0.020	0.047	0.026	0.026	0.048	0.075
Parameter equality: Intercept (p-value)	0.648		0.529		0.316	
Parameter equality: All other parameters (p-value)	0.080*		0.292		0.021**	

Parentheses show standard errors, which allow for clustering by microfinance group.
Significance: $* \Leftrightarrow p < 0.1$, $** \Leftrightarrow p < 0.05$, $*** \Leftrightarrow p < 0.01$.

Table 20: **Heterogeneity by whether the respondent reports difficulty in saving**

	(1)	(2)	(3)	(4)	(5)	(6)
Respondent reports difficulty saving?	**YES**	**NO**	**YES**	**NO**	**YES**	**NO**
***Dependent variable:* Whether the respondent accepted the offer**						
Dummy: Negative interest	-0.139	-0.112			-0.157	-0.057
	(0.046)***	(0.033)***			(0.058)**	(0.068)
Dummy: Positive interest	0.018	0.096			0.032	0.122
	(0.042)	(0.025)***			(0.053)	(0.066)*
Dummy: Payment day is 1			0.144	0.115	0.143	0.161
			(0.037)***	(0.042)**	(0.062)**	(0.073)**
Dummy: Payment day is 6			-0.057	-0.046	-0.073	-0.016
			(0.044)	(0.036)	(0.077)	(0.076)
Dummy: Negative interest and payment day is 1					-0.009	-0.126
					(0.073)	(0.115)
Dummy: Negative interest and payment day is 6					0.081	-0.039
					(0.084)	(0.101)
Dummy: Positive interest and payment day is 1					0.020	-0.040
					(0.085)	(0.079)
Dummy: Positive interest and payment day is 6					-0.025	-0.048
					(0.070)	(0.087)
Constant	0.646	0.684	0.580	0.661	0.618	0.635
	(0.064)***	(0.051)***	(0.047)***	(0.063)***	(0.060)***	(0.077)***
Obs.	1015	1332	1015	1332	1015	1332
R^2	0.021	0.034	0.029	0.020	0.053	0.055
Parameter equality: Intercept (p-value)	0.591		0.481		0.844	
Parameter equality: All other parameters (p-value)	0.188		0.321		0.802	

Parentheses show standard errors, which allow for clustering by microfinance group.
Significance: $* \Leftrightarrow p < 0.1$, $** \Leftrightarrow p < 0.05$, $*** \Leftrightarrow p < 0.01$.

Table 21: **Heterogeneity by whether the respondent described a lumpy purchase at baseline**

	(1)	(2)	(3)	(4)	(5)	(6)
Respondent described a lumpy consumption good?	**YES**	**NO**	**YES**	**NO**	**YES**	**NO**
***Dependent variable:* Whether the respondent accepted the offer**						
Dummy: Negative interest	-0.168	-0.108			-0.117	-0.091
	(0.042)***	(0.035)***			(0.076)	(0.051)*
Dummy: Positive interest	0.049	0.069			0.044	0.099
	(0.036)	(0.028)**			(0.080)	(0.047)**
Dummy: Payment day is 1			0.139	0.122	0.222	0.133
			(0.039)***	(0.037)***	(0.079)***	(0.058)**
Dummy: Payment day is 6			-0.026	-0.067	-0.055	-0.037
			(0.047)	(0.030)**	(0.117)	(0.054)
Dummy: Negative interest and payment day is 1					-0.227	-0.026
					(0.118)*	(0.074)
Dummy: Negative interest and payment day is 6					0.055	-0.008
					(0.142)	(0.080)
Dummy: Positive interest and payment day is 1					-0.036	-0.008
					(0.084)	(0.056)
Dummy: Positive interest and payment day is 6					0.029	-0.070
					(0.143)	(0.054)
Constant	0.716	0.649	0.643	0.621	0.667	0.612
	(0.037)***	(0.054)***	(0.045)***	(0.053)***	(0.075)***	(0.063)***
Obs.	657	1690	657	1690	657	1690
R^2	0.040	0.023	0.023	0.026	0.074	0.050
Parameter equality: Intercept (p-value)	0.212		0.695		0.508	
Parameter equality: All other parameters (p-value)	0.517		0.743		0.513	

Parentheses show standard errors, which allow for clustering by microfinance group.
Significance: $* \Leftrightarrow p < 0.1$, $** \Leftrightarrow p < 0.05$, $*** \Leftrightarrow p < 0.01$.

Appendix 4: Time and Attrition

Table 22 tests how behaviour varies across experiment waves. First, we test the effect of previous take-up on future behaviour. To do this, we include lagged acceptance as an additional explanatory variable; we instrument lagged acceptance with the lagged contractual offer (in a saturated specification). Two key conclusions emerge. First, lagged acceptance has a large and highly significant effect: accepting in period t causes a respondent to be about 30 percentage points more likely to accept in period $t + 1$. This speaks to possible 'familiarity' or 'reassurance' effects: it suggests that trying the product improves respondents' future perceptions of the offer. Second, because the experiment was randomised, this lag effect does not substantially change any of the parameters we estimated in Table 7.

< Table 22 here. >

Table 23 first tests the effect of experiment wave on product take-up (columns (1) and (2)). The table then estimates the 'saturated' specification separately for each experiment wave (columns (4), (5) and (6)), and reports p-values for parameter equality across waves (column (7)). The results show a large and highly significant general decline in willingness to adopt (that is, the intercept term is significantly smaller in the third experiment wave); this is in addition to a significant increase in sensitivity to a positive interest rate, and to receiving a negative interest rate on the first payment day.

< Table 23 here. >

Table 24 tests the effect of the offered contract on attrition — that is, the effect of an offer in period t on whether the respondent attrits before period $t + 1$. We find that respondents are more likely to attrit having just been offered a contract with payment on day 6 (regardless of whether the interest rate was positive, negative or zero). We find no other significant effect of contractual terms on attrition. A separate estimation (omitted for brevity) tests attrition as a function of a large number of baseline characteristics; none of the characteristics significant predicts attrition.

< Table 24 here. >

Finally, Table 25 compares the saturated estimations from Table 7 with a saturated estimation using only those respondents who remained in the experiment for all three rounds: we find that this attrition has no significant effect on our parameter estimates ($p = 0.334$).

< Table 25 here. >

Table 22: **Determinants of take-up: Dynamics**

	(1)	(2)	(3)	(4)	(5)	(6)
***Dependent variable:* Whether the respondent accepted the offer**						
Lag: Acceptance (dummy)	0.335	0.311	0.311	0.312	0.322	0.294
	(0.111)***	(0.111)***	(0.111)***	(0.105)***	(0.106)***	(0.107)***
Interest rate		1.093				
		(0.135)***				
Payment day				-0.031		
				(0.007)***		
Dummy: Negative interest			-0.114			-0.067
			(0.031)***			(0.054)
Dummy: Positive interest			0.105			0.134
			(0.020)***			(0.042)***
Dummy: Payment day is 1					0.113	0.169
					(0.032)***	(0.049)***
Dummy: Payment day is 6					-0.046	-0.048
					(0.028)*	(0.050)
Dummy: Negative interest and payment day is 1						-0.149
						(0.083)*
Dummy: Negative interest and payment day is 6						0.027
						(0.079)
Dummy: Positive interest and payment day is 1						-0.050
						(0.057)
Dummy: Positive interest and payment day is 6						-0.031
						(0.055)
Dummy: Experiment round 3	-0.081	-0.081	-0.081	-0.074	-0.076	-0.074
	(0.049)*	(0.048)*	(0.049)*	(0.048)	(0.048)	(0.047)
Constant	0.439	0.448	0.451	0.556	0.419	0.411
	(0.085)***	(0.084)***	(0.086)***	(0.090)***	(0.087)***	(0.095)***
Obs.	1418	1418	1418	1418	1418	1418
R^2	0.201	0.228	0.228	0.211	0.216	0.246
Kleibergen-Paap (p-value)	0.009***	0.008***	0.008***	0.009***	0.009***	0.009***
Hansen J test (p-value)	0.760	0.842	0.844	0.636	0.589	0.654

Table 23: **Determinants of take-up: Heterogeneity by experiment wave**

	(1)	(2)	(3)	(4)	(5)	Equality (p-value)
Dependent variable: **Whether the respondent accepted the offer**						
Experiment wave	-0.052					
	(0.021)**					
Dummy: Experiment wave 2		-0.017				
		(0.041)				
Dummy: Experiment wave 3		-0.107				
		(0.042)**				
Dummy: Negative interest			-0.171	-0.122	0.012	**0.257**
			(0.066)**	(0.061)*	(0.091)	
Dummy: Positive interest			-0.029	0.112	0.194	**0.024****
			(0.066)	(0.057)*	(0.090)**	
Dummy: Payment day is 1			0.146	0.115	0.222	**0.437**
			(0.069)**	(0.059)*	(0.082)**	
Dummy: Payment day is 6			-0.025	-0.132	0.039	**0.229**
			(0.068)	(0.084)	(0.076)	
Dummy: Negative interest and payment day is 1			0.087	-0.117	-0.241	**0.061***
			(0.089)	(0.091)	(0.132)*	
Dummy: Negative interest and payment day is 6			-0.001	0.078	-0.053	**0.701**
			(0.089)	(0.105)	(0.141)	
Dummy: Positive interest and payment day is 1			0.031	-0.037	-0.050	**0.723**
			(0.081)	(0.075)	(0.103)	
Dummy: Positive interest and payment day is 6			-0.012	0.029	-0.149	**0.420**
			(0.083)	(0.102)	(0.099)	
Constant	0.752	0.690	0.714	0.667	0.473	**0.011****
	(0.058)***	(0.044)***	(0.072)***	(0.064)***	(0.072)***	
Obs.	2347	2347	889	745	713	
R^2	0.008	0.009	0.060	0.070	0.065	

Parentheses show standard errors, which allow for clustering by microfinance group.
Significance: $* \Leftrightarrow p < 0.1$, $** \Leftrightarrow p < 0.05$, $*** \Leftrightarrow p < 0.01$.

Table 24: **Determinants of attrition: Contractual terms**

	(1)	(2)	(3)	(4)	(5)
Dependent variable: **Whether the respondent attrited in a given period**					
Lag: Interest rate	-0.068				
	(0.091)				
Lag: Payment day			0.015		
			(0.004)***		
Lag: Dummy: Negative interest		-0.018			0.015
		(0.022)			(0.030)
Lag: Dummy: Positive interest		-0.031			0.006
		(0.016)*			(0.026)
Lag: Dummy: Payment day is 1				-0.028	-0.017
				(0.020)	(0.034)
Lag: Dummy: Payment day is 6				0.049	0.124
				(0.018)**	(0.038)***
Lag: Dummy: Negative interest and payment day is 1					-0.018
					(0.041)
Lag: Dummy: Negative interest and payment day is 6					-0.100
					(0.056)*
Lag: Dummy: Positive interest and payment day is 1					-0.014
					(0.044)
Lag: Dummy: Positive interest and payment day is 6					-0.114
					(0.038)***
Dummy: Experiment round 3	-0.118	-0.119	-0.112	-0.112	-0.112
	(0.024)***	(0.024)***	(0.023)***	(0.023)***	(0.024)***
Constant	0.164	0.182	0.109	0.155	0.149
	(0.021)***	(0.024)***	(0.022)***	(0.025)***	(0.031)***
Obs.	1634	1634	1634	1634	1634
R^2	0.036	0.037	0.045	0.045	0.051

Table 25: **Attrition: Sensitivity analysis**

	Original estimation	Respondents never attriting
Dependent variable: **Whether the respondent accepted the offer**		
Dummy: Negative interest	-0.099 (0.048)**	-0.111 (0.049)**
Dummy: Positive interest	0.082 (0.045)*	0.074 (0.046)
Dummy: Payment day is 1	0.152 (0.052)***	0.149 (0.053)***
Dummy: Payment day is 6	-0.042 (0.056)	-0.061 (0.061)
Dummy: Negative interest and payment day is 1	-0.077 (0.073)	-0.071 (0.076)
Dummy: Negative interest and payment day is 6	0.011 (0.071)	0.017 (0.078)
Dummy: Positive interest and payment day is 1	-0.010 (0.054)	0.010 (0.053)
Dummy: Positive interest and payment day is 6	-0.042 (0.060)	-0.004 (0.065)
Constant	0.628 (0.056)***	0.633 (0.059)***
Obs.	2347	2127
R^2	0.053	0.061
H_0: All parameters equal (p-value)	0.334	

Appendix 5: Solving the structural model numerically

We solve the structural model as follows:

(i) We consider each possible path for $(L_1, \ldots, L_T)$. For each path, we solve two optimisation problems:

  (a) We find whether *any* vector $(m_1, \ldots, m_T)$ is feasible; this is a *linear programming* problem.

  (b) If and only if there exists a feasible solution, we use a 'direct attack' method (Adda and Cooper, 2003, p.10) to solve for optimal $(m_1, \ldots, m_T)$ and record the indirect utility; we implement this as a one-shot *non-linear program*.

(ii) There are 2^T possible paths $(L_1, \ldots, L_T)$. Having solved across each of them, we then choose the single optimal path. This is a simple *binary integer programming* problem.

(iii) We repeat this entire process for each unique value of (r, p) (*i.e.* for each of the 12 contracts that we offered).

(iv) We repeat again, across a fine grid of possible values for γ.[29] For each possible value, we solve both for the case $m_t \geq 0$ and the case $m_t = 0$.

[29] We rule out any cases where $\gamma > \log(1039) - \log(139) \approx 2.01$ (implying $\gamma_{ev} \approx 5827$). Once γ becomes so large, the respondent will purchase the lumpy good in every period without the contract and without saving. This is not a meaningful case to consider in this context.