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 for both credit and saving, with the same individuals often accepting both a credit contract and a saving contract 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; Bernheim, Ray, and Yeltekin, 2015; Kaur, Kremer, and Mullainathan, 2015; John, 2015; Gugerty, 2007). 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); the latter behaviour is termed by Morduch (2010) as 'borrowing to save' (see also Collins, Morduch, Rutherford, and Ruthven (2009)). 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. The focus on daily deposits is motivated by the nature of our study population, which is composed of urban and peri-urban households who are not, as a rule, in permanent employment. As we document in the data section, nearly all subject households have a daily income flow — typically from casual wage labour, self-employment in a small business (*e.g.*, retail shop, personal services, rickshaw driver), or the sale of dairy farm products. Only 28% of households in our study population have a household head or spouse with a permanent wage job, which is the only form of earned income that would not generate a daily income in our study area. But nearly all of these households also have a source of daily income. By opting for a frequency of deposits that matches the periodicity of income, we seek to maximise the commitment value of the microfinance product we offer.[1]

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.[2] 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.[3]

[1] Of course, the 'hand-to-mouth' phenomenon need not be restricted to poor households with a daily income: for example, Kaplan, Violante, and Weidner (2014) argue that a substantial proportion of households in developed economies are 'wealthy hand-to-mouth', in the sense of holding "little or no liquid wealth, whether in cash or in checking or savings accounts, despite owning sizable amounts of illiquid assets".

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

[3] 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; Laureti, 2015).[4] 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.[5]

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.[6] 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*.[7]

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 finan-

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

[5] 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.

[6] 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."

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

cial 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).[8]

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 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

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

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, 2014), 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).[9] 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 showing that the same respondent population has high demand for both microcredit and microsaving (see also Gross and Souleles (2002), Collins, Morduch, Rutherford, and Ruthven (2009), Morduch (2010), Kast and Pomeranz (2014) and Laureti (2015)). 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.

[9] 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.

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 simplified 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 or demand a loan product, but not both. We then show how this prediction changes when we impose that people find it difficult to hold cash balances, *e.g.*, because of self-commitment problems due to time inconsistency. 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 start by noting that the simple credit and savings products used by the poor can be nested into a generalised ROSCA contract. 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 maximising 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 that 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.[10] The value from *refusing* a contract (s, p, r) is:

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

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.

The more interesting case is when the individual wishes to finance a lumpy expenditure (*e.g.*, consumer durable, rent, utility bill, or business expense). 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 expenditure 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:

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

[10] 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.

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

$$V_c = \max_{\{m_t \geq 0, L_t = \{0,1\}\}} \left\{ \sum_{t \neq p} \left[\beta^t \cdot u \left(y_t - s + m_{t-1} - m_t, L_t \right) \right] \right.$$
$$\left. + \quad \beta^p \cdot u \left[y_p + (T-1) \cdot s \cdot (1+r) + m_{p-1} - m_p - \alpha, L_p \right] \right\}. \qquad (2)$$

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 incurring the lumpy expenditure 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 such 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 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, $m_t = 0$). It is of course possible to construct a more complete model in which $m_t = 0$ is not an assumption but an equilibrium outcome.[11] This would make the model more complicated without adding any new insight. The key idea is that, when individuals cannot accumulate cash balances on their own, whatever the reason, then the only way for them to make 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

[11] For example, quasi-hyperbolic preferences as in Ambec and Treich (2007); pressure from the spouse as in Anderson and Baland (2002) and Somville (2014); pressure from non-household members as in Goldberg (2011).

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 $u(.)$.

(iv) The model also predicts that demand for an (s, p, r) contract should depend on the frequency of income flow y_t. Individuals with daily income but weekly consumption or business expenses would be most interested in an (s, p, r) contract that would help them aggregate daily income into a weekly lump sum. In contrast, we expect less demand from individuals whose income is already aggregated into a weekly or monthly payment from which they can cover lumpy expenditures – unless they also earn daily income that they wish to aggregate.

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.[12] 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.[13] 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

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

[13] This short delay serves to mitigate against distortions in take-up arising from differences in the credibility of lump-sum payment between contracts (Coller and Williams, 1999; Dohmen, Falk, Huffman, and Sunde, 2013).

US$9.50. (As we explain in more detail shortly, the median daily household income for Sargodha district is approximately 600 PKR.)

The following table illustrates the payment schedule for a contract with lump-sum 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			

Since there are three possible interest rate values and four possible days for the lump-sum 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. 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 individually 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 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 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 the city of Sargodha. We implemented the experiment in 32 microfinance groups. In three of these groups, there were breaches of experiment protocol.[14] 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.[15]

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. Our 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. (These summary statistics are presented in detail in the Online Appendix.)

Table 1 describes the main variables used in the analysis. As the table shows, the overwhelming

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

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

majority of our subjects (88%) have at least one source of daily income – from casual labor (i.e., paid daily wages), self-employment in a business, or sales of dairy farm products.[16] In the population at large, 42% of households have a member in permanent wage employment (PSLM, 2010-11). This proportion is smaller (28%) among our experimental subjects, who are selected among clients of a microfinance organization that targets self-employed individuals. Most households with permanent wage employment also have daily income: 19% of all participating households have both. Some 3% of participating households do not report an occupation associated with either a daily income or permanent wage employment – they must have a source of income that enables them to pay daily installments, but we do not know what it is.

< Table 1 here. >

Table 1 also reports p-values for randomisation balance across each variable; this is calculated by regressing each baseline variable on the subsequent interest rate and payment day (using a saturated specification). We find one variable of the ten to be unbalanced at the 90% confidence level. We provide a more extensive set of balance tests on other covariates in the Online Appendix; we conclude that our randomisation is balanced.[17]

Attrition from the experiment comes from two sources: 80 subjects defaulted on a contract, and another 98 simply stopped attending.[18] 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

[16] Since subjects were not asked whether they derive income from the sale of dairy products, this is inferred from livestock ownership (cow or bullock). Given the widespread use of livestock as source of dairy income, this is a relatively innocuous assumption – and is the best we can do with the data at hand.

[17] The analysis in this appendix shows that two of the 22 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 re-run our main estimations to control for these two variables, but doing so does not affect our results.

[18] Four subjects are recorded as having defaulted in one of the rounds but have participated in the remaining rounds.

default than women drawing $p = 3$, $p = 4$ or $p = 6$. In Section 4.3 and the Online Appendix, we show that attrition does not affect our other results.

It is worth noting 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 behaviour is akin to the type of 'naive sophisticates' studied by John (2015), namely, individuals with a mistaken anticipation about their future ability to comply with an incentivised commitment contract.[19]

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 PKR 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 expenditure, that is, an expenditure not easily made in small increments. Of the lumpy expenditures described, the most common are sewing equipment, chickens or goats, and school materials (particularly school uniforms). Based on responses given to this question, we also created a dummy variable equal to one if the respondent would invest or save the funds, as opposed to spending them on divisible consumption.

[19] 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).

4 Reduced-form results

Before launching a full-fledged structural analysis, we begin by reporting simple reduced-form results in tabular and regression format. The purpose of this approach is to reassure the reader that our main findings are immediately apparent in the data, and are not an artifact of structural estimation.

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 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. As Table 4 shows, 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%).[20] 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 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, income frequency, and commitment needs

The take-up response of experimental subjects to variation in contract terms is summarized in a compact way using regression analysis. We begin by documenting the sensitivity of take-up to interest rates and to the timing of the lump-sum payment. Formally, let us define y_{iw} as a dummy variable for whether individual i agreed to the offered contract in experiment wave $w \in \{1, 2, 3\}$. Define $rneg_{iw}$ as a dummy for $r_{iw} = -0.1$ and $rpos_{iw}$ as a dummy for $r_{iw} = 0.1$ (with zero interest

[20] 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.

as the omitted category); symmetrically, let $p1_{iw}$ and $p6_{iw}$ be corresponding dummy variables for time of payment (leaving days 3 and 4 as the joint omitted category). We can then test sensitivity to contract terms by estimating the following linear probability model:

$$y_{iw} = \beta_0 + \beta_1 \cdot rneg_{iw} + \beta_2 \cdot rpos_{iw} + \beta_3 \cdot p1_{iw} + \beta_4 \cdot p6_{iw} + \mu_{iw}, \tag{3}$$

where we cluster by microfinance group.[21]

We estimate this regression for the entire sample as a whole. We then examine variation in take-up associated with differences in the frequency of income flows and in the commitment needs of the household. We start by considering variation in income frequency.[22] As discussed in the conceptual section, we expect demand for a financial product with daily deposits to be highest among households that have daily income flows. It is also possible that households in permanent wage employment have less demand for a lump sum because they can finance lumpy expenditures from monthly wage earnings. If this is true, such households should be primarily interested in contracts that generate a positive return (i.e., $r = 0.1$). To investigate these issues, we split households into four categories according to whether they have daily income or monthly wage income, and estimate equation 3 separately for each group. Results are presented in Table 7. The majority of households have daily income, but there is a small proportion that only report monthly wage income. Very few households report neither daily or monthly income, hence the small number of observations in that category.

< Table 7 here. >

We see that households with a daily income have a higher intercept and thus higher take-up in general, in agreement with predictions. Households without daily income seem to be more sensitive

[21] In the Online Appendix, we show a battery of alternative specifications, including a saturated specification; these reflect the original regression specifications outlined in our Pre-Analysis Plan. All of our conclusions are robust to relying on these alternative specifications rather than the simpler specification presented in this paper.

[22] The Online Appendix discusses subgroup variation in further detail, and shows regression results for all subgroups, including all subgroups that were listed in the pre-analysis plan.

to $r > 0$ and to $p = 1$, suggesting that their take-up is more motivated by standard motives (e.g., profitabililty and impatience) than by demand for commitment saving. Take-up is highest among households with both daily and monthly income. One possible explanation is that these households are richer and more financially secure, and thus have higher demand for credit and savings instruments, which they can finance from their daily income. It remains that take-up is high even among households that have no identifiable daily income, suggesting they too have high demand for a commitment saving product with daily installments.[23]

Next we investigate whether take-up varies with various proxies for the commitment needs of the household. Table 8 shows these results. We find that takeup is higher among households that face many financial requests from family members and among households that find it easier to save. The latter result seems at first glance to contradict our model, but given the context of the experiment, participants who state it is difficult for them to save may include many who are too poor to save. More to the point, we also find that respondents who stated that they would save or invest 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 consistent with the idea that these respondents value the product — whether offered in the credit or the savings domain — as a means to save for a lump-sum expenditure.

< Table 8 here. >

4.3 Extensions and robustness

We now investigate the robustness of our results. Detailed results are available in the Online Appendix. First, we test for the effect of lagged acceptance (which we instrument using the lagged

[23] This may be because they have an source of daily income that was not reported to us. This could arise because the daily income is earned from activities that participants wish to keep secret (*e.g.*, mendicity, hawking, other demeaning work). Another possibility is that part of the income from permanent wage employment comes in the form of tips, bribes, or moonlighting (*e.g.*, private tutoring by teachers).

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 a possible 'familiarity' or 'reassurance' effect, whereby trying the product would improve respondents' future perceptions of the offer. The Online Appendix also reports a test of parameter stability across experiment waves. We find a large and significant decline in willingness to adopt in the third experimental round. In addition, we observe a significant increase in the sensitivity to a positive interest rate, and to a negative interest rate when $p = 1$. This could be due to a variety of causes, including respondent fatigue. The Online Appendix reports a reduced form regression regressing take-up on past contractual terms. We find that a negative interest in the previous round decreases take-up in the current period. This result disappears in the saturated model. These findings do not affect our main results of interest.

We run several other robustness checks. The Online Appendix reports a battery of estimations on attrition. We find that respondents are more likely to attrite after having 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, the Online Appendix compares estimation results with 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-value$= 0.334$).[24] We also test for parameter stability when attrition is taken to be an indication of refusal of the product; the Online Appendix shows that our parameter estimates are not significantly affected when we consider attrition as implying refusal.

[24] We also confirmed that our results are not driven by a 'day of week' effect. We have further 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 additional checks.

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 income frequency and 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 model 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 use a discrete finite mixture model. This model exploits the panel dimension of our data to estimate the distribution of underlying behavioural types in our sample. To endow those behavioural types with economic meaning, we use a structural framework. In this section, we parameterise the model developed in section 2 and use numerical methods to obtain predictions about the take-up behaviour of different types of decision-makers. 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.[25]

[25] In our original Pre-Analysis Plan, we had specified a simpler structural model that we intended to estimate. We have abandoned that model in favour of the current model. Results from that model add nothing of substance to the current structural results.

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 at the heart of 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.[26]

To give a meaningful interpretation to the magnitudes of c and γ, we need a normalisation for income. We use $y_{iw} = 599$ PKR. This is the median daily household income across the district of Sargodha from the 2010-11 PSLM survey (corrected for CPI inflation since 2011). 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 ROSCAs typically 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 ($\beta = 1$).[27]

We solve the problem numerically by a series of nested optimisations – see the Online Appendix. Table 9 shows the take-up predictions coming out of the model, for different parameter values. Note the close congruence to the predictions made in section 2: the structural specification is a parameterised version of our 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

[26] 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 to capture preference for lumpy consumption.

[27] 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.

static setting, a respondent holding the daily income y. We imagine her as facing a cost of lumpy consumption α, and we allow her to spend this either by purchasing the lumpy consumption good or by increasing divisible consumption. We define γ_{ev} as the additional money transfer required to persuade her not to consume the lumpy good — that is, $\ln(y) + \gamma \equiv \ln(y + \alpha + \gamma_{ev})$.

< Table 9 here. >

Of course, the current structural framework is necessarily stylised. We therefore do not ask the reader to interpret Table 9 literally. Rather, the purpose of Table 9 is to present stylised predictions about the different patterns of adoption that we might expect to observe, each of which is grounded in explicit behavioural assumptions. We interpret our results in light of their structural underpinning. However, we stress that the results of the mixture model are informative more generally about patterns of heterogeneity in adoption, whether or not we use a structural interpretation.

5.2 A discrete finite mixture estimator

We want to estimate the structural model with maximal heterogeneity, i.e., we want to allow different respondents to have different values of γ, and to differ in terms of whether they are 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 how laboratory behaviour can be analysed empirically 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): the model implies a number of different types of potential respondent, and we estimate the proportion of each type in the population.[28] Mixture models for experimental analysis typically require the estimation of *both* mixing proportions *and* other parameters — typically, parameters characterising the shape of participants' utility functions. In our

[28] 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).

context, Table 9 makes joint discrete predictions. Hence, in contrast to previous papers, we develop a simple Non-Parametric Maximum Likelihood estimator to recover the 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 contracts offered in the first, second, and third waves. We index all contract offer combinations by $k \in \{1, \ldots, K\}$, where K is the total number of contract combinations possible.[29] 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 the model implies seven distinct types; we index these types as $t \in \{1, \ldots, T\}$. 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 $\text{rank}(\boldsymbol{X}) = T; T \leq KC$. (In the current application, $\text{rank}(\boldsymbol{X}) = T = 7$ and $K \times C = 4432$; $\boldsymbol{\beta}$ 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

[29] There are $12^3 = 1728$ possible contract combinations that could have been offered; in practice, only 554 of these possible combinations were actually offered.

be n_k. Then the log-likelihood for the sample is:

$$\ell(\boldsymbol{\beta}) = \sum_{k=1}^{K} n_k \cdot \sum_{c=1}^{C} \boldsymbol{y}_{[C\cdot(k-1)+c]} \cdot \ln\left(\sum_{t=1}^{T} \boldsymbol{\beta}_t \cdot \boldsymbol{x}_{[C\cdot(k-1)+c],t}\right). \tag{4}$$

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 65% of respondents are constrained in holding cash between periods (namely, Types D, E, F and G). For about 55% of respondents (*i.e.* Types G and H), this is coupled with a large value on lumpy consumption purchases (in the sense of $\gamma_{ev} > 1950$ PKR). 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 10% (Types A, B and C).

< Table 10 here. >

In Table 11, we estimate our mixture model separately for different subsets, mirroring the reduced form regressions presented in Table 8. We find that the mix of types does not vary massively by the frequency of income flows. Only a small proportion of participants can be classified as adhering to the standard model. This particularly true of households with a mix of daily and monthly income, who in Table 8 displayed the strongest interest in our financial product: only 2.4% of them fall in Types A, B or C. These participants also demonstrate the strongest interest in lump-sum accumulation, with nearly 60% of them following types G and H. These findings are in line with those reported in Table 8, but confirm that reduced-form differences can be rationalised as implying different behavioural models.

< Table 11 here. >

In Table 12, we mirror Table 9 and disaggregate by (i) whether the respondent faces pressure from family members to share available funds, (ii) whether the respondent reports difficulty in saving, (iii) whether the respondent describes a lumpy purchase at baseline, and (iv) whether the respondent indicates a desire to save/invest a hypothetical loan of 1000 PRK.

The contrast is strongest between participants who report they would invest or save a 1000 PRK lump sum, and those who do not. We strongly reject the 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 $m_t = 0$. We also find significantly different proportion of types between participants who report receiving requests for money from family members, and those who do not. But these differences are hard to rationalise — e.g., more Type B and fewer Type E among those who receive requests. In the other two cases, we cannot reject the null that the proportions of types are equal across subsamples.

Taken together, these results confirm that, in general, the breakdown of study participants into different behavioural types is quite stable irrespective of their circumstances. This also implies that, in general, answers to survey questions are not good predictors of the type of motivation people have when saving. This motivation is better captured in the structural analysis. The only exceptions relate to (i) individuals who earn both daily and monthly income and (ii) individuals who report wanting to save or invest. Both categories exhibit a higher demand for lump-sum expenditures – perhaps because they have a higher income. These are also the households who, according to theory, are most interested in the commitment saving aspect of our product.

< Table 12 here. >

5.4 Structural results: Robustness

We run three 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. (For example, the Online Appendix 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.[30] Thus, for example, Type A accepts if and only if $r = 0.1$ and $p = 1$; Type A$\star$ accepts if and only if $r = 0.1$ and $p = 1$, but always rejects in the final wave.

Table 13 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 about 75% of respondents act as if they are constrained in holding cash between periods (that is, types D, D$\star$ and onwards), and over 60% of respondents also have a preference for lumpy consumption (that is, types E, E$\star$ and onwards).

< Table 13 here. >

Second, we split our mixture model to run it separately for (i) a pooled sample across waves 1 and 2 and (ii) a pooled sample across waves 2 and 3. We use a 'naive Bayes classifier', assigning each respondent her most likely type, given the estimates of our mixture model (Frühwirth-Schnatter, 2006, p.27). Of the 575 respondents whose behaviour can be rationalised in both separate estimation, 450 (*i.e.* almost 80%) received the same classification in both estimations. We interpret this as intuitive reassurance that it is reasonable to pool all three waves in the same structural estimation.[31] We show the cross-tabulation in the Online Appendix.

Third, 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.[32] Table 14 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

[30] The model remains identified under this extension: $\text{rank}(\boldsymbol{X}) = T = 13$.

[31] Of course, we should *not* conclude that the remaining 125 individuals therefore 'switched types' between waves; the naive Bayes classifier is crude in that it assigns the single most likely type to each individual, rather than allowing for a probabilistic distribution across types. For this reason, it is entirely possible for an individual of a fixed type to be classified in two different ways in two different samples.

[32] The model remains identified under this extension, too: $\text{rank}(\boldsymbol{X}) = T = 8$.

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 50% of respondents act as if constrained in holding cash (Types D, E, F and G), and that about 45% of respondents also have a preference for lumpy consumption (types E, F and G).

< Table 14 here. >

6 Conclusions

In this paper, we have introduced a new design for a framed field experiment to distinguish 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 roughly the same time. We hypothesise that saving and borrowing are substitutes for many microfinance clients, satisfying the same 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.

Although we did find sizeable demand for our product from households deriving all their income from monthly wages, take-up was nonetheless lower among them. However, we would not necessarily expect much interest in daily instalments among monthly wage earners because they could use their monthly wage to finance lump-sum expenditures of the magnitude covered by our experiment. But these households may nonetheless have pent up demand for commitment saving instruments with a longer horizon – *e.g.*, to save for retirement or set up a college fund for their children. Such financial instruments are indeed offered in many developed economies, either by commercial banks (e.g., saving set-aside), by life insurance institutions, or as part of government- or employer-sponsored programs.

Regarding the external validity of our results, we can offer some evidence from subsequent work we conducted in Pakistan. We conducted an experiment with a similar subject population in the same region of Pakistan. The design of the microfinance product offered is identical, but instalments are due weekly instead of daily. With weekly instalments, take-up falls by more than half compared to the experiment presented in this paper. Furthermore, the large fall in take-up occurred even though we set the weekly deposit amount at 500 PKR only, compared to 200 PKR daily deposit in this experiment (*i.e.*, less than half the amount of savings mobilization per week). Even more striking: we investigated the possibility of offering a similar microfinance product with a monthly instalment. When we floated the idea to the subject population, we were told that the maximum monthly deposit that would generate any enthusiasm in the product would be of the order of 1000 PKR. In other words, less than a quarter the savings per month than could be mobilized through daily instalments. While this final evidence is only impressionistic, it is consistent with the idea that our study population has pent up demand for savings and credit products with daily instalments, something that is perfectly consistent with (i) having daily income and (ii) finding it difficult to save at home. This also explains why participants take up our daily instalment product even though they also receive medium-term loans with monthly installments from the MFI. The reason is that our product serves a different purpose, namely, to accumulate small lump sums from daily income. For that purpose, credit and savings are largely equivalent in the eyes of the study population.

Table 1: **Description of main variables**

	Mean	Balance (p)
Dummy: Respondent or husband earns from casual work	0.46	0.037
Dummy: Respondent or household owns a business	0.34	0.852
Dummy: Respondent or husband earns daily income	0.88	0.637
Dummy: Respondent or husband earns monthly wage income	0.28	0.170
Dummy: Respondent or husband earns daily and monthly wage income	0.19	0.112
Dummy: Respondent or husband earn neither daily nor monthly wage income	0.03	0.891
Dummy: ‘Whenever I have money on hand, my spouse or other family members always end up requesting some of it’	0.69	0.443
Dummy: ‘I find it hard to save money for the future’	0.43	0.420
Dummy: Respondent would use PKR 1000 loan for a lumpy purchase	0.27	0.357
Dummy: Respondent would use PKR 1000 loan to save/invest	0.27	0.490

This table provides basic summary statistics for the main variables used in our analysis. We have 889 baseline observations for each variable (excluding the final variable, for which we have 888).

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: Heterogeneity by payment frequency**

	(1)	(2)	(3)	(4)	(5)	(6)
DAILY INCOME?	(WHOLE SAMPLE)	NO	NO	YES	YES	*equality tests*
SALARY INCOME?	(WHOLE SAMPLE)	NO	YES	NO	YES	*(p-values)*
Dummy: $r = -0.1$	-0.120	-0.017	-0.123	-0.112	-0.180	0.657
	(0.029)***	(0.131)	(0.086)	(0.030)***	(0.052)***	
Dummy: $r = +0.1$	0.066	0.133	0.136	0.068	0.022	0.480
	(0.023)***	(0.124)	(0.077)*	(0.028)**	(0.051)	
Dummy: $p = 1$	0.125	0.258	0.283	0.105	0.096	0.155
	(0.031)***	(0.126)**	(0.083)***	(0.028)***	(0.051)*	
Dummy: $p = 6$	-0.055	0.038	-0.090	-0.054	-0.060	0.881
	(0.027)*	(0.129)	(0.075)	(0.029)*	(0.052)	
Constant	0.641	0.548	0.559	0.630	0.744	0.098*
	(0.049)***	(0.112)***	(0.073)***	(0.026)***	(0.049)***	
					joint test of all parameters:	0.000***
Observations	2347	77	203	1616	451	
R^2	0.051	0.081	0.127	0.042	0.065	

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.
'Equality tests' refer to coefficient equality across columns (2), (3), (4) and (5).
Significance: $* \Leftrightarrow p < 0.1$, $** \Leftrightarrow p < 0.05$, $*** \Leftrightarrow p < 0.01$.

Table 8: **Determinants of take-up: Heterogeneity by measures of savings pressure**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	FAMILY MEMBERS REQUEST MONEY?		*equality (p-values)*	DIFFICULTY SAVING?		*equality (p-values)*	LUMPY PURCHASE?		*equality (p-values)*	WOULD SAVE/INVEST?		*equality (p-values)*
	YES	NO		YES	NO		YES	NO		YES	NO	
Dummy: $r = -0.1$	-0.115	-0.136	0.707	-0.134	-0.108	0.609	-0.168	-0.102	0.196	-0.179	-0.101	0.260
	(0.036)***	(0.046)***		(0.045)***	(0.032)***		(0.045)***	(0.032)***		(0.060)***	(0.032)***	
Dummy: $r = +0.1$	0.041	0.119	0.119	0.029	0.095	0.164	0.044	0.074	0.459	0.018	0.086	0.133
	(0.030)	(0.037)***		(0.041)	(0.026)***		(0.034)	(0.027)**		(0.040)	(0.026)***	
Dummy: $p = 1$	0.106	0.165	0.247	0.147	0.108	0.462	0.136	0.122	0.773	0.123	0.123	0.995
	(0.037)***	(0.038)***		(0.037)***	(0.042)**		(0.043)***	(0.036)***		(0.043)***	(0.034)***	
Dummy: $p = 6$	-0.079	-0.005	0.138	-0.057	-0.046	0.870	-0.026	-0.066	0.490	0.035	-0.096	0.004***
	(0.033)**	(0.036)		(0.046)	(0.036)		(0.051)	(0.031)**		(0.036)	(0.033)***	
Constant	0.666	0.592	0.407	0.611	0.661	0.530	0.684	0.625	0.367	0.736	0.608	0.079*
	(0.050)***	(0.085)***		(0.060)***	(0.065)***		(0.051)***	(0.058)***		(0.046)***	(0.061)***	
		joint test:	0.066*		*joint test:*	0.286		*joint test:*	0.553		*joint test:*	0.003***
Obs.	1629	718		1015	1332		657	1690		631	1715	
R^2	0.045	0.073		0.051	0.052		0.062	0.048		0.055	0.057	

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.
'Equality tests' refer to pairwise coefficient equality tests.
Significance: $* \Leftrightarrow p < 0.1$, $** \Leftrightarrow p < 0.05$, $*** \Leftrightarrow p < 0.01$.

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 $\gamma_{ev} \in [-900, 1320)$	0	0	0	0	0	0	0	0	1	0	0	0
‘B’	$m_t \geq 0$ and $\gamma_{ev} \in [\ 1320, 1410)$	0	0	0	0	0	0	0	0	1	1	0	0
‘C’	$m_t \geq 0$ and $\gamma_{ev} \geq 1410$	0	0	0	0	0	0	0	0	1	1	1	0
‘D’	$m_t = 0$ and $\gamma_{ev} \in [-900, 1950)$	0	0	0	0	0	0	0	0	0	0	0	0
‘E’	$m_t = 0$ and $\gamma_{ev} \in [\ 1950, 2430)$	0	0	0	0	0	0	0	0	1	1	1	1
‘F’	$m_t = 0$ and $\gamma_{ev} \in [\ 2430, 3110)$	0	0	0	0	1	1	1	1	1	1	1	1
‘G’	$m_t = 0$ and $\gamma_{ev} \geq 3110$	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. As a benchmark, we normalise daily income to 599 PKR: the median daily household income for the district of Sargodha from the PSLM 2010-11 survey (corrected for CPI inflation).

Table 10: **Structural estimates**

TYPE	ESTIMATED PROPORTION	95% CONFIDENCE	
		LOWER	UPPER
'TYPE A'	0.1%	0.0%	4.7%
'TYPE B'	3.6%	0.0%	5.9%
'TYPE C'	5.0%	1.8%	8.4%
'TYPE D'	11.7%	7.9%	14.5%
'TYPE E'	3.2%	1.0%	5.8%
'TYPE F'	11.7%	8.4%	14.9%
'TYPE G'	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 income flow**

	ESTIMATED PROPORTIONS		
	(1)	(2)	(3)
DAILY INCOME?	NO	YES	YES
SALARY INCOME?	NO	NO	YES
'TYPE A'	0.0%	5.0%	0.0%
'TYPE B'	4.4%	1.6%	4.7%
'TYPE C'	4.6%	6.5%	0.2%
'TYPE D'	14.2%	4.6%	18.0%
'TYPE E'	0.0%	2.7%	5.8%
'TYPE F'	16.0%	13.0%	8.8%
'TYPE G'	36.7%	40.3%	41.7%
NOT RATIONALISED	24.1%	26.3%	20.9%
N	83	377	249
log-likelihood	-62.145	-261.008	-196.646
H_0: column (1) = column (2)		(p-value):	0.561
H_0: column (1) = column (3)		(p-value):	0.618
H_0: column (2) = column (3)		(p-value):	0.013**
H_0: column (1) = column (2) = column (3)		(p-value):	0.089*

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 columns; these are implemented as Likelihood Ratio tests (respectively with six degrees of freedom for the first three tests and 12 degrees of freedom for the final test).

Table 12: **Structural estimates: Disaggregating by baseline characteristics**

	ESTIMATED PROPORTIONS							
	FAMILY MEMBERS REQUEST MONEY?		DIFFICULTY SAVING?		LUMPY PURCHASE?		WOULD SAVE/INVEST?	
	YES	NO	YES	NO	YES	NO	YES	NO
'TYPE A'	0.0%	5.1%	0.0%	0.2%	3.9%	0.0%	1.4%	0.8%
'TYPE B'	4.2%	0.0%	3.8%	3.6%	0.0%	4.2%	5.4%	2.1%
'TYPE C'	4.9%	5.5%	3.4%	5.8%	6.0%	4.7%	4.3%	5.8%
'TYPE D'	11.4%	9.4%	15.6%	9.0%	8.7%	12.6%	2.8%	14.5%
'TYPE E'	1.0%	8.5%	3.7%	3.2%	0.0%	3.9%	0.0%	4.1%
'TYPE F'	11.4%	12.7%	8.7%	13.6%	14.3%	10.9%	13.5%	11.1%
'TYPE G'	40.9%	39.3%	36.5%	43.6%	42.8%	39.5%	47.0%	38.1%
NOT RATIONALISED	26.1%	19.5%	28.3%	20.9%	24.2%	24.1%	25.7%	23.6%
N	494	215	307	402	198	511	189	522
log-likelihood	-351.3	-172.4	-213.2	-312.0	-136.8	-389.6	-112.9	-406.6
H_0 : Same (p)	0.08*		0.23		0.44		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 13: **Structural estimates: Allowing automatic refusal in wave 3**

TYPE	ESTIMATED PROPORTION	95% CONFIDENCE	
		LOWER	UPPER
'TYPE A'	0.0%	0.0%	3.3%
'TYPE A⋆'	1.2%	0.0%	5.7%
'TYPE B'	3.4%	0.0%	5.9%
'TYPE B⋆'	0.0%	0.0%	3.6%
'TYPE C'	2.6%	0.0%	5.7%
'TYPE C⋆'	1.1%	0.0%	4.9%
'TYPE D/D⋆'	10.4%	6.1%	13.8%
'TYPE E'	2.5%	0.6%	4.8%
'TYPE E⋆'	0.9%	0.0%	2.6%
'TYPE F'	8.7%	5.7%	12.0%
'TYPE F⋆'	4.6%	2.2%	7.0%
'TYPE G'	41.5%	37.7%	45.4%
'TYPE G⋆'	9.0%	6.6%	11.5%
NOT RATIONALISED	14.1%	11.4%	16.9%
N	709		
log-likelihood	-749.576		

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 14: **Structural estimates: Allowing a type with random play**

TYPE	ESTIMATED PROPORTION	95% CONFIDENCE	
		LOWER	UPPER
'TYPE A'	0.9%	0.0%	5.7%
'TYPE B'	0.8%	0.0%	4.1%
'TYPE C'	4.5%	0.1%	7.5%
'TYPE D'	8.3%	3.8%	11.7%
'TYPE E'	0.0%	0.0%	3.3%
'TYPE F'	8.5%	4.9%	11.9%
'TYPE G'	36.6%	32.5%	41.0%
RANDOM PLAY	40.5%	35.0%	45.6%
NOT RATIONALISED	0.0%	0.0%	0.0%
N	709		
log-likelihood	-1183.7		

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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