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The Role of Flexibility and Planning in Repayment Discipline: Evidence from a Field Experiment on Pay-as-You-Go Off-Grid Electricity

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Abstract

Flexibility can help households with irregular income flows meet their payment obligations. On the other hand, the rigidity of payment schedules is believed to foster discipline and reduce defaults. We test the impact of a novel form of flexibility, the ability to set one's own payment schedule within a month, on payment performance through a field experiment with customers of a prepaid solar systems provider in rural southern Pakistan. We combine contract flexibility with planning prompts, to mitigate its potentially negative effects on repayment. We find that flexibility in isolation negatively affects payment quality, but that combining it with planning prompts offsets this negative effect, producing behavioral outcomes that are indistinguishable from those associated with a rigid payment schedule. While treatment impacts are short-lived, they result in significant effects on contract cancellation in the long term. Our findings have implications for the applicability of planning interventions to behavioral outcomes requiring sustained effort, and for the design of contract flexibility when technological developments make frequent payments possible.

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1 Introduction

A large body of evidence points to the important role of commitment problems in financial decisions, such as saving, debt repayment and investment (Casaburi and Macchiavello, 2019; Ashraf et al., 2006; Dupas and Robinson, 2013a; Afzal et al., 2018, 2019; Bonan et al., 2019). Commitment problems, and the resulting time inconsistency of behavior, are examples of behavior-intention gap: individuals intend to perform a certain behavior, for instance saving or paying their dues on time, but then fail to actually follow through. Typical solutions to these problems take the form of hard commitment devices, restricting decision-makers' choice sets or increasing the costs of deviating from pre-determined goals. Frequent, regular and rigid repayment schedules, associated with penalties from deviating from them, are an example of restriction aimed at addressing such commitment problems in the financial domain. Rigidity is thought to provide discipline to borrowers and reduce the cognitive costs of keeping track of finances (Haushofer, 2015). Indeed, lack of flexibility is a common feature of formal and informal financial products, such as microfinance loans and rotating saving and credit associations, and is found to lead to lower default rates (Field and Pande, 2008).[1]

The welfare and growth implications of restricting agents' choices to address behavioral biases are a subject of much debate. Recent contributions show the limited or even negative welfare effects of policies, such as bans of fines, aimed at steering consumers' behavior away from borrowing, or towards healthy or environmentally friendly choices (Allcott and Kessler, 2019; Allcott et al., 2020). Imposing a rigid payment schedule may particularly hurt the poor, who are typically recipients of volatile and irregular income flows and have limited ability to cope with income shocks, due to lack of access to social security systems and insurance markets (Field et al., 2012). Among individuals who have no commitment problems, flexibility should increase debt repayment, by allowing borrowers to align repayments with their income streams.[2] Partly in response to these concerns, soft commitment devices, relying on psychological motivations, have emerged as alternative solutions to commitment problems. Insights from psychology and behavioral sciences suggest that non-coercive and low-cost interventions can help individuals close the gap between intentions and behavior (Gollwitzer and Sheeran, 2006; Ashraf et al., 2006; Brune et al., 2016; Dupas and Robinson, 2013a; Karlan et al., 2016a; Stango and Zinman, 2014).

In this paper, we test whether commitment problems in financial decisions can be addressed through a

[1] Commitment saving devices are common in developed countries too, taking the form of automatic drafts from checking to saving accounts, direct debits from paychecks to saving accounts, etc.

[2] In addition, rigidity, by discouraging high-risk but high-return investments and by limiting the ability of credit to serve insurance purposes, is increasingly seen as one of the reasons behind the limited impact of microfinance on business growth (Gulesci and Madestam, 2018; Barboni, 2017; Barboni and Agarwal, 2019).

combination of flexibility and a soft commitment device. We test whether a previously unexplored form of flexibility has negative consequences on repayment discipline, and whether these consequences can be alleviated through planning prompts. The formulation of implementation plans is believed to foster the development of strategies for overcoming logistical obstacles, as well as to increase salience of the objective and perceived commitment to a goal (Smith et al., 2014). A growing body of evidence finds that prompting individuals to formulate plans, about when and how they will follow through on their intentions, is an effective strategy to improve the consistency between intentions and actual behaviors in a wide range of settings, from job search (Abel et al., 2019) to health-related behaviors (Milkman et al., 2011, 2013), voting (Nickerson and Rogers, 2010) and exercising (Prestwich et al., 2003). We thus expect planning to compensate for the reduced commitment features of a flexible repayment schedule.

We test these predictions in the context of prepaid off-grid electricity. We conduct a randomized control trial with a private company providing solar-powered energy systems, on rent or lease, to households and small businesses in rural southern Pakistan. Energy services are provided under a pay-as-you-go contract, such that the system is remotely disconnected if the credit balance does not cover the daily rate. We recruit customers for our study right after they adopt a system and sign a contract specifying their payment obligations. Within our sample, initial commitment to complying with the contract terms is high, yet failure to follow through is widespread: over 50% of customers have their contract cancelled within a year due to default.[3] The experiment aims to assist individuals in acting upon their intentions through two treatments, in a two-by-two factorial design. The first experimental treatment varies whether customers, after signing a contract, are told that they have to pay a fixed amount in monthly instalments, or according to a flexible schedule of their choosing within each month. The second treatment randomly requires customers to formulate a plan for when and how they will make payments.

We find that increasing flexibility, on its own, has a weak negative effect on repayment, in that it increases the number of days when customers' systems are disconnected due to insufficient payment. Planning prompts, when combined with flexibility, are effective in improving repayment and reducing contract cancellation due to default. Overall, the combination of flexibility and planning yields repayment outcomes that are statistically indistinguishable from those associated with a rigid repayment schedule. However, the impact of implementation plans on payment quality rapidly fades away over time: after six months from the start of the contract, no treatment effects are detectable. Treatment effects, and particularly the positive combined impact of flexibility and planning, are also significant only in the short term when we consider contract cancellation. However, these initial effects generate divergent patterns of contract cancellation

[3] As explained below, due to extensive eligibility screening on the part of the company, customers' initial ability to meet their payment obligations should not be an issue in our setting.

over time, so that differences are large and statistically significant over the long term. Finally, we show that planning works better when it succeeds in making individuals formulate specific plans, and that individuals who experienced repayment issues are more likely to take-up planning prompts when offered them.

Our study makes four main contributions to the literature. First, we contribute to the current debate in the microfinance literature on the trade-off between discipline and flexibility in repayment schedule. Existing evidence on the relative impact of rigid and flexible contracts on repayment is mixed (McIntosh, 2008; Field et al., 2013; Field and Pande, 2008; Czura, 2015; Labie et al., 2016; Barboni, 2017; Barboni and Agarwal, 2019). With respect to other studies on microfinance, which evaluate the impact of grace periods or of varying the size of instalments to reflect seasonality, we examine a novel form of flexibility. In our setting, the only contractual obligation for customers is to pay the rate to keep their systems active. While in principle such amount can be paid according to a schedule of the customer's liking, the partner institution does not make this possibility explicit, suggesting instead that customers stick to a rigid monthly payment schedule. Flexibility within our experiment thus simply implies emphasizing the possibility for customers to tailor the repayment schedule to their needs, by setting both the frequency and the amount of payments within each month. Given the technological advances that lower the administrative cost of small, frequent payments, such as mobile money in the financial realm and pay as you go systems in the service sector, and poor customers' preference for small frequent payments and schedules that match their irregular cash flows (Suri, 2017; Jack and Smith, 2015; Afzal et al., 2018), this represents potentially a cheap and scalable solution to ensure quality repayments. Our insights on the impact of this form of flexibility, and on the conditions under which it improves the quality of payments, are thus widely applicable and timely.

Second, we push the frontier of the behavioural and microfinance literature, by testing the impact of planning prompts on timely repayment. Implementation intentions have provided cost effective means of increasing the likelihood of follow-through in contexts characterized by simple actions, such as voting, exercising, vaccination, getting medical screening or job search (Nickerson and Rogers, 2010; Prestwich et al., 2003; Milkman et al., 2011, 2013; Abel et al., 2019).[4] Indeed, the existing evidence suggests that plans work best when follow-through requires overcoming an obstacle, and when they concern tasks not requiring multiple actions over time (Rogers et al., 2015). Being the first to test this behavioural tool in the setting of product repayment, we confirm that its effectiveness is detectable only when flexibility makes the formulation of plans important, and is limited to the short-term. These results have important implications for the design of planning prompts in the context of microfinance and service payment, suggesting to

[4] However, other works find null effects of planning on public transport usage (Gravert and Olsson Collentine, 2019). See Hagger and Luszczynska (2014) and Rogers et al. (2015) for reviews.

combine them with flexibility and with reminders to make the plan salient over time. Our results suggest that, implemented in this way, planning prompts could allow financial institutions and service providers to reduce their reliance on hard commitment devices, such as rigid payment schedules. These insights could guide the adoption of planning interventions in different decision and policy realms.

Third, our focus on planning prompts and on their combination with flexibility enriches the evidence on the impact of behavioral tools in the financial domain. Defaults and earmarking, which increase the psychological costs of deviating from a goal, and reminders, aimed at making goals more salient, have been shown to be effective in increasing saving and loan repayment rates (Karlan et al., 2016b; Dupas and Robinson, 2013b). On the other hand, other soft commitment strategies, such as pledges, have shown limited effectiveness in improving loan repayment (Bhanot, 2017). Proponents of softer forms of commitments, and of nudging more in general, see these tools as alleviating the negative welfare consequences of limiting agents' decision-making autonomy associated with the use of traditional policy tools (Thaler and Sunstein, 2008). Our results on the similar performance of rigidity, on one hand, and the interaction of flexibility and planning, on the other, is supportive of the view that behavioral interventions may be able to replace traditional ones.

Fourth, we contribute to the literature on sustainable energy provision and technological innovations in payment technologies in developing countries. The solutions we test are made possible by the availability of mobile payment technologies. Existing evidence shows the impact of mobile payments on risk, savings, labour market outcomes, health, poverty, and migration (De Mel et al., 2018; Jack and Suri, 2014; Suri and Jack, 2016; Lipscomb and Schechter, 2018; Batista and Vicente, 2019)[5] Being the first to test the impact of flexibility and planning in the context of energy payments, we suggest ways to improve the financial sustainability of off-grid solar systems.

The paper is organized as follows: Section 2 presents our study context. Section 3 discusses the experimental design and Section 4 describes the data. Section 5 outlines the empirical strategy and Section 6 reports our main results. Section 7 concludes.

[5] See Suri (2017) and Aron (2018) for reviews.

2 Context

2.1 The energy sector

About 860 million people worldwide have no access to electricity (IEA, 2019). In Pakistan, approximately 144 million individuals reside in either completely off-grid areas or in on-grid areas with load shedding exceeding 12 hours per day (IFC, 2015). Poor access to modern electricity services is associated with severe consequences on household welfare, particularly among the poor and marginalized, and prevents economic development, although the causal evidence on such a link is still debated (Greenstone and Hanna, 2014; Bonan et al., 2017; Lee et al., 2020a,b). The lack of reliable electric infrastructures leads firms to self-generate energy, with consequent higher costs, decreased economic activity and negative business outcomes (Rud, 2012; Alam, 2013; Allcott et al., 2014). According to an IFC report, USD 2.3 billions a year are spent by people in Pakistan on kerosene oil and candles to meet their lighting needs. At the national level, the direct and indirect costs of unreliable energy supply and load shedding are estimated as USD 14 billions for 2011-12 (Pasha and Saleem, 2013).

The high costs of grid expansion and the wide availability of renewable sources such as wind, solar and biomass in developing countries, such as Pakistan, make the diversification of energy sources an important strategy for increasing access to electricity and meeting increasing energy demand. The provision of off-grid energy products by private companies has greatly increased throughout the developing world in recent years. About 20% of the population in Africa and South Asia, where the bulk of the population without access to grid electricity lives, use off-grid solar systems (Lighting Global Program, 2020). Recent studies have shown positive impacts from the use of solar systems (lights, chargers, radios) on household budget, productivity and convenience, and highlight their role in the energy transition (Grimm et al., 2016; Furukawa, 2014; Samad et al., 2013; Sievert and Steinbuks, 2020; Grimm et al., 2020)[6].

The fact that these technologically sophisticated systems are primarily targeted to low income populations with irregular income flows makes payment quality a key challenge for the sustainability of these companies' business model. Technological and business innovations have been introduced to this purpose, but their impact on the viability of these businesses is still under-researched and limited to the study of pay as you go and rent-to-own systems (Guajardo, 2016, 2019).[7] We study one such innovation.

[6] Conversely, other studies suggest that off-grid solutions, i.e., electricity systems and mini-grids, are imperfect substitutes of the grid and are likely to be a stop-gap solution (Burgess et al., 2020; Lee et al., 2016; Fowlie et al., 2019).

[7] Jack and Smith (2015, 2020) are studies of pay as you go metering in an on-grid setting.

2.2 Setting of the study

We collaborate with EcoEnergy (EE), a for-profit company supplying sustainable and efficient solar energy solutions in rural Pakistan. The solar units are capable of charging a 17Ah battery and can power multiple bulbs or fans, 2 mobile phones via USB charger, radio or a 15" TV, corresponding to monthly fees that range from USD 8 to 50. Customers access the systems under a pay as you go monthly scheme, choosing between two versions of the contract: perpetual rental and rent-to-buy. The rent-to-buy contract transfers ownership of the unit to the customer after agreed upon payments have been made, roughly equivalent to the sales value of the unit. The two contracts differ in terms of monthly fees: rent-to-buy contracts are more expensive than perpetual rental ones.[8] The solar units are remotely disconnected as credit expires. After 30 disconnection days, customers have their status turned into "default". This sets-off the process of repossession of the product by EE, which eventually leads to contract cancellation. Beside disconnection and eventual contract cancellation, there was, at the time of our study, no financial penalty for late payments. Disconnection days thus represent a pure loss for EE, and timely repayments are crucial for business sustainability.

EE targets areas that are off-grid (no electricity) or have 'bad' grid (more than 12 hours of loadshedding a day). Our study followed EE's expansion in new areas, specifically the districts of Thatta, Badin, Sujawal, Mirpur Khas and Tando Muhammad Khan in the South of the province of Sindh. With the exception of Mirpur Khas, these are some of the poorest districts of Pakistan, with approximately half of their population living below the official poverty line.[9] Average household income in sample districts is approximately PKR 9,000 (USD 267 PPP) per month.[10] Economic activity in these districts is predominantly agrarian, employing between 50-70% of the labor force; and a small percentage of the labor force is self employed.[11]

In each area where it enters, EE first conducts product demonstrations at the village or *bazaar* (market) level. At the end of the demonstrations, EE field staff meet interested individuals and businesses one-to-one and offer their products to applicants that fulfill their eligibility criteria. Applicants are screened through a quick questionnaire conducted by the salesperson, which includes questions on the current en-

[8] Another advantage of the perpetual rental scheme, according to customers choosing it, is that it gives access to free technical assistance from EE for the entire duration of the contract. Customers choosing the rent-to-buy scheme instead have to pay for technical assistance once they own the system.

[9] As reported in Government of Pakistan's Data for Pakistan Portal (http://www.data4pakistan.com/). Proportion of population below the poverty line for Thatta, Badin, Sujawal, Mirpur Khas and Tando Muhammad Khan are 51%, 47%, 52%, 41% and 49%, respectively as of 2014. The official poverty line in Pakistan in 2014 was based on recommended nutritional requirements of 2350 calories per person per day.

[10] All PKR values reported in USD PPP are using the 2018 World Bank PPP conversion factor for private consumption rate of 1 USD = 33.54 PKR.

[11] Self employment rates range from 8% for Tando Muhammad Khan to 11% for Mirpur Khas.

ergy use, average amount spent on alternative energy sources, and household income. This information is used to determine the customers' payment ability and needs. Customers whose payment ability is deemed sufficient to meet the monthly payment related to the system are then offered the contract. The contract specifies the capacity of the solar system that will be installed and the amount of payments that will be required to keep the product active.

3 Experimental design

The experimental design varies the terms of the product offered to treatment group clients along two dimensions: the salience of the possibility to flexibly set the repayment schedule, and the administration of a planning intervention. This results in a 2x2 factorial design.

The flexibility treatment was administered by EE's salespersons after all other contractual aspects - such as the set of electric items, price, rent versus ownership - were explained, agreed upon and accepted. The treatment assignment therefore occurs after the client has accepted the general contractual conditions. This prevents our design from generating selection into contractual features.[12] In practice, a random generator number was incorporated in the software used by the salespersons to register new customers leading to either one or the other specification of the repayment schedule. Hence, we stratify the flexibility treatment by salesperson.

Following the signing of a new contract and the administration of the flexibility treatment, EE transferred the customer's information to the research team, and an enumerator then visited the client to administer a survey and the planning treatment. The planning treatment was therefore randomized by the research team via the survey software and conducted within few weeks from the contract start.

We now describe each treatment in detail.

Flexibility of payment. We vary flexibility in the monthly instalment payment through the following contract variations:

- Default: the default contract is EE's standard contract, under which clients are required to make their entire monthly payments on the same fixed date each month.

[12] We find no qualitative evidence of differential contract waiver by different experimental conditions.

- Flexible: under the flexible contract clients are explicitly told that they can decide when and at what frequency to make their monthly payment. As long as they pay for their consumption, clients in this group are essentially free to plan their payment schedule. For illustration purposes, at take-up, these customers are informed of the daily rate and given examples of payments at different frequencies (e.g., weekly, bi-weekly, monthly).

To reiterate, under both treatment conditions the clients can actually pay whenever they like without economic consequences. The flexible treatment simply makes the possibility of setting the payment schedule autonomously more salient to the customer. Appendix A reports the script used to present the treatments to the customers.

Implementation Intention Plan (IIP). We focus on inattention and lack of salience of payment obligations as key factors behind default in our setting. This focus is justified by the extensive screening protocol used by EE to identify eligible customers, which makes *ex-ante* liquidity constraints an unlikely explanation for late or non-repayment. The experimental design randomizes the offer of planning prompts to clients drawing from the psychology literature on the use of implementation plans (Gollwitzer and Sheeran, 2006). We ask customers in the IIP treatment to state their commitment to making timely payments; to identify the main obstacles they face in meeting this commitment; to formulate strategies for overcoming each obstacle; and to consolidate the resulting saving plan and payment schedule by circling the corresponding dates on a calendar, delivered by the enumerator, to be kept by the customers in their work place or house. This process should help treated customers anticipate possible issues in repayment and devise strategies to overcome them. Appendix A provides the IIP script.

4 Data, variables and sample characteristics

Two sources of data are used in the analysis: EE administrative data and survey data. We describe each dataset in detail, and then present the characteristics of the study sample.

4.1 Administrative data

We have access to EE's administrative records on customers' subscription, type of system installed, amount due, deadlines and flows of payments made every day. These data allow the timely monitoring of payments and system status (active, inactive, cancelled) from each customer's installation date until the end of the monitoring period, in September 2019. This means that we observe each customer for at least one year after the contract was signed and the treatments administered. We use the administrative data to construct our main outcome variables, capturing quality of payments to EE and defaults by customers following the pre-analysis plan, in two forms.

First, we collapse the daily panel of customers' interactions with EE into a cross-sectional dataset, and consider the following 3 outcome families, measured over the entire monitoring period:

(i). Inactivity: this is defined as the customer balance going to PKR 0, which leads to the system becoming inactive.

- Extensive margin: an indicator for if the customer experienced at least one inactive day over the contract duration.[13]
- Intensive margin: share of inactive days over the contract duration[14].

(ii). Cancellation: an indicator for contract cancellation.[15]

(iii). Top-ups: frequency of payments, measured as the number of payments made on average in a month.

Second, we exploit the longitudinal dimension of the administrative data, and construct a monthly panel. Specifically, we collapse daily information on the status of the system and payments made at the month level, and construct the indicators for the three families of outcomes described above: (i). a variable equal to one if the customer experienced at least one inactive day over the month; (ii). the share of inactive days in the month; and (iii). the number of payments made over the month. The panel analysis was not pre-specified, but we include it because it allows us to shed light on the dynamics of repayment.

4.2 Survey data

The second source of data is the survey, administered within few weeks from contract signing and conducted by an independent survey firm. The questionnaires collected information on customers' demographic and socioeconomic characteristics; on their energy usage and other household expenditures; and on a set of behavioral measures, from time preferences, to locus of control, to perceived constraints to meeting payment obligations and following through on plans. Survey data were collected via tablets using

[13] Note that in the pre-analysis plan, we erroneously specified two different outcome variables for delayed payments and switch-off because of missed payments when it captures the same event. We define it throughout this paper as 'inactivity'.
[14] This is referred to as 'Share of days of delay' in the pre-analysis plan.
[15] This is referred to as 'Dropout after installation' in the pre-analysis plan. Note that we do not have the data available to analyse the outcome 'Dropout before installation' that we pre-specified.

SurveyCTO.

We use the survey data to construct some relevant pre-specified measures, which we expect to be associated with heterogeneous treatment impacts. Such measures pertain to the domains of the ability to smooth consumption, mental and behavioural constraints, and time inconsistency. First, we construct an index of customers' ability to smooth consumption. It is obtained through principal component analysis (PCA) by aggregating information on the share of household active members who earn on a regular basis, dummies for availability of savings (both formal and informal) and for access to credit in the past, and an index for asset owned.[16] Second, we construct an index for mental constraints from measures of cognitive skills, self-reported ability to pay bills on time, an index for the (in)ability to resist temptations, self-control, locus of control, grit and discipline with previous loans.[17] Third, we measure time preferences using Multiple Price Lists (MPLs) approach by presenting the clients with a series of amounts to choose between either tomorrow or in a month or between 5 or 6 months. These choices were incentivised through a lottery and payments were made through mobile talk time credit. We define a dummy variable to capture 'time inconsistency' which is equal to one when the customer switched to the (higher) future amount later in the short-term frame (tomorrow vs one month), than in the long-term frame (5 vs 6 months), and zero otherwise.

As part of the IIP treatment, which was built into the survey for treated customers, we collected measures of commitment with meeting the payment obligations implied by the contract with EE, and of the outcome of the planning exercise. Before prompting participants to identify obstacles to making timely payments and to formulate a saving and payment plan, enumerators asked them to what extent they were committed to this goal. Answers range between 1 and 10, with higher values denoting higher commitment, and are a measure of initial commitment to complying with the EE contract among the sub-sample of customers randomly allocated to the IIP treatment. The success of the planning exercise lies in whether it actually prompted individuals to formulate a specific plan. One way to measure this outcome is by checking whether individuals set any specific dates for making payments or setting aside the money for payments. At the end of the IIP exercise, enumerators took note on whether customers used the calendar, provided by enumerators themselves, to organize their saving and payment schedule.

[16] The index aggregates through Principal Component Analysis dummies for the ownership of assets such as stove/gas cooker, fridge/freezer, fans,mobile phones, radios, CD/DVD/video players, TVs, computers, cars, motor cycle/scooters, bicycles, goats, camels, buffalo/cows.

[17] Each variable, together with its source and construction, is described in detail in appendix B. The variables are first reverse-coded, if needed, and then aggregated following Anderson (2012), so that the index is increasing in the degree of mental constraints.The fixed-no IIP group is used as the 'reference/control' group for standardising.

4.3 Sample characteristics

The study sample includes 728 customers with finalized contracts and activated systems between March 2017 and December 2018. Of these, 351 are in the flexible treatment, evenly split between customers receiving and not receiving planning prompts. Similarly, the 412 individuals assigned to the IIP treatment are roughly evenly distributed between flexible and rigid contracts – 197 participants receive the combination of flexibility and planning. The fact that randomization to each treatment occurs at the individual level through two separate procedures implies that clients were not equally divided into the four treatment cells and we observe a slight imbalance in the number of customers assigned to each one.

Table 1 shows summary statistics of customers' characteristics that we use as controls in the analysis by treatment arm – flexibility of payment versus fixed schedule, and IIP versus no IIP.[18] Almost all of the individuals in our sample are residential customers. Clients are on average nearly 36 years of age, 82% of them are literate, about 25% have savings and 17% have access to credit. They report an average household monthly income of PKR 24,350 (USD 726 PPP) and a median income of PKR 20,000 (USD 596 PPP). Nearly a third of our respondents earn income primarily from agricultural activities; another 27% are government employees (with regular monthly salaries); while 19% are laborers, earning irregular, often weekly wages. A small percentage (13%) are self-employed. Overall, almost half of the members of sampled households are recipients of regular income flows. About 8% of our sample reveals time inconsistent preferences. Respondents' characteristics are balanced across treatments (p-value of two-sided t-tests of equality of means across treatment groups reported in columns 4 and 7 of Table 1).

Grid connectivity is low and the quality of electricity is poor. About 20% of individuals in our sample have no access to any source of electric power, while 66% of them are connected to the national grid or to mini-grids and 14% have home solar systems. The vast majority (99%) of those connected to the grid experience loadshedding daily: 33% between 1 and 6 times, 24% between 7 to 10 times and 41% more than 10 times a day. Only 0.65% of the sample experience no outages in a typical day. Off-grid households live on average 7 Km from the closest on-grid location.[19]

As a result, households expend a considerable portion of their income on fuel (kerosene, diesel) and gas costs for alternative energy and on purchase of firewood, lamps, candles and torches. Every month, an average household in our sample spends approximately PKR 7,500 (USD 234 PPP) on fuels; PKR 1,000 (USD 30 PPP) on firewood and lighting implements; in addition to PKR 500 (USD 15 PPP) for electricity

[18] In Appendix Table C1 we show the summary statistics for each treatment arm relative to the control (fixed-no IIP).
[19] These variables are not reported in Table 1 as they are not used in the regression analysis.

(before solar UPS installation). Fuel and electricity are needed to power energy-using durables: the average respondent owns 3 electrical appliances that require energy - 98% have mobile phones that require charging; 97% have fans, 60% have electric lights; and 43% have TVs.

The solar systems acquired by study participants from EE do not appear, on average, to satisfy households' entire energy needs. Almost all (98.5%) systems installed can power a light, while a vast majority (87.4%) can power a fan. Only 1% of customers have systems able to support a TV, while 6.6% have a system with a mobile charger. On average, keeping systems active costs customers PKR 43 (USD 1.3 PPP) per day. On a monthly basis, this would correspond to PKR 1,290, i.e. about 5% of monthly household income. Just above half of the sample choose perpetual rental over rent-to-own contracts. A majority (99%) of respondents report wanting the solar kit in order to improve their lifestyle.[20]

Table 2 provides the descriptive statistics for the main outcome variables of interest for the study sample (column 1). Repayment quality is a serious issue: the cross-sectional data (Panel A) shows that 96.2% of customers experience at least one inactive day over the duration of the contract; that their systems are inactive for more than a quarter of the time (25.8% of contract days); and that 56% of them have their contracts cancelled due to default. This corresponds to average monthly figures of 36.1% for customers experiencing at least one inactive day; and of 13.1% inactive days within the month on average (Panel B). Customers make on average one payment per month.

In spite of widespread inactivity and default, respondents at baseline report a commitment to making timely payments: among customers randomly allocated to the IIP treatment, the average self-reported intention to meet their payment obligations is 6.7 (on a scale from 1 to 10). This discrepancy suggests the presence among sampled customers of a gap between intentions and behaviors, which the IIP treatment tries to address.

About 45.4 and 41.3% of IIP treated subjects marked on the calendar dates for making payments to EE or saving money for payments, respectively. These figures are low, and dampen our expectations on the effectiveness of the IIP treatment. These shares are significantly higher among customers in the flexible treatment as compared to those in the fixed treatment (p = 0.034), consistent with the greater need to consolidate a plan in the presence of a self-imposed payment schedule.

[20] For the few businesses in our sample, a similar motivation is to attract more customers to the business (97%).

5 Empirical strategy

We follow the pre-specified estimation strategy.[21] First, we investigate treatment effects in the cross-section dataset. For the main effects, we estimate the following equation:

$$y_i = \alpha + \beta_1 Flex_i + \beta_2 IIP_i + X\gamma + \varepsilon_i \tag{1}$$

since this specification will mask any heterogeneous effect of the treatments, depending on whether they are administered in isolation or jointly, our preferred specification estimates the interaction effects:

$$y_i = \alpha + \beta_1 Flex_i + \beta_2 IIP_i + \beta_3 Flex_i \times IIP_i + X\gamma + \varepsilon_i \tag{2}$$

$Flex_i$ is an indicator variable equal to one if the client is told about flexibility by the salesperson, and zero otherwise. The actual frequency of payment represents an endogenous decision, therefore β_1 should be considered as ITT, i.e. the effect of the possibility to choose the schedule of payments, not of a particular frequency per se. IIP_i is an indicator variable equal to one if the client received the IIP intervention at the end of the baseline survey and zero otherwise. Specifications also include, in vector X, respondent controls: age, literacy, access to credit, presence of savings, the proportion of household members with regular income, if system is installed in business or home; and contract characteristics: average daily rate, dummies for whether at least one fan, tv, light and mobile charger is installed, perpetual rental vs rent-to-own contract. We also control for salesperson, enumerators and tehsil fixed effects. Models are estimated through OLS with robust standard errors.

Second, we exploit the panel nature of our data by estimating the main and interaction treatment effects through the following equation:

$$y_{it} = \alpha + \beta_1 Flex_i + \beta_2 IIP_i + \beta_3 Flex_i \times IIP_i + X\gamma + \omega_t + \eta_{it} \tag{3}$$

Panel specifications are similar to the cross-sectional ones, estimated through OLS. We add months fixed effects, ω_t, and cluster standard errors at the individual level to account for the panel structure of the data. In order to look at the dynamics of treatment effects, we assess the impacts over different non-overlapping time periods, namely from month one to three, from four to six, and from seven to twelve since the start of the contract. We also consider different overlapping periods since the start of the contract, i.e., months one to three, one to six, and one to twelve of the contract: this second approach allows us to see the cumulative

[21] We collected data on far fewer business customers than expected (about 5% of the study sample), impeding us from providing evidence on the pre-specified research question 7 on differential treatment effects for customers who installed the system for their household versus for their business activity.

impact of the treatments over progressively longer time horizons. Since customers leave the sample over time due to contract cancellations, the size of the sample is 728 at baseline, and 630, 485 and 308 after three, six and 12 months, respectively. Figure C.1 in Appendix shows the number of customers whose contracts are cancelled over time, for each month and cumulatively since the start of the contract.

In the (pre-specified) cross-sectional analysis of treatment effects, following Haushofer and Shapiro (2016), we compute and report the ex-post Minimum Detectable Effect (MDE) for each statistically insignificant coefficient. MDE is defined as the effect that would have been detectable with 80% power at the 5% significance level ex post.[22] This allows us to discuss whether our results are affected by issues of low statistical power. This approach also facilitates comparisons with similar studies. In doing that, we will calculate the relative effect size, defined as the percentage change between the dependent variable of the (sub) treatment group and the control group.

Third, we explore whether the effect of the IIP treatment varies with the degree, to which it succeeded in fostering people to produce concrete plans. As mentioned above, customers in the IIP treatment group were asked to define plans and strategies for repayment and were then given the opportunity to consolidate their plans on a calendar. We see the formulation of a precise plan as a proxy of the effectiveness of the IIP exercise. We use the variables capturing whether clients marked on the calendar their saving and payment plans in the estimation of Local Average Treatment Effects (LATE), where the randomly assigned IIP treatment is used as instrument for whether individuals made specific plans, which is endogenous. Hence, we estimate the following equation with two-stage least-squares.[23]

$$IIP\_Eff_i = \alpha + \beta_1 IIP_i + X\gamma + \upsilon_i \tag{4}$$

$$Y_{it} = \alpha + \beta_1 IIP\_Eff_i + X\gamma + \omega_t + \nu_{it} \tag{5}$$

The exercise is repeated separately for the two variables measuring IIP effectiveness: actual application of IIP for payment and for setting money aside (both dummies).

Finally, we analyze the heterogeneous treatment effects of the flexible schedule and of IIP. We do it by augmenting equation 1:

$$y_i = \alpha + \beta_1 Flex_i + \beta_2 Flex_i \times Het_i + \beta_3 IIP_i + X\gamma + \varepsilon_i \tag{6}$$

[22] Ex-post MDs are computed as SE(β)*2.8.

[23] We acknowledge that this analysis was not pre-specified.

$$y_i = \alpha + \beta_1 IIP_i + \beta_2 IIP_i \times Het_i + X\gamma + \beta_3 Flex_i + \varepsilon_i \tag{7}$$

where Het_i takes the value, in different specifications, of (i) an index for the ability to smooth consumption, (ii) an index increasing in mental and behavioural constraints, and (iii) a dummy variable equal to one for time-inconsistent individuals and zero otherwise. Similarly, we explore the heterogeneity in the panel analysis, by adding interaction effects to equation 3.

6 Results

6.1 Treatment effects

We examine the results for each family of outcomes, both as a cross-section and as a panel in Tables 3-5.[24] In each table, column 1 shows the average effect of flexibility and planning, pooling the sub-samples exposed to the other treatment, while the remaining columns also report their interaction: in these cases, the coefficients on the $Flex$ and IIP dummies capture the main effect of each treatment when administered in isolation, while the interaction terms report the effect of the combined treatment, relative to the sum of the two main effects. We also report whether the marginal effect of the combined treatment is significantly different from the control (default-no IIP) by displaying the p-value of a Wald test of equality of coefficients. When reporting the panel results, we display effects both over non-overlapping time periods (columns 3, 4 and 5), and over different cumulative periods since the start of the contract (columns 6 and 7). In Appendix C, we report the same results differently, by displaying the marginal effect of each condition with respect to the control, and show MDEs for each non statistically significant coefficients (Tables C5 - C7).

We start by discussing treatment effects on inactivity (Table 3). Overall, neither the flexibility nor the planning treatment have any statistically significant effect on the likelihood of experiencing at least one inactive day and on the share of inactive days over the contract period (column 1). This average effect masks heterogeneous impacts depending on the combination of flexibility and planning. In the cross-section, flexibility without planning increases the likelihood of inactivity by 3.8 percentage points ($p < 0.1$), an effect which is reversed when it is combined with planning (Panel A column 2; $p < 0.05$): indeed, subjects in the flexibility plus planning conditions are no more likely to experience an inactive day over

[24] Tables C2 - C4 report results without any controls or fixed effects. Note that there is one more observation in these tables since we are missing information on controls ('share of household members with regular income') for one respondent. Overall, results hold.

the duration of the contract than subjects facing a rigid payment schedule (Wald test p-value, $p = 0.759$).[25] Similarly, the combined treatment more than outweighs the negative effect of flexibility and planning in isolation on the share of inactive days over the contract duration, but this result is statistically significant only within three months since the contract activation ($p < 0.05$).[26] When combined with a rigid repayment schedule, the IIP treatment generally has a negative, but not statistically significant, impact on the extensive and intensive margin of inactivity, with the exception of the seven-to-twelve months periods since contract activation ($p < 0.1$). The absence of long-term treatment effects in the panel analysis is confirmed when we examine the cumulative effect since the start of the contract (columns 6 and 7). Absolute MDEs for inactivity range from 4 to 7 percentage points in cross-section specifications, corresponding to relative MDEs ranging between 4 and 27%.

The treatments have no effect on the second family of outcomes – the number of monthly top-ups – with the exception of an increase due to the IIP treatment in the cross-section when estimating equation 1 ($p < 0.1$, Table 4 column 1). Contrary to expectations, flexibility does not affect the average number of top-ups per month. This is consistent with the fact that 85% of respondents in the IIP treatment claim that they wish to make payments once a month. Relative MDEs for frequency of top-ups range from 25 to 44%.

Focusing on contract cancellation, we observe that, in isolation, both treatments increase it in the panel analysis: these effects are statistically significant over the first three (column 3) and the first six (column 6) months of the contract. Flexibility without planning aids and planning in the presence of payment rigidity thus appear to be detrimental, at least in the short to medium term. Combining the two treatments more than offsets these effects: in the first three months of the contract, flexibility and planning together lead to statistically significant reduction in contract cancellation with respect to the sum of the main effects of the two treatments in isolation ($p < 0.01$), and to rates of contract cancellation that are indistinguishable from those of the standard rigid contract. While these results disappear when we consider the medium to long term, i.e., the four-to-six (column 4) and the seven-to-twelve (column 5) months periods since contract activation, the cumulative effects over the first six (column 6) and twelve (column 7) months of the contract show that the initial impact of the combined treatment has long-lasting implications (both $p < 0.01$). This result echoes findings from the literature on behavioral microfinance (Schaner, 2018). The overall effect is confirmed in the cross-section (column 2, $p < 0.05$).[27] Relative MDEs for contract cancellation range from 19 to 28% in cross-section.

[25] See also Appendix C Table C5, column 2.

[26] Only in the three-months period the combined treatment yields a significantly lower share of inactive days than the control ($p = 0.098$).

[27] We test the robustness of our results to the inclusion of controls selected through the post-double LASSO selection procedure: Tables D3 - D5 in Appendix D show that they hold.

6.2 Impact of planning prompts through plan-making

The behavioral literature on planning prompts outlines two conditions behind their effectiveness (Rogers et al., 2015). First, planning helps when there are obstacles, that can be overcome with the help of a plan. In our setting, flexibility increases the complexity of payment decisions. Our results on treatment effects support this claim: only individuals assigned to the flexible payment schedule benefit from planning, i.e., planning is more useful when subjects have to devise their own payment schedule.

Second, prompting people to focus on the obstacles to following through on their intentions and to devise a plan to overcome them works only if individuals actually consolidate their strategy into a concrete plan. In order to test this prediction, we distinguish between individuals who formulated specific plans and those who did not. We focus on the sample of individuals assigned to the flexibility treatment and estimate through LATE the IIP treatment effects, instrumenting the definition of a specific timeline for saving and making payments with IIP treatment assignment.[28] Table 6 shows that the IIP treatment has a negative and statistically significant effect on the likelihood of experiencing at least one inactive day over the month (column 3) and on the share of inactive days in a month (Panel A, column 4; all $p < 0.05$). This effect disappears by six months from the activation of the contract,[29] however, and is not observed on any other payment outcome, with the exception of a positive effect on the frequency of payments four-to-six months since the contract start.[30]

The LATE analysis also confirms the treatment effects on contract cancellation. Customers assigned to the flexible payment schedule, who actually make savings and payment plans prompted by the IIP treatment, are almost 7 percentage points less likely to have their contract cancelled in the first three months (Panel A, column 6, $p < 0.05$), an effect whose magnitude and statistical significance persists over the first six and twelve months since the contract activation.

6.3 Heterogeneity

Finally, we expected flexibility to benefit less those individuals with greater ability to smooth consumption; and to hurt individuals with lower discipline and ability to stick to a regular repayment schedule.

[28] This analysis was not pre-specified.

[29] Moreover, the effect is even stronger if we focus on the first two months of the contract. Results available upon request.

[30] In appendix C we replicate the analysis of the main effects and LATE on the full sample (Table C8). Overall, results hold.

Moreover, we expected planning to be most helpful for these same individuals in combination with flexibility. We thus examine heterogeneous treatment effects on the basis of the index for the ability to smooth consumption, the index for mental constraints and the proxy of time inconsistency constructed from the survey data, using the cross-section and panel datasets. We find little evidence of heterogeneity in the effect of flexibility or planning along any of the dimensions that we consider (Appendix C Tables C9 - C13).

6.4 Discussion

To summarise, our results confirm that flexibility alone is detrimental to payment quality, but that the addition of planning prompts can counterbalance its negative effects in the short term. We also find large short-term effects of combining the IIP treatment with flexibility on reducing the likelihood of contract cancellation, which translate in persistent impacts in the medium to long term. Overall, the combination of flexibility and planning does no worse than the rigid payment schedule across all outcomes: this implies that the same level of inactivity, payment frequencies and contract cancellation can be achieved through a milder nudge, which starts from and respects each individual's preferred payment schedule, rather than encouraging customers to stick to a rigid one.

Two explanations may lie behind the temporal dynamics of our results. First, the short-lived impact of planning on payment behavior is consistent with existing results on the limited duration of the effects of behavioral interventions (Gneezy and List, 2006; Allcott, 2016). Second, selection effects may be responsible for the decreasing treatment effects over time: since individuals with payment problems progressively leave the sample due to contract cancellation, the remaining customers are on average better payers, thus likely to benefit less from any behavioral intervention aimed at supporting payment discipline. Our data does not allow us to test the relative importance of these two explanations. One way to test the relative role of lack of persistence and selection would have required randomly varying the provision of reinforcement of the IIP treatment over time: repeating the treatment would impact repayment if salience were the main issue, but have no impact if selection were mostly responsible for lack of persistence. While we did not run this test, it is an interesting direction for further research.

Non-significant results may also be the outcome of low statistical power. However, our relative MDEs in the pre-specified cross-section models, ranging from 4 to 27% for inactivity, 25-44% for payment frequency, and 19-28% for cancellation, appear in line with the effect sizes found in many nudge interventions. Hummel and Maedche (2019) review 100 behavioural studies and find that nudges have a median relative effect size of 21% and average of 55% (30% if outliers are removed). In the case of studies on implementation intentions (on a limited sample of 3), the median relative effect size is 39%, while the average is 85%. More recently, Della Vigna and Linos (2020) review behavioural intervention trials from academic literature and nudge units and find average MDEs of 33.4 and 8%, respectively. Specific trials on reminders and planning prompts have an average relative MDE of 9.3% within nudge units trials and 20% within academic papers. Hence, while we cannot rule out the presence of low power for some outcomes, namely frequency of payment, for other key dimensions, such as inactivity and cancellation, this does not seem to be the case.

Next, we may want to ask whether customers see the value of planning prompts. To address this question, we conducted a phone survey with about 37% of the sample of customers between March and April 2019. The phone survey targeted currently active customers as of March 2019: out of 385 eligible clients, we conducted 271 interviews, for an overall response rate of 70%. We analyze the determinants of phone survey participation in column 1 of Table 7. We find that, apart from a negative impact of the flexibility treatment ($p < 0.1$), treatment assignment or baseline characteristics do not seem to systematically predict participation.[31] Hence, the sample participating to the phone survey is mostly representative of the overall study sample remaining at that time.

The phone survey asked treated respondents about their experience of the IIP intervention and if they wanted to hold another similar discussion on future payments with EE. Overall, a vast majority of the respondents (94%) would like to make payments to EE on time, primarily in order to avoid disconnection. However, when asked specifically about participating in IIP discussions to help make payments on time, only 16% of the sample that had participated in the IIP discussions earlier agreed to being contacted by EE for a similar discussion regarding future payments. Among respondents who did not participate in the IIP intervention earlier, the demand for IIP was lower, at 12%, though this difference is not statistically significant ($p = 0.425$). The main reason for refusing the IIP discussion was lack of need, cited by 70% of refusers. These take-up figures are in line with demand for novel commitment devices (Karlan et al., 2014).[32]

In Table 7, columns 3 and 4, we analyse the correlates of IIP take-up during the phone survey. We find that customers assigned to the flexible treatment without planning are significantly less likely to take-up

[31] The only variable significantly predicting survey participation is perpetual vs rental contract. Coefficients on covariates are not shown but are available on request.

[32] The proportion of respondents who value paying on time and those who experienced difficulties in making payments on time do not differ by baseline characteristics. Results are available upon request.

$(p < 0.1)$, while no other treatment combination is significantly correlated with take-up. Customers' actual or perceived experience of repayment problems is positively and significantly correlated with demand for IIP. In particular, having experienced at least one inactive day before the survey increases the likelihood of take-up by 14.1 percentage points $(p < 0.01)$, while reporting to have experienced difficulties in paying on time induces a 8.1 percentage points increase in take-up $(p < 0.01)$. Reassuringly, therefore, those individuals who are expected to benefit the most from planning prompts are those with higher demand for them.

7 Conclusion

We study the impact of introducing flexibility in payment schedules on the repayment performance of clients of a for-profit organization. While flexibility should help poor households pay their bill in the presence of volatile income flows, introducing flexibility may hurt repayment quality if rigidity provides discipline. We test empirically which effect prevails. In addition, we combine flexibility with soft, behavioral interventions to improve payment performance. Since individuals in our sample display an intention to meet their payment obligations, but at the same time appear unable to follow through, we adopt planning prompts to mitigate the potentially negative effect of flexibility on payment quality and reduce this intention-behavior gap. We are interested in testing whether adding a repayment nudge to flexibility leads to similar repayment performance as a standard rigid payment schedule.

Our sample consists of individuals living in off-grid areas of rural Sindh, Pakistan who have rented a pay-as-you-go solar system which is remotely disconnected when credit expires. We find that, while the two treatments in isolation have no or even negative effects on repayment quality, their combination performs just as well as the rigid payment schedule in terms of days, when the system is inactive due to insufficient payments, and of the likelihood that customers cancel their contracts. While the effect of planning on inactivity fades away over time, treatment effects on contract cancellation are persistent. Given the threat that low quality payments represent for the sustainability of businesses providing off-grid energy solutions in developing countries, these results are of great policy relevance.

Our findings also speak to the broader literature on microfinance, showing the impact of a novel, and broadly applicable, form of flexibility, and evaluating the applicability of planning prompts to the domain of financial discipline. Flexibility has mildly negative effects on payment quality, which can be offset through the addition of planning prompts. Planning is less effective in this setting, characterised by decisions taken over time, than on other simple behaviors, such as appointment taking, and its effect on payment disappear quickly over time. However, our results on contract cancellation, which remain strong and positive over the medium term, suggest that even short-term effects can have longer term implications. Understanding the mechanisms behind these results is an interesting and important area for further research.

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Tables

Table 1: Contract and respondent characteristics, descriptive statistics

	(1) All	(2) Flex	(3) Fix	(4) *p*-value	(5) IIP	(6) No IIP	(7) *p*-value
Panel A: Treatments							
Flexible treatment	0.482				0.476	0.491	0.693
IIP treatment	0.566	0.558	0.573	0.679			
Panel B: Respondent characteristics							
Type of customer: business	0.052	0.057	0.048	0.576	0.058	0.044	0.402
Age	35.545	35.755	35.350	0.458	35.323	35.835	0.351
Can read and write	0.821	0.823	0.820	0.896	0.823	0.820	0.911
Any savings	0.255	0.279	0.233	0.157	0.223	0.297	0.023
Access to credit	0.170	0.165	0.175	0.725	0.170	0.171	0.972
Share of HH members with regular income	0.458	0.465	0.451	0.624	0.454	0.463	0.761
Index for ability to smooth consumption	0.011	0.058	-0.032	0.276	-0.024	0.057	0.333
Index for mental constraints	-0.036	-0.078	0.003	0.285	-0.030	-0.045	0.846
Time inconsistent	0.078	0.085	0.072	0.488	0.068	0.092	0.236
Panel C: contract characteristics							
Average day rate	43.033	42.669	43.373	0.63	43.186	42.834	0.811
Fan installed	0.874	0.869	0.878	0.714	0.879	0.867	0.643
Tv installed	0.098	0.085	0.109	0.291	0.102	0.092	0.647
Light installed	0.985	0.983	0.987	0.672	0.985	0.984	0.890
Mobile charger installed	0.066	0.057	0.074	0.348	0.056	0.079	0.210
Perpetual rental vs rent-to-buy	0.547	0.553	0.541	0.754	0.532	0.566	0.349

Notes: Columns 4 and 7 report the p-value of two-sided t-tests of equality of means across treatment groups. Flexible treatment and contract characteristics are obtained from administrative data. 'Share of HH members with regular income' and, as a result, 'the index for ability to smooth consumption', are missing for one respondent. Respondent characteristics are obtained from the survey.

Table 2: Outcomes, descriptive statistics

	(1) All	(2) Flex	(3) Fix	(4) p-value	(5) IIP	(6) No IIP	(7) p-value
Panel A: Cross-section							
N. observations	728	351	377		412	316	
At least one inactive day over the period	0.962	0.96	0.963	0.83	0.959	0.965	0.641
Inactive days as % of contract duration	0.258	0.272	0.245	0.077	0.259	0.257	0.906
Cancelled, system repossessed	0.56	0.561	0.56	0.947	0.541	0.585	0.23
Average n. of top-ups per month	0.942	0.925	0.958	0.699	1.007	0.857	0.103
Panel B: Panel							
N. observations (12 months)	6343	2984	3359		3625	2718	
At least one inactive day in the month	0.527	0.534	0.521	0.317	0.532	0.521	0.39
Share of inactive days in the month	0.191	0.198	0.185	0.069	0.193	0.188	0.548
N. of top-ups in the month	1.354	1.35	1.358	0.838	1.413	1.275	0.00
Panel C: IIP intensity							
Set payment schedule	0.257	0.282	0.233	0.134	0.454		
Set saving schedule	0.234	0.268	0.202	0.035	0.413		

Notes: Columns 4 and 7 report the p-value of two-sided t-tests of equality of means across treatment groups.

Table 3: Impact of flexibility and IIP on inactivity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Non-overlapping periods		Cumulative effect	
	Cross-section		Months 1 - 3	Months 4 - 6	Months 7 - 12	Months 1 - 6	Months 1 - 12
Panel A: Extensive – At least one inactive day							
Flex	0.004	0.038*	0.025	-0.009	0.034	-0.008	0.003
	(0.015)	(0.020)	(0.034)	(0.048)	(0.056)	(0.034)	(0.036)
IIP	0.001	0.030	-0.007	0.012	0.084*	0.013	0.047
	(0.015)	(0.020)	(0.030)	(0.045)	(0.048)	(0.032)	(0.034)
Flex*IIP		-0.060**	-0.061	0.012	-0.045	-0.044	-0.049
		(0.031)	(0.044)	(0.065)	(0.072)	(0.046)	(0.048)
Fixed no IIP group mean	0.950	0.950	0.351	0.628	0.567	0.478	0.513
P-val of Flex + IIP + Flex*IIP		0.759	0.189	0.747	0.149	0.242	0.970
Panel B: Intensive – Share of inactive days							
Flex	0.023	0.036	0.012	0.008	0.016	0.006	0.009
	(0.016)	(0.024)	(0.017)	(0.034)	(0.036)	(0.021)	(0.023)
IIP	0.002	0.013	0.006	0.025	0.029	0.016	0.024
	(0.015)	(0.021)	(0.015)	(0.028)	(0.031)	(0.019)	(0.020)
Flex*IIP		-0.023	-0.045**	-0.023	-0.029	-0.042	-0.037
		(0.031)	(0.022)	(0.045)	(0.046)	(0.028)	(0.030)
Fixed no IIP group mean	0.239	0.239	0.102	0.231	0.205	0.161	0.178
P-val of Flex + IIP + Flex*IIP		0.248	0.098	0.761	0.634	0.292	0.822
Observations	727	727	2,134	1,720	2,477	3,854	6,331

Notes: Columns 1 and 2 report cross-section OLS estimates. The dependent variables are calculated over the entire period, i.e. at least one inactive day over contract duration and the share of inactive days over contract duration. Columns 3 to 7 report monthly panel estimates for different time horizons: months 1 to 3, months 4 to 6, months 1-6 and months 1-12 since the contract activation, respectively. The dependent variables are calculated over each month, i.e. at least one inactive day in the month and number of inactive days in the month. The reference category in each regression are individuals in the fixed payment schedule and no-IIP group. 'Fixed no IIP group mean' refers to the average outcome over corresponding time period for the reference category. 'P-value of Flex + IPP + Flex*IIP' is the p-value from joint significance of coefficients on Flex, IIP and FLEX*IPP. Specifications include salespersons, enumerators, tehsil and month fixed effects; controls that include individual characteristics: respondent age, literacy, access to credit, savings, the proportion of household members with regular income, if system is installed in business or home; contract characteristics: average daily rate, dummies for whether at least one fan, tv, light and mobile charger is installed, perpetual rental vs rent-to-own contract. Robust standard errors, clustered at the individual level, in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Impact of flexibility and IIP on frequency top ups

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Non-overlapping periods			Cumulative effect	
	Cross-section		Months 1 - 3	Months 4 - 6	Months 7 - 12	Months 1 - 6	Months 1 - 12
Flex	0.022	-0.135	0.005	-0.119	-0.291	-0.045	-0.145
	(0.098)	(0.124)	(0.075)	(0.157)	(0.209)	(0.095)	(0.123)
IIP	0.152*	0.017	-0.033	0.164	0.018	0.060	0.074
	(0.087)	(0.121)	(0.068)	(0.155)	(0.191)	(0.093)	(0.119)
Flex*IIP		0.283	0.122	0.082	0.328	0.092	0.151
		(0.172)	(0.107)	(0.219)	(0.295)	(0.140)	(0.180)
Fixed no IIP group mean	0.964	0.964	1.069	1.258	1.614	1.156	1.337
P-val of Flex + IIP + Flex*IIP		0.279	0.350	0.447	0.820	0.365	0.606
Observations	727	727	2,134	1,720	2,477	3,854	6,331

Notes: Columns 1 and 2 report cross-section OLS estimates. The dependent variable is calculated over the entire period, i.e. average number of tops ups per month over the contract period. Specifications include individual controls listed below, salespersons, enumerators and tehsil fixed effects. ‘Fixed no IIP group mean’ refers to the average outcome over corresponding time period for the reference group. Columns 3 to 7 report monthly panel estimates for different time horizons: months 1 to 3, months 4 to 6, months 1-6 and months 1-12 since the contract activation, respectively. The dependent variable is calculated over each month, i.e. whether the contract was cancelled in that month. The reference group in each regression are individuals in the fixed payment schedule and no-IIP group. ‘Fixed no IIP group mean’ refers to the average outcome over corresponding time period for the reference group. ‘P-value of Flex + IPP + Flex*IIP’ is the p-value from joint significance of coefficients on Flex, IIP and FLEX*IPP. Specifications include salespersons,enumerators, tehsil and month fixed effects. Controls include individual characteristics: respondent age, literacy, access to credit, savings, the proportion of household members with regular income, if system is installed in business or home; contract characteristics: average daily rate, dummies for whether at least one fan, tv, light and mobile charger is installed, perpetual rental vs rent-to-own contract. Robust standard errors clustered at the individual level in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Impact of flexibility and IIP on contract cancellation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Non-overlapping periods		Cumulative effect	
	Cross-section		Months 1 - 3	Months 4 - 6	Months 7 - 12	Months 1 - 6	Months 1 - 12
Flex	-0.013	0.088	0.028**	0.017	0.003	0.022*	0.015
	(0.036)	(0.054)	(0.014)	(0.023)	(0.016)	(0.012)	(0.010)
IIP	-0.039	0.048	0.026**	0.007	0.003	0.018*	0.011
	(0.037)	(0.050)	(0.012)	(0.019)	(0.015)	(0.010)	(0.008)
Flex*IIP		-0.183**	-0.053***	-0.036	-0.032	-0.046***	-0.036***
		(0.072)	(0.019)	(0.030)	(0.021)	(0.016)	(0.013)
Fixed no IIP group mean	0.528	0.528	0.0293	0.077	0.072	0.051	0.060
P-val of Flex + IIP + Flex*IIP		0.389	0.898	0.594	0.083	0.627	0.223
Observations	727	727	2134	1720	2477	3,854	6,331

Notes: Columns 1 and 2 report cross-section OLS estimates. The dependent variable is calculated over the entire period, i.e. if the contract was cancelled. Specifications include individual controls listed below, salespersons, enumerators and tehsil fixed effects. Columns 3 to 7 report monthly panel estimates for different time horizons: months 1 to 3, months 4 to 6, 6 and 12 months since the contract activation, respectively. The dependent variable is calculated over each month, i.e. the number of top-ups in that month. The reference group in each regression are individuals in the fixed payment schedule and no-IIP group. 'Fixed no IIP group mean' refers to the average outcome over corresponding time period for the reference group. 'P-value of Flex + IPP + Flex*IIP' is the p-value from joint significance of coefficients on Flex, IIP and FLEX*IPP. Specifications include salespersons,enumerators, tehsil and month fixed effects. Controls include individual characteristics: respondent age, literacy, access to credit, savings, the proportion of household members with regular income, if system is installed in business or home; contract characteristics: average daily rate, dummies for whether at least one fan, tv, light and mobile charger is installed, perpetual rental vs rent-to-own contract. Robust standard errors clustered at the individual level in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Effectiveness of planning on repayment

	(1) 1st stage	(2) F-stat of 1st stage	(3) At least one inactive day in the month	(4) Share of inactive days in the month	(5) N. of top-ups in the month	(6) Cancelled in the month
Panel A: Months 1 - 3 (N=1,022)						
Set payment schedule	0.467***	181.2	-0.154**	-0.0945**	0.149	-0.0640*
	(0.0347)		(0.0746)	(0.0374)	(0.174)	(0.0332)
Set saving schedule	0.435***	152.6	-0.165**	-0.101**	0.160	-0.0687*
	(0.0352)		(0.0799)	(0.0403)	(0.187)	(0.0356)
Panel B: Months 4 - 6 (N=804)						
Set payment schedule	0.471***	151.9	-0.00837	-0.0213	0.497*	-0.0537
	(0.0382)		(0.1000)	(0.0740)	(0.285)	(0.0496)
Set saving schedule	0.453***	134.3	-0.00871	-0.0222	0.518*	-0.0560
	(0.0391)		(0.104)	(0.0772)	(0.298)	(0.0516)
Panel C: Months 7 - 12 (N=1,146)						
Set payment schedule	0.524***	132.9	-0.0127	-0.0700	0.523	-0.0648**
	(0.0455)		(0.102)	(0.0680)	(0.416)	(0.0314)
Set saving schedule	0.502***	113.3	-0.0133	-0.0731	0.546	-0.0678**
	(0.0472)		(0.107)	(0.0712)	(0.435)	(0.0331)
Panel D: Months 1 - 6 (N=1,826)						
Set payment schedule	0.470***	186	-0.0994	-0.0747	0.293	-0.0608**
	(0.0345)		(0.0735)	(0.0470)	(0.212)	(0.0287)
Set saving schedule	0.444***	158	-0.105	-0.0791	0.310	-0.0643**
	(0.0353)		(0.0778)	(0.0500)	(0.225)	(0.0303)
Panel E: Months 1 - 12 (N=2,972)						
Set payment schedule	0.486***	179.1	-0.0530	-0.0585	0.394	-0.0545***
	(0.0363)		(0.0734)	(0.0471)	(0.263)	(0.0211)
Set saving schedule	0.462***	151.3	-0.0558	-0.0616	0.414	-0.0574**
	(0.0375)		(0.0772)	(0.0497)	(0.278)	(0.0223)

Notes: The table reports LATE estimates of different degrees of effectiveness of the IIP treatment on repayment only for the sample assigned to the flex treatment. Estimations are obtained via IV where "Set payment schedule" and "Set saving schedule" are individually instrumented by the IIP treatment dummy. Each cell of column 1 reports the coefficient attached to IIP treatment in the first stage, estimated in separate regressions. The F-stat of the first stage is reported in column 2. Columns 3 to 6 report the second stage results. Each cell shows the impact of the endogenous regressor on the outcome reported in the column heading, estimated in separate regressions. All specifications include salespersons, enumerators, tehsil and month fixed effects. Controls include individual characteristics: respondent age, literacy, access to credit, savings, the proportion of household members with regular income, if system is installed in business or home; contract characteristics: average daily rate, dummies for whether at least one fan, tv, light and mobile charger is installed, perpetual rental vs rent-to-own contract. Panels A, B, C, D and E report estimates for different time horizons: months 1 - 3, months 4 - 6, months 7 - 12, 6 months and 12 months since contract activation, respectively. Standard errors clustered at the individual level in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Participation in the phone survey and IIP take-up

	(1)	(2)	(3)	(4)
	Participated in phone survey		IIP take-up at phone survey	
Flex	-0.094*	-0.094*	-0.122*	-0.089
	(0.054)	(0.054)	(0.063)	(0.058)
IIP	-0.044	-0.045	0.011	-0.016
	(0.051)	(0.050)	(0.062)	(0.054)
Flex*IIP	0.103	0.096	0.072	0.082
	(0.072)	(0.072)	(0.083)	(0.075)
At least one inactive day		-0.223***	0.141***	
before the phone survey (admin)		(0.070)	(0.042)	
Had difficulties to pay on time				0.811***
(self-reported)				(0.071)
Constant	0.081	0.316*	-0.294	-0.071
	(0.169)	(0.185)	(0.188)	(0.180)
Fixed no IIP group mean	0.350	0.350	0.180	0.180
P-val of Flex+IIP+Flex*IIP=0	0.503	0.408	0.538	0.684
Obs	727	727	270	245

Notes: In columns (1) and (2), 'Participated in phone survey' is an indicator variable for if the respondent participated in the phone survey. In columns (3) and (4), 'IIP take-up at phone survey' is an indicator for if the respondent agreed to take up IIP plan during the phone survey. Each column displays results of OLS estimations. The sample for column 3-4 is restricted to those who participated in the phone survey. The reference group in each regression are individuals in the fixed payment schedule and no-IIP group. 'Fixed no IIP group mean' refers to the average outcome over corresponding time period for the reference group. 'P-value of Flex + IPP + Flex*IIP' is the p-value from joint significance of coefficients on Flex, IIP and FLEX*IPP. All specifications include individual characteristics: respondent age, literacy, access to credit, savings, the proportion of household members with regular income, if system is installed in business or home, index for ability to smooth consumption, mental constraints index and time inconsistent preferences; contract characteristics: average daily rate, dummies for whether at least one fan, tv, light and mobile charger is installed, perpetual rental vs rent-to-own contract. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Appendix

A Treatments scripts

A.1 Script for fixed and flexible repayment frequencies

EE sales field staff proposes a contract to interested applicants and then communicates one of the following payment frequencies, randomised using a random number generator in EE sales software.

Script for the sales person: You have selected the model [*specify model here*] with the rent-to-buy/ perpetual rental option.

- **Fixed**: Your plan costs a daily rate of Rs [*calculated rate*]. You are expected to pay on a monthly basis the amount of Rs *XX*. This means that, for example, if you are connected on February 3rd, you are expected to pay Rs *XX* by March 3rd .
- **Flexible**: Your plan costs a daily rate of Rs [*calculated rate*]. You are expected to pay the total amount of of Rs *XX* every month. However, you can pay in different installments. This means, FOR EXAMPLE, that you can pay *XX*/4 every week or *XX*/2 every two week. In sum, you can top-up your credit as many time as you like, as long as the total monthly credit reaches Rs *XX*.

You have to visit the closest Easypaisa agent in order to make your payment. Easypaisa commission fees for the payment will be covered by EcoEnergy. You will be notified two days before your credit is expiring with an SMS. If you do not provide to top-up your credit timely, your system will be disconnected.

Payment frequency is made salient at two other points of contact with the client: once at instalment, and once when reminders are sent out when credit is about to expire.
A confirmation SMS is sent after the installation as follows:

- **Fixed**: Your plan costs a daily rate of Rs *[calculated rate]*. You are expected to pay on the amount of Rs *XX* every month. You have to visit the closest Easypaisa agent in order to make your payment. Commission fees for the payment will be covered by EcoEnergy
- **Flexible**: Your plan costs a daily rate of Rs *[calculated rate]*. You are expected to pay on the amount of Rs *XX* every month,but you have the option of paying this amount through smaller installments. You can do so by going to the Easypaisa agent as many times as you like every month as long as the total amount paid sums to at least Rs. *XX* in a month. You have to visit the closest Easypaisa agent in order to make your payment. Commission fees for the payment will be covered by EcoEnergy

SMS reminders at the time when credit is about to expire can be customized

- **Fixed**: Your credit will expire in WW days. Please top-up your monthly credit by visiting the closest Easypaisa agent.
- **Flexible**: Your credit will expire in WW days. Please top-up your credit by visiting the closest Easypaisa agent.

A.2 Script for IIP administration

Enumerator: For each question below, try to let the participant speak without interruption.
1. I will now ask you to discuss with me about your contract with EE. Would you agree that the contract requires you to make payments on time, and that you intend to respect the terms of the contract?
2. Did you sign the contract because you thought that it is possible for you to achieve this goal each month?
3. Do you feel committed to achieving this goal?" Answer on a scale 1-10 or 1-5.

Definition of plan and strategy
Enumerator: For the following questions: ask each question separately and wait for an answer before moving on to the next question.
In order to achieve your goal of paying for energy on time you need to have a plan. For this plan to work it has to be as specific and detailed as possible. That is, you need to have a strategy for what to do if something unexpected happens that challenges your plan. Such strategy could be, for example, to agree with your family members that you will sit down together and discuss what to do if something unexpected happens that challenges your plan. Another strategy could be to set aside the money for the energy payment in a safe place.

4A. I will now tell you about obstacles that are commonly mentioned by individuals who are in the same situation as you are, that is, who have to set aside money for timely payments. For each of these obstacles, tell me if it is one that you also face.
1. Setting aside the money needed for the payment
2. Keeping the money set aside for payment safe from others' requests
3. Keeping the money set aside for payment safe from temptation
4. Remembering to make the payment
5. Actually making the payment (going to the bazaar, to the easypaisa agent, etc)

4B. The obstacles can be different from person to person. What other obstacles do you face, that I haven't mentioned? *Enumerator: list the additional obstacles mentioned by the respondent.*

4C. *Enumerator: ask for each obstacle that the person has recognized as relevant*
What works as a good strategy can be very different from person to person, so what can you do to avoid giving up on your goal if you encounter this obstacle?
Enumerator: record the number of the obstacle from tables 4A and 4B in the first column, and the main strategies to overcome it in the second column.

Consolidation of plan on calendar
Enumerator: on the monthly calendar, mark together with the respondents the dates he/she identifies as suitable for setting aside and making payments. According to the payment frequency treatment, the respondent will be able to set one or more dates on the calendar for making payments.

5. Now please think of your sources of income. Given the frequency of your income flow, what would be a good strategy, in terms of timing, for setting aside the money to pay for energy? *Enumerator: mark on calendar the days identified for setting aside money (for instance, once per week, or even every day).*

6. Now please think of the timing of your visits to the bazaar. Given the frequency of your trips to the bazaar where the easypaisa agent is, what would be a good strategy, in terms of timing, for making payments for energy? *Enumerator: mark on calendar the days identified for making payments (not more than once per month in the fixed treatment).*

Enumerator: mark on calendar the days identified for making payments (not more than once per month in the fixed treatment).

Reflection (contrasting)
7. How would it make you feel to achieve this goal?

Goodbye and reinforcement
Great work [name of participant]! You now have determined plans and strategies that will help you achieve your goal of paying for energy on time.
Remind me again, what are you going to do today or over the next week in order to achieve your goal of paying energy on time?

Enumerator: Pause for response and provide support if needed. Record if the respondent was able to report her strategy correctly or not.

Keep the calendar as a reminder of your plan. We hope you will use it to help you achieve your goal. For example, you can put it on the wall as a reminder of your plan. You can also show it to your spouse or parents to engage them in working towards your goal. Please keep it and not dispose of it until the next time we meet (specify number of months), even if you do not use it.

Thank you for your participation today and I hope you have found this time we have spent to be useful!

B Variables construction

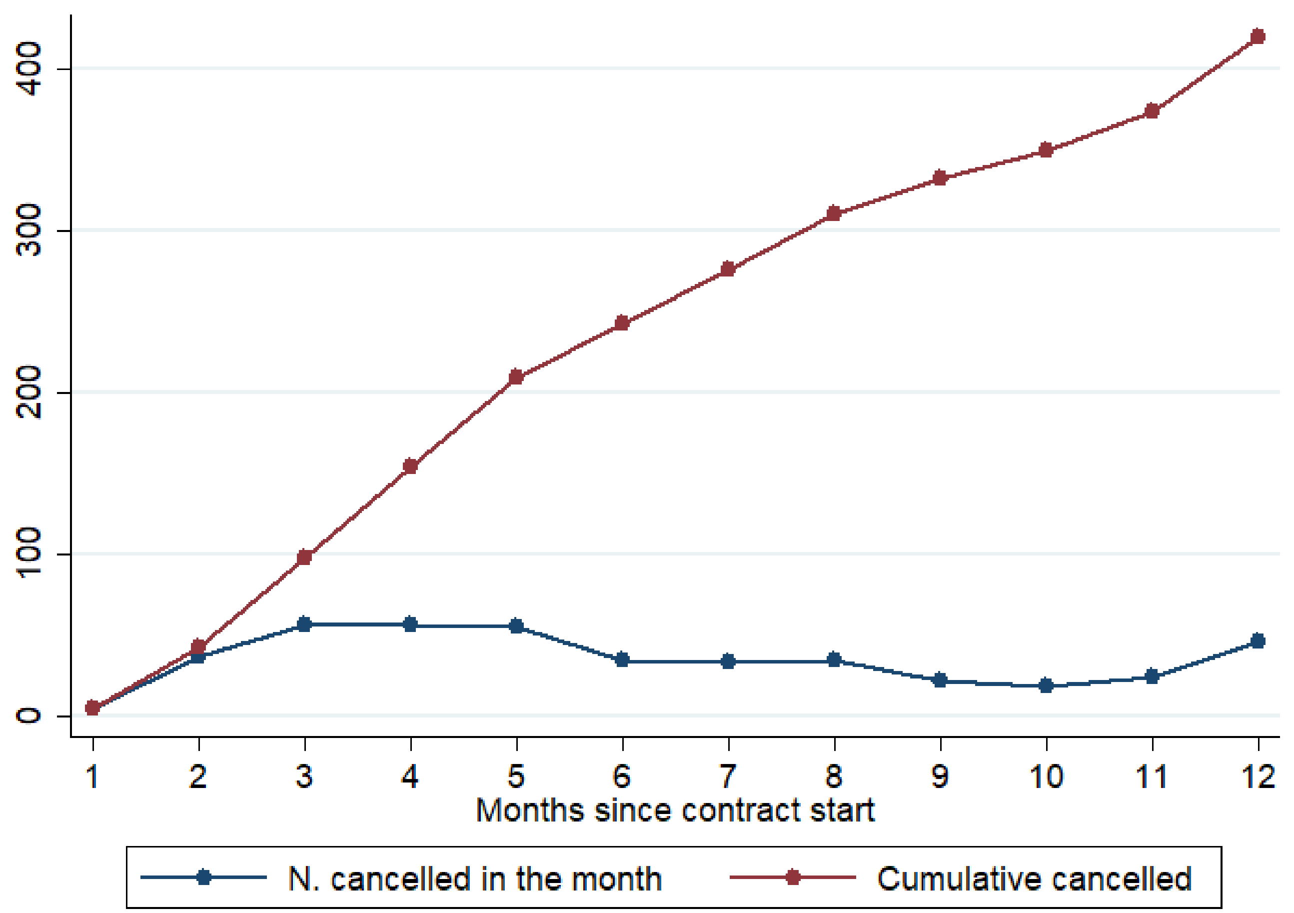
The index for mental constraints is constructed following Anderson (2012)[33] from the following variables:

- **Calculus skill:** Index aggregating answers to three calculus questions, each coded as dummy variable for correct answer. The index is the sum of correct answers. It is then reverse-coded for the aggregation.
- **Memory skill:** Performance index in a memory task consisting in repeating a series of numbers which increase as the task gets more difficult. Each series is coded as a dummy equal to 1 when the individual correctly repeats the series. The index is the sum of correct answers. It is then reverse-coded for the aggregation.
- **Ability to pay on time:** Index given by the mean of answers to self-reported ability to perform all the steps required to pay a bill on time. It is then reverse-coded for the aggregation.
- **Ability to resist temptation:** Index created from the 'Implicit Theory about the Willpower to Resist Temptations scale' by Job et al. (2010). Answers to the questions are coded such that the index is increasing in inability to resist temptation.
- **Self-control:** Index created from the 10 item self-control scale from Tangney et al. (2004). Specifically, the index is constructed by adding up all the points for the checked boxes and dividing by 10. The maximum score on this scale is 5 (extremely self-controlled), and the lowest scale on this scale is 1 (not at all self-controlled). It is then reverse-coded for the aggregation.
- **Locus control:** Index given by the mean of seven items of the locus of control scale (Levenson, 1973). It is then reverse-coded for the aggregation.
- **Grit:** Index constructed from the GRIT Scale (Duckworth et al., 2007). Specifically, the index is constructed by summing 8 items, each scored on a 1 to 5 point scale. Items are coded such that higher score means lower grit.
- **Discipline with previous loans:** Two dummy variables for whether the individual ever failed to pay back a loan or missed at least one installment due in the past.

[33] Standardization is done using the average and standard deviation of the control group, intended as the one with fixed schedule and no IIP.

C Further results

Figure C.1: Number of contracts cancelled in a month and cumulatively since contract start



Note: The figure shows the month wise contract cancellation for the sample of 728 respondents being used in this study. Cumulative cancelled are the total number of clients out of the 728 who have cancelled by that month since the start of their respective contracts. N. cancelled in the month is the number of contracts cancelled in a particular month since the start of the contract. The start of the contract is when the flex and IIP treatments were administered.

Table C1: Contract and respondent characteristics descriptive statistics, by treatment arms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Fixed no IIP	Fixed IIP		Flex IIP		Flex no IIP		F test
	Mean	Coeff	*p*-value	Coeff	*p*-value	Coeff	*p*-value	*p*-value
Contract characteristics								
Average day rate	45.339	-3.43	0.094	-0.743	0.722	0.063	0.021	0.079
Fan installed	0.876	0.004	0.912	0.002	0.96	-0.018	0.637	0.893
TV installed	0.118	-0.016	0.601	-0.016	0.613	-0.053	0.11	0.283
Light installed	0.981	0.009	0.462	-0.002	0.891	0.006	0.677	0.685
Mobile charger installed	0.099	-0.044	0.09	-0.043	0.102	-0.041	0.14	0.054
Perpetual rental vs. rent-to-buy	0.528	0.023	0.658	-0.018	0.738	0.318	0.162	0.531
Respondent characteristics								
Type of customer: business	0.037	0.018	0.431	0.024	0.313	0.014	0.567	0.345
Age	35.571	-0.386	0.614	-0.097	0.901	0.538	0.515	0.978
Can read and write	0.807	0.021	0.595	0.009	0.828	0.025	0.566	0.594
Any savings	0.298	-0.113	0.013	-0.033	0.478	-0.001	0.978	0.208
Access to credit	0.168	0.013	0.743	-0.01	0.812	0.006	0.878	0.923
Share of HH members with regular income	0.433	0.032	0.445	0.01	0.822	0.062	0.169	0.336
Index for ability to smooth consumption	-0.002	-0.052	0.655	0.012	0.918	0.121	0.335	0.785
Index for mental constraints	0.005	-0.005	0.966	-0.069	0.525	-0.102	0.375	0.522
Time inconsistent	0.087	-0.027	0.34	-0.01	0.716	0.01	0.746	0.705
Obs	161	216		196		155		

Notes: Coefficients and p-values are obtained from the regression of the covariate on each treatment indicator and the corresponding test of the null that the coefficient equals zero. In column 8 is the *p*-value for the F-test that the treatments arms are jointly zero. Contract characteristics are obtained from administrative data. 'Share of HH members with regular income' and, as a result, 'the index for ability to smooth consumption', are missing for one respondent. Respondent characteristics are obtained from the survey.

Table C2: Impact of flexibility and IIP on inactivity, robustness check

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Non-overlapping periods		Cumulative effect	
	Cross-section		Months 1 - 3	Months 4 - 6	Months 7 - 12	Months 1 - 6	Months 1 - 12
Panel A: Extensive – At least one inactive day							
Flex	-0.003	0.030	0.050	0.003	0.011	0.023	0.016
	(0.014)	(0.020)	(0.033)	(0.048)	(0.055)	(0.033)	(0.036)
IIP	-0.006	0.022	-0.023	-0.014	0.069	-0.022	0.014
	(0.014)	(0.021)	(0.030)	(0.045)	(0.050)	(0.031)	(0.033)
Flex*IIP		-0.059**	0.014	0.010	-0.050	0.018	-0.007
		(0.029)	(0.043)	(0.064)	(0.072)	(0.044)	(0.047)
Fixed no IIP group mean	0.950	0.950	0.351	0.628	0.567	0.478	0.513
P-val of Flex + IIP + Flex*IIP		0.787	0.182	0.979	0.548	0.549	0.496
Panel B: Intensive – Share of inactive days							
Flex	0.027*	0.037	0.024	0.032	0.019	0.025	0.022
	(0.015)	(0.023)	(0.016)	(0.034)	(0.035)	(0.021)	(0.022)
IIP	0.002	0.011	0.000	-0.000	0.030	-0.001	0.011
	(0.015)	(0.021)	(0.015)	(0.029)	(0.030)	(0.018)	(0.020)
Flex*IIP		-0.019	-0.014	-0.012	-0.023	-0.010	-0.014
		(0.031)	(0.022)	(0.044)	(0.045)	(0.027)	(0.029)
Fixed no IIP group mean	0.239	0.239	0.102	0.231	0.205	0.161	0.178
P-val of Flex + IIP + Flex*IIP		0.176	0.482	0.517	0.423	0.483	0.384
Observations	728	728	2,137	1,723	2,483	3,860	6,343

Notes: Columns 1 and 2 report cross-section OLS estimates. The dependent variables are calculated over the entire period, i.e. at least one inactive day over contract duration and the share of inactive days over contract duration. Columns 3 to 7 report monthly panel estimates for different time horizons: months 1 to 3, months 4 to 6, months 7 to 12, months 1-6 and months 1-12 since the contract activation, respectively. The dependent variables are calculated over each month, i.e. at least one inactive day in the month and number of inactive days in the month. The reference group in each regression are individuals in the fixed payment schedule and no-IIP group. 'Fixed no IIP group mean' refers to the average outcome over corresponding time period for the reference group. 'P-value of Flex + IPP + Flex*IIP' is the p-value from joint significance of coefficients on Flex, IIP and FLEX*IPP. Robust standard errors clustered at the individual level in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table C3: Impact of flexibility and IIP on frequency top ups, robustness check

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Non-overlapping periods		Cumulative effect	
	Cross-section		Months 1 - 3	Months 4 - 6	Months 7 - 12	Months 1 - 6	Months 1 - 12
Flex	-0.032	-0.218*	-0.040	-0.097	-0.216	-0.069	-0.135
	(0.093)	(0.127)	(0.070)	(0.154)	(0.223)	(0.094)	(0.131)
IIP	0.150	-0.009	-0.036	0.167	0.011	0.053	0.036
	(0.091)	(0.127)	(0.069)	(0.163)	(0.207)	(0.099)	(0.132)
Flex*IIP		0.329*	0.135	0.071	0.366	0.110	0.218
		(0.183)	(0.109)	(0.222)	(0.320)	(0.142)	(0.196)
Fixed no IIP group mean	0.964	0.964	1.069	1.258	1.614	1.156	1.337
P-val of Flex + IIP + Flex*IIP		0.501	0.532	0.415	0.536	0.426	0.470
Observations	728	728	2,137	1,723	2,483	3,860	6,343

Notes: Columns 1 and 2 report cross-section OLS estimates. The dependent variable is calculated over the entire period, i.e. average number of top ups per month over the contract period. Columns 3 to 7 report monthly panel estimates for different time horizons: months 1 to 3, months 4 to 6, months 7 to 12, months 1-6 and months 1-12 since the contract activation, respectively. The dependent variable is calculated over each month, i.e. whether the contract was cancelled in that month. The reference group in each regression are individuals in the fixed payment schedule and no-IIP group. 'Fixed no IIP group mean' refers to the average outcome over corresponding time period for the reference group. 'P-value of Flex + IPP + Flex*IIP' is the p-value from joint significance of coefficients on Flex, IIP and FLEX*IPP. Robust standard errors clustered at the individual level in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table C4: Impact of flexibility and IIP on contract cancellation, robustness check

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Non-overlapping periods			Cumulative effect	
	Cross-section		Months 1 - 3	Months 4 - 6	Months 7 - 12	Months 1 - 6	Months 1 - 12
Flex	0.001	0.117**	0.029**	0.035	0.008	0.026***	0.016*
	(0.037)	(0.055)	(0.013)	(0.022)	(0.016)	(0.010)	(0.008)
IIP	-0.044	0.055	0.021*	-0.007	-0.001	0.008	0.004
	(0.037)	(0.052)	(0.011)	(0.018)	(0.014)	(0.008)	(0.007)
Flex*IIP		-0.206***	-0.035*	-0.019	-0.017	-0.022*	-0.018*
		(0.074)	(0.018)	(0.028)	(0.021)	(0.013)	(0.011)
Fixed no IIP group mean	0.528	0.528	0.0293	0.0769	0.0724	0.0403	0.0494
P-val of Flex + IIP + Flex*IIP		0.535	0.166	0.635	0.508	0.159	0.819
Observations	728	728	2,137	1,723	2,483	4,069	6,707

Notes: Columns 1 and 2 report cross-section OLS estimates. The dependent variable is calculated over the entire period, i.e. it the contract was cancelled. Columns 3 to 7 report monthly panel estimates for different time horizons: months 1 to 3, months 4 to 6, months 7 to 12, months 1-6 and months 1-12 since the contract activation, respectively. The dependent variable is calculated over each month, i.e. the number of top-ups in that month. The reference group in each regression are individuals in the fixed payment schedule and no-IIP group. 'Fixed no IIP group mean' refers to the average outcome over corresponding time period for the reference group. 'P-value of Flex + IPP + Flex*IIP' is the p-value from joint significance of coefficients on Flex, IIP and FLEX*IPP. Robust standard errors clustered at the individual level in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table C5: Impact of flexibility and IIP on inactivity, by treatment arms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Non-overlapping periods			Cumulative effect	
	Cross-section		Months 1 - 3	Months 4 - 6	Months 7 - 12	Months 1 - 6	Months 1 - 12
Panel A: Extensive – At least one inactive day							
Flex-no IIP	0.004	0.038*	0.025	-0.009	0.034	-0.008	0.003
	(0.015)	(0.020)	(0.034)	(0.048)	(0.056)	(0.034)	(0.036)
	[0.042]	[0.056]					
Fix-IIP	0.001	0.030	-0.007	0.012	0.084*	0.013	0.047
	(0.015)	(0.020)	(0.030)	(0.045)	(0.048)	(0.032)	(0.034)
	[0.042]	[0.056]					
Flex-IIP		0.008	-0.043	0.015	0.072	-0.040	0.001
		(0.024)	(0.033)	(0.046)	(0.050)	(0.034)	(0.035)
		[0.067]					
Fixed no IIP group mean	0.950	0.950	0.351	0.628	0.567	0.478	0.513
P-val of Flex-IIP		0.759	0.189	0.747	0.149	0.242	0.97
Panel B: Intensive – Share of inactive days							
Flex-no IIP	0.023	0.036	0.012	0.008	0.016	0.006	0.009
	(0.016)	(0.024)	(0.017)	(0.034)	(0.036)	(0.021)	(0.023)
	[0.045]	[0.067]					
Fix-IIP	0.002	0.013	0.006	0.025	0.029	0.016	0.024
	(0.015)	(0.021)	(0.015)	(0.028)	(0.031)	(0.019)	(0.020)
	[0.042]	[0.059]					
Flex-IIP		0.025	-0.026*	0.009	0.016	-0.021	-0.005
		(0.022)	(0.016)	(0.031)	(0.033)	(0.020)	(0.021)
		[0.062]					
Fixed no IIP group mean	0.239	0.239	0.102	0.231	0.205	0.161	0.178
P-val of Flex-IIP		0.248	0.0976	0.761	0.634	0.292	0.822
Observations	727	727	2,134	1,720	2,477	3,854	6,331

Notes: This table displays the marginal effect of each condition with respect to the reference group. Columns 1 and 2 report cross-section OLS estimates. The dependent variables are calculated over the entire period, i.e. at least one inactive day over contract duration and the share of inactive days over contract duration. Columns 3 to 7 report monthly panel estimates for different time horizons: months 1 to 3, months 4 to 6, months 7 to 12, months 1-6 and months 1-12 since the contract activation, respectively. The dependent variables are calculated over each month, i.e. at least one inactive day in the month and number of inactive days in the month. The reference group in each regression are individuals in the fixed payment schedule and no-IIP group. 'Fixed no IIP group mean' refers to the average outcome over corresponding time period for the reference group. 'P-value of Flex + IPP + Flex*IIP' is the p-value from joint significance of coefficients on Flex, IIP and FLEX*IPP. Specifications include salespersons, enumerators, tehsil and month fixed effects. Controls include individual characteristics: respondent age, literacy, access to credit, savings, the proportion of household members with regular income, if system is installed in business or home; contract characteristics: average daily rate, dummies for whether at least one fan, tv, light and mobile charger is installed, perpetual rental vs rent-to-own contract. Standard errors clustered at the individual level in round parentheses; Minimum Detectable Effect sizes (MDEs) in square parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table C6: Impact of flexibility and IIP on frequency top ups, by treatment arms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Non-overlapping periods		Cumulative effect	
	Cross-section		Months 1 - 3	Months 4 - 6	Months 7 - 12	Months 1 - 6	Months 1 - 12
Flex-no IIP	0.022	-0.135	0.005	-0.119	-0.291	-0.045	-0.145
	(0.098)	(0.124)	(0.075)	(0.157)	(0.209)	(0.095)	(0.123)
	[0.274]	[0.347]					
Fix-IIP	0.152*	0.017	-0.033	0.164	0.018	0.060	0.074
	(0.087)	(0.121)	(0.068)	(0.155)	(0.191)	(0.093)	(0.119)
	[0.244]	[0.339]					
Flex-IIP		0.164	0.094	0.127	0.055	0.107	0.080
		(0.152)	(0.100)	(0.167)	(0.243)	(0.118)	(0.156)
		[0.426]					
Fixed no IIP mean group	0.964	0.964	1.069	1.258	1.614	1.156	1.337
P-val of Flex-IIP		0.279	0.350	0.447	0.820	0.365	0.606
Observations	727	727	2,134	1,720	2,477	3,854	6,331

Notes: This table displays the marginal effect of each condition with respect to the reference group. Columns 1 and 2 report cross-section estimates. The dependent variable is calculated over the entire period, i.e. if the contract was cancelled. Columns 3 to 7 report monthly panel estimates for different time horizons: months 1 to 3, months 4 to 6, months 7 to 12, months 1-6 and months 1-12 since the contract activation, respectively. The dependent variable is calculated over each month, i.e. whether the contract was cancelled in that month. The reference group in each regression are individuals in the fixed payment schedule and no-IIP group. 'Fixed no IIP group mean' refers to the average outcome over corresponding time period for the reference group. 'P-value of Flex + IPP + Flex*IIP' is the p-value from joint significance of coefficients on Flex, IIP and FLEX*IPP. Specifications include salespersons, enumerators, tehsil and month fixed effects. Controls include individual characteristics: respondent age, literacy, access to credit, savings, the proportion of household members with regular income, if system is installed in business or home; contract characteristics: average daily rate, dummies for whether at least one fan, tv, light and mobile charger is installed, perpetual rental vs rent-to-own contract. Robust standard errors clustered at the individual level in parentheses; Minimum Detectable Effect sizes (MDEs) in square parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table C7: Impact of flexibility and IIP on contract cancellation, by treatment arms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Non-overlapping periods		Cumulative effect	
	Cross-section		Months 1 - 3	Months 4 - 6	Months 7 - 12	Months 1 - 6	Months 1 - 12
Flex-no IIP	-0.013	0.088	0.028**	0.017	0.003	0.022*	0.015
	(0.036)	(0.054)	(0.014)	(0.023)	(0.016)	(0.012)	(0.010)
	[0.101]	[0.151]					
Fix-IIP	-0.039	0.048	0.026**	0.007	0.003	0.018*	0.011
	(0.037)	(0.050)	(0.012)	(0.019)	(0.015)	(0.010)	(0.008)
	[0.104]	[0.140]					
Flex-IIP		-0.047	0.002	-0.012	-0.026*	-0.006	-0.011
		(0.054)	(0.013)	(0.022)	(0.015)	(0.012)	(0.009)
		[0.151]					
Fixed no IIP group mean	0.528	0.528	0.029	0.077	0.072	0.051	0.060
P-val of Flex-IIP		0.389	0.898	0.594	0.083	0.627	0.223
Observations	727	727	2134	1720	2477	3,854	6,331

Notes: This table displays the marginal effect of each condition with respect to the reference group. Columns 1 and 2 report cross-section estimates. The dependent variable is calculated over the entire period, i.e. average number of tops ups per month over the contract period.Specifications include individual controls listed below, salespersons, enumerators and tehsil fixed effects. Columns 3 to 7 report monthly panel estimates for different time horizons: months 1 to 3, months 4 to 6, months 7 to 12, months 1-6 and months 1-12 since the contract activation, respectively. The dependent variable is calculated over each month, i.e. the number of top-ups in that month. The reference group in each regression are individuals in the fixed payment schedule and no-IIP group. 'Fixed no IIP group mean' refers to the average outcome over corresponding time period for the reference group. 'P-value of Flex + IPP + Flex*IIP' is the p-value from joint significance of coefficients on Flex, IIP and FLEX*IPP. Specifications include salespersons,enumerators, tehsil and month fixed effects. Controls include individual characteristics: respondent age, literacy, access to credit, savings, the proportion of household members with regular income, if system is installed in business or home; contract characteristics: average daily rate, dummies for whether at least one fan, tv, light and mobile charger is installed, perpetual rental vs rent-to-own contract. Robust standard errors clustered at the individual level in parentheses; Minimum Detectable Effect sizes (MDEs) in square parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table C8: Effectiveness of planning on repayment, robustness check

	(1) 1st stage	(2) F-stat of 1st stage	(3) At least one inactive day in the month	(4) Share of inactive days in the month	(5) N. of top-ups in the month	(6) Cancelled in the month
Panel A: Months 1 - 3 (N=1,022)						
Set payment schedule	0.436***	370.7	-0.082*	-0.034	0.055	0.00271
	(0.023)		(0.049)	(0.025)	(0.119)	(0.0216)
Set saving schedule	0.392***	299.8	-0.092*	-0.037	0.061	0.00301
	(0.023)		(0.054)	(0.027)	(0.133)	(0.0240)
Panel B: Months 4 - 6 (N=1,720)						
Set payment schedule	0.442***	307.7	0.038	0.031	0.456*	-0.021
	(0.025)		(0.072)	(0.049)	(0.236)	(0.033)
Set saving schedule	0.398***	247.8	0.043	0.035	0.506*	-0.023
	(0.025)		(0.079)	(0.054)	(0.262)	(0.036)
Panel C: Months 7 - 12 (N=2,477)						
Set payment schedule	0.452***	223.7	0.140*	0.034	0.365	-0.024
	(0.030)		(0.077)	(0.051)	(0.305)	(0.023)
Set saving schedule	0.409***	180.9	0.155*	0.038	0.404	-0.027
	(0.030)		(0.086)	(0.056)	(0.336)	(0.025)
Panel D: Months 1 - 6 (N=3,854)						
Set payment schedule	0.438***	362.7	-0.017	-0.009	0.234	-0.008
	(0.023)		(0.051)	(0.031)	(0.152)	(0.018)
Set saving schedule	0.394***	290.1	-0.019	-0.010	0.260	-0.008
	(0.023)		(0.056)	(0.035)	(0.169)	(0.021)
Panel E: Months 1 - 12 (N=6,331)						
Set payment schedule	0.444***	328.8	0.055	0.015	0.324*	-0.013
	(0.024)		(0.053)	(0.033)	(0.192)	(0.014)
Set saving schedule	0.398***	256.2	0.062	0.016	0.361*	-0.015
	(0.025)		(0.060)	(0.037)	(0.214)	(0.016)

Notes: The table reports LATE estimates of different degrees of effectiveness of the IIP treatment on repayment for the full sample. Estimations are obtained via IV where "Set payment schedule" and "Set saving schedule" are individually instrumented by the IIP treatment dummy. Each cell of column 1 reports the coefficient attached to IIP treatment in the first stage, estimated in separate regressions. The F-stat of the first stage is reported in column 2. Columns 3 to 6 report the second stage results. Each cell shows the impact of the endogenous regressor on the outcome reported in the column heading, estimated in separate regressions. All specifications only include salespersons fixed effects. Panels A, B, C, D and E report estimates for different time horizons: months 1 - 3, months 4 - 6, months 7 - 12, 6 months and 12 months since contract activation, respectively. Standard errors clustered at the individual level in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table C9: Heterogeneous impact of flexibility and IIP on at least one inactive day

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Cross-section		Months 1 - 3		Months 4 - 6		Months 7 - 12	
Panel A: X=Index for ability to smooth consumption								
Flex	0.005	0.004	-0.008	-0.008	0.001	-0.000	0.015	0.012
	(0.015)	(0.015)	(0.023)	(0.023)	(0.033)	(0.034)	(0.037)	(0.037)
IIP	0.001	0.002	-0.036*	-0.036*	0.021	0.022	0.069**	0.072**
	(0.015)	(0.015)	(0.022)	(0.022)	(0.032)	(0.032)	(0.035)	(0.035)
X	0.006	-0.001	0.004	-0.017	-0.085	-0.087	-0.085	-0.091
	(0.029)	(0.030)	(0.036)	(0.036)	(0.059)	(0.058)	(0.058)	(0.060)
Flex*X	-0.021		-0.014		-0.022		-0.044	
	(0.013)		(0.019)		(0.031)		(0.031)	
IIP*X		-0.002		0.020		-0.013		-0.017
		(0.013)		(0.018)		(0.030)		(0.031)
Panel B: X=Index for mental constraints								
Flex	0.004	0.004	-0.009	-0.010	-0.000	0.002	0.015	0.020
	(0.015)	(0.015)	(0.023)	(0.023)	(0.034)	(0.034)	(0.037)	(0.037)
IIP	0.001	0.001	-0.036*	-0.035	0.017	0.015	0.065*	0.062*
	(0.015)	(0.015)	(0.022)	(0.022)	(0.032)	(0.032)	(0.035)	(0.035)
X	-0.002	0.001	-0.017	-0.019	0.017	0.037	0.052*	0.055
	(0.012)	(0.013)	(0.018)	(0.021)	(0.027)	(0.031)	(0.030)	(0.035)
Flex*X	0.003		0.004		-0.003		-0.039	
	(0.014)		(0.020)		(0.031)		(0.033)	
IIP*X		-0.002		0.006		-0.030		-0.033
		(0.014)		(0.022)		(0.033)		(0.035)
Panel C: X=Time inconsistent								
Flex	0.013	0.004	-0.009	-0.008	-0.013	-0.001	-0.005	0.012
	(0.015)	(0.015)	(0.024)	(0.023)	(0.035)	(0.034)	(0.038)	(0.036)
IIP	0.001	0.005	-0.036*	-0.037	0.016	0.021	0.062*	0.074**
	(0.015)	(0.015)	(0.022)	(0.022)	(0.032)	(0.033)	(0.035)	(0.036)
X	0.052***	0.017	-0.023	-0.016	-0.120	-0.018	-0.202**	0.014
	(0.020)	(0.042)	(0.059)	(0.056)	(0.097)	(0.089)	(0.099)	(0.099)
Flex*X	-0.114**		0.023		0.145		0.243*	
	(0.055)		(0.081)		(0.123)		(0.134)	
IIP*X		-0.050		0.010		-0.056		-0.181
		(0.067)		(0.080)		(0.127)		(0.140)
Obs	727	727	2,134	2,134	1,720	1,720	2,477	2,477

Notes: Columns 1 and 2 report cross-section OLS estimates. The dependent variable is calculated over the entire period, i.e. at least one inactive day over contract duration. Columns 3 to 8 report monthly panel estimates for different time horizons: months 1 to 3, months 4 to 6 and months 7 to 12 since contract activation. The dependent variables are calculated over each month, i.e. at least one inactive day in the month and number of inactive days in the month. The reference group in each regression are individuals in the fixed rate and no-IIP group. Specifications include salespersons, enumerators, tehsil and month fixed effects; controls that include individual characteristics: respondent age, literacy, access to credit, savings, the proportion of household members with regular income, if system is installed in business or home; contract characteristics: average daily rate, dummies for whether at least one fan, tv, light and mobile charger is installed, perpetual rental vs rent-to-own contract. Robust standard errors, clustered at the individual level, in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table C10: Heterogeneous impact of flexibility and IIP on share of inactive days

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Cross-section		Months 1 - 3		Months 4 - 6		Months 7 - 12	
Panel A: X=Index for ability to smooth consumption								
Flex	0.023	0.023	-0.012	-0.012	-0.003	-0.004	0.001	-0.000
	(0.016)	(0.016)	(0.011)	(0.011)	(0.023)	(0.023)	(0.024)	(0.024)
IIP	0.003	0.003	-0.014	-0.014	0.017	0.017	0.016	0.018
	(0.016)	(0.016)	(0.011)	(0.011)	(0.022)	(0.022)	(0.024)	(0.024)
X	-0.030	-0.020	-0.008	-0.015	-0.057*	-0.040	-0.013	0.001
	(0.024)	(0.024)	(0.015)	(0.016)	(0.033)	(0.034)	(0.036)	(0.040)
Flex*X	-0.004		-0.013		0.006		-0.012	
	(0.014)		(0.009)		(0.021)		(0.020)	
IIP*X		-0.016		0.001		-0.020		-0.024
		(0.013)		(0.009)		(0.020)		(0.020)
Panel B: X=Index for mental constraints								
Flex	0.023	0.023	-0.012	-0.012	-0.004	-0.002	-0.003	0.001
	(0.016)	(0.016)	(0.011)	(0.011)	(0.023)	(0.023)	(0.024)	(0.024)
IIP	0.001	0.001	-0.015	-0.015	0.014	0.012	0.016	0.014
	(0.015)	(0.015)	(0.011)	(0.011)	(0.022)	(0.022)	(0.023)	(0.023)
X	-0.000	0.012	-0.009	0.006	0.008	0.021	0.010	0.018
	(0.013)	(0.014)	(0.009)	(0.010)	(0.018)	(0.021)	(0.018)	(0.022)
Flex*X	0.009		0.012		-0.004		-0.024	
	(0.014)		(0.010)		(0.021)		(0.020)	
IIP*X		-0.012		-0.013		-0.021		-0.029
		(0.015)		(0.010)		(0.022)		(0.023)
Panel C: X=Time inconsistent								
Flex	0.019	0.023	-0.014	-0.012	-0.007	-0.004	-0.004	0.002
	(0.016)	(0.016)	(0.011)	(0.011)	(0.024)	(0.023)	(0.025)	(0.024)
IIP	0.001	0.004	-0.015	-0.015	0.014	0.019	0.015	0.018
	(0.015)	(0.016)	(0.011)	(0.011)	(0.022)	(0.022)	(0.023)	(0.024)
X	-0.073*	-0.028	-0.028	-0.016	-0.024	0.033	-0.105*	-0.034
	(0.043)	(0.044)	(0.032)	(0.032)	(0.068)	(0.074)	(0.062)	(0.064)
Flex*X	0.054		0.024		0.035		0.088	
	(0.057)		(0.042)		(0.089)		(0.078)	
IIP*X		-0.031		0.002		-0.076		-0.050
		(0.055)		(0.040)		(0.090)		(0.078)
Obs	727	727	2,134	2,134	1,720	1,720	2,477	2,477

Notes: Columns 1 and 2 report cross-section OLS estimates. The dependent variable is calculated over the entire period, i.e. the share of inactive days over contract duration. Columns 3 to 8 report monthly panel estimates for different time horizons: months 1 to 3, months 4 to 6 and months 7 to 12 since contract activation. The dependent variables are calculated over each month, i.e. at least one inactive day in the month and number of inactive days in the month. The reference group in each regression are individuals in the fixed rate and no-IIP group. Specifications include salespersons, enumerators, tehsil and month fixed effects; controls that include individual characteristics: respondent age, literacy, access to credit, savings, the proportion of household members with regular income, if system is installed in business or home; contract characteristics: average daily rate, dummies for whether at least one fan, tv, light and mobile charger is installed, perpetual rental vs rent-to-own contract. Robust standard errors clustered at the individual level in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table C11: Heterogeneous impact of flexibility and IIP on top-ups

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Cross-secion		Months 1 - 3		Months 4 - 6		Months 7 - 12	
Panel A: X=Index for ability to smooth consumption								
Flex	0.023	0.021	0.071	0.071	-0.074	-0.083	-0.097	-0.110
	(0.098)	(0.098)	(0.064)	(0.064)	(0.117)	(0.117)	(0.173)	(0.174)
IIP	0.156*	0.156*	0.020	0.020	0.193*	0.200*	0.162	0.178
	(0.087)	(0.087)	(0.053)	(0.053)	(0.106)	(0.105)	(0.141)	(0.140)
X	-0.065	0.007	0.090	0.124	0.120	0.201	-0.002	0.047
	(0.125)	(0.130)	(0.097)	(0.102)	(0.149)	(0.159)	(0.221)	(0.222)
Flex*X	-0.063		-0.012		-0.116		-0.164	
	(0.081)		(0.047)		(0.096)		(0.123)	
IIP*X		-0.134		-0.055		-0.196**		-0.150
		(0.082)		(0.042)		(0.091)		(0.120)
Panel B: X=Index for mental constraints								
Flex	0.029	0.030	0.078	0.084	-0.052	-0.052	-0.032	-0.042
	(0.100)	(0.100)	(0.064)	(0.064)	(0.119)	(0.119)	(0.181)	(0.182)
IIP	0.151*	0.151*	0.023	0.018	0.195*	0.192*	0.163	0.167
	(0.087)	(0.087)	(0.053)	(0.053)	(0.106)	(0.105)	(0.140)	(0.140)
X	0.087	0.092	0.082	0.154*	0.055	0.185**	0.140	0.252**
	(0.059)	(0.066)	(0.066)	(0.083)	(0.068)	(0.089)	(0.098)	(0.122)
Flex*X	-0.011		-0.023		0.100		0.179*	
	(0.063)		(0.052)		(0.072)		(0.101)	
IIP*X		-0.016		-0.124*		-0.115		-0.030
		(0.063)		(0.065)		(0.076)		(0.102)
Panel C: X=Time inconsistent								
Flex	0.019	0.024	0.080	0.073	-0.037	-0.069	-0.075	-0.116
	(0.102)	(0.099)	(0.065)	(0.064)	(0.120)	(0.115)	(0.179)	(0.173)
IIP	0.151*	0.149	0.023	0.034	0.202*	0.255**	0.169	0.164
	(0.087)	(0.092)	(0.053)	(0.054)	(0.105)	(0.109)	(0.140)	(0.146)
X	-0.149	-0.125	-0.012	0.004	0.236	0.360	0.604	0.238
	(0.265)	(0.245)	(0.169)	(0.167)	(0.408)	(0.401)	(0.463)	(0.451)
Flex*X	0.068		-0.101		-0.487		-0.620	
	(0.327)		(0.205)		(0.480)		(0.582)	
IIP*X		0.023		-0.137		-0.725		0.074
		(0.309)		(0.193)		(0.455)		(0.567)
Obs	727	727	2,134	2,134	1,720	1,720	2,477	2,477

Notes: Columns 1 and 2 report cross-section OLS estimates. The dependent variable is calculated over the entire period, i.e. average number of tops ups per month over the contract period. Specifications include individual controls listed below, salespersons, enumerators and tehsil fixed effects. Columns 3 to 5 report monthly panel estimates for different time horizons: months 1 to 3, months 4 to 6 and months 7 to 12 since contract activation. The dependent variable is calculated over each month, i.e. whether the contract was cancelled in that month. The reference group in each regression are individuals in the fixed rate and no-IIP group. Specifications include salespersons,enumerators, tehsil and month fixed effects. Controls include individual characteristics: respondent age, literacy, access to credit, savings, the proportion of household members with regular income, if system is installed in business or home; contract characteristics: average daily rate, dummies for whether at least one fan, tv, light and mobile charger is installed, perpetual rental vs rent-to-own contract. Robust standard errors clustered at the individual level in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table C12: Heterogeneous impact of flexibility and IIP on cancellation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Cross-secion		Months 1 - 3		Months 4 - 6		Months 7 - 12	
Panel A: X=Index for ability to smooth consumption								
Flex	-0.013	-0.013	-0.000	-0.000	-0.001	-0.001	-0.016	-0.016
	(0.036)	(0.036)	(0.010)	(0.010)	(0.016)	(0.016)	(0.011)	(0.011)
IIP	-0.040	-0.040	-0.000	-0.000	-0.008	-0.008	-0.012	-0.012
	(0.037)	(0.037)	(0.010)	(0.010)	(0.015)	(0.015)	(0.011)	(0.011)
X	0.022	0.018	0.032*	0.025	-0.016	-0.028	0.015	0.028
	(0.063)	(0.063)	(0.018)	(0.018)	(0.024)	(0.026)	(0.022)	(0.024)
Flex*X	0.001		-0.010		-0.013		0.010	
	(0.034)		(0.008)		(0.013)		(0.009)	
IIP*X		0.006		0.004		0.008		-0.010
		(0.033)		(0.008)		(0.013)		(0.009)
Panel B: X=Index for mental constraints								
Flex	-0.012	-0.013	0.000	-0.000	0.001	-0.000	-0.018	-0.018
	(0.036)	(0.036)	(0.010)	(0.010)	(0.017)	(0.017)	(0.011)	(0.011)
IIP	-0.040	-0.041	0.001	0.001	-0.010	-0.010	-0.011	-0.012
	(0.037)	(0.037)	(0.010)	(0.010)	(0.015)	(0.015)	(0.011)	(0.011)
X	-0.041	0.026	-0.004	0.004	-0.001	0.015	-0.016	-0.006
	(0.031)	(0.034)	(0.008)	(0.010)	(0.013)	(0.016)	(0.010)	(0.010)
Flex*X	0.065*		0.010		0.023		0.006	
	(0.036)		(0.009)		(0.015)		(0.010)	
IIP*X		-0.052		-0.005		-0.006		-0.009
		(0.037)		(0.010)		(0.015)		(0.010)
Panel C: X=Time inconsistent								
Flex	-0.005	-0.014	-0.000	-0.001	-0.003	-0.003	-0.013	-0.014
	(0.038)	(0.036)	(0.010)	(0.010)	(0.017)	(0.016)	(0.011)	(0.011)
IIP	-0.039	-0.030	0.001	0.004	-0.009	-0.015	-0.011	-0.007
	(0.037)	(0.038)	(0.010)	(0.010)	(0.015)	(0.015)	(0.010)	(0.011)
X	0.114	0.105	0.026	0.037	0.027	-0.014	0.010	0.026
	(0.102)	(0.094)	(0.028)	(0.029)	(0.035)	(0.035)	(0.030)	(0.028)
Flex*X	-0.121		-0.003		0.010		-0.022	
	(0.134)		(0.037)		(0.054)		(0.037)	
IIP*X		-0.109		-0.026		0.089		-0.058*
		(0.135)		(0.038)		(0.055)		(0.034)
Obs	727	727	2,134	2,134	1,720	1,720	2,477	2,477

Notes: Columns 1 and 2 report cross-section OLS estimates. The dependent variable is calculated over the entire period, i.e. if the contract was cancelled. Specifications include individual controls listed below, salespersons, enumerators and tehsil fixed effects. Robust standard errors in parenthesis.Columns 3 to 8 report monthly panel estimates for different time horizons: months 1 to 3, months 4 to 6 and months 7 to 12 since contract activation. The dependent variable is calculated over each month, i.e. the number of top-ups in that month. The reference group in each regression are individuals in the fixed rate and no-IIP group. Specifications include salespersons,enumerators, tehsil and month fixed effects. Controls include individual characteristics: respondent age, literacy, access to credit, savings, the proportion of household members with regular income, if system is installed in business or home; contract characteristics: average daily rate, dummies for whether at least one fan, tv, light and mobile charger is installed, perpetual rental vs rent-to-own contract. Robust standard errors clustered at the individual level in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table C13: Heterogeneous impacts of flexibility and IIP on repayment (triple interaction)

	(1)	(2)	(3)	(4)
	Cross-secion	Months 1 - 3	Months 4 - 6	Months 7 - 12
Panel A: Extensive – At least one inactive day				
Flex*IIP*X1	0.006	0.037	0.029	-0.018
	(0.024)	(0.037)	(0.059)	(0.063)
Flex*IIP*X2	0.035	-0.038	-0.030	-0.023
	(0.028)	(0.043)	(0.065)	(0.073)
Flex*IIP*X3	-0.038	0.161	-0.040	0.093
	(0.119)	(0.159)	(0.251)	(0.263)
Panel B: Intensive – Share of inactive days				
Flex*IIP*X1	0.004	0.025	-0.038	-0.053
	(0.027)	(0.018)	(0.040)	(0.039)
Flex*IIP*X2	-0.033	-0.009	-0.050	-0.027
	(0.030)	(0.021)	(0.044)	(0.046)
Flex*IIP*X3	0.070	0.079	0.074	0.091
	(0.110)	(0.080)	(0.175)	(0.150)
Panel C: Top-ups				
Flex*IIP*X1	0.196	0.083	0.432**	0.436*
	(0.165)	(0.094)	(0.199)	(0.248)
Flex*IIP*X2	0.135	0.065	0.056	0.206
	(0.132)	(0.118)	(0.163)	(0.224)
Flex*IIP*X3	0.463	0.292	0.597	1.248
	(0.622)	(0.387)	(0.792)	(1.017)
Panel C: Cancellation				
Flex*IIP*X1	0.020	0.023	0.006	0.002
	(0.067)	(0.016)	(0.026)	(0.017)
Flex*IIP*X2	-0.006	-0.040**	-0.001	-0.006
	(0.073)	(0.020)	(0.031)	(0.021)
Flex*IIP*X3	0.107	-0.050	0.006	0.036
	(0.266)	(0.076)	(0.110)	(0.068)
Obs	727	2,134	1,720	2,477

Notes: X1=Index for ability to smooth consumption, X2==Index for mental constraints, X3=Time inconsistent. Each cell shows coefficient from separate regressions on the triple interaction term indicated in each row. Columns 1 reports cross-section OLS estimates. Columns 2 to 4 report monthly panel estimates for different time horizons: months 1- 3, months 4 - 7, and months 7 - 12 since the contract activation, respectively. The dependent variables are calculated over the entire period. Specifications include salespersons, enumerators, tehsil and month fixed effects. Controls include individual characteristics: respondent age, literacy, access to credit, savings, the proportion of household members with regular income, if system is installed in business or home; contract characteristics: average daily rate, dummies for whether at least one fan, tv, light and mobile charger is installed, perpetual rental vs rent-to-own contract. Robust standard errors clustered at the individual level in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

D Additional analysis specified in the PAP

We provide here results for analysis specified in the pre-analysis plan but not reported in the main text and appendix.

- What is the heterogeneous effect of the flexibility treatment with the distance from *bazar*, as a proxy for transaction costs? We provide results that both above/below median distance and continuous distance do not matter (Table D1).

- What is the impact of actual payment frequency, as predicted by our random treatments, on the outcomes of interest? In order to test this, we run LATE analysis. However, we do not have a sufficiently strong first stage. The F-stat is usually around 2 which is below the rule-of-thumb value of 8 (D2). Results are similar if we use panel specifications (not reported but available upon request).

- The main results are robust to using post-double selection LASSO in line with Belloni et al. (2014a,b) (Tables D3 - D5).

- We do not find any significant impact of the treatments on an outcome variable defined as the number of inactivity cycles over the contract period (Table D6).

Table D1: Heterogeneous impacts of flexibility and IIP on repayment along distance from the bazar, cross-section analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	At least one inactive day over the period		Inactive days as a share of contract duration		Cancelled, system repossesed		Avg n. of top-ups per month	
Panel A: X=Distance from bazar, Km								
Flex	0.033	0.004	0.015	0.028*	0.004	0.016	0.122	-0.039
	(0.025)	(0.015)	(0.024)	(0.015)	(0.056)	(0.037)	(0.154)	(0.098)
IIP	-0.003	0.006	0.003	0.013	-0.035	0.002	0.140	0.109
	(0.015)	(0.024)	(0.016)	(0.024)	(0.038)	(0.057)	(0.091)	(0.135)
X	0.002	0.000	-0.002	0.001	-0.007	-0.002	0.021	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.006)	(0.013)	(0.009)
Flex*X	-0.005		0.002		0.002		-0.026	
	(0.003)		(0.003)		(0.007)		(0.016)	
IIP*X		-0.001		-0.002		-0.006		0.006
		(0.003)		(0.003)		(0.007)		(0.013)
Panel B: X=Above median distance from bazar								
Flex	0.018	0.004	0.029	0.026*	0.023	0.012	-0.038	-0.037
	(0.020)	(0.015)	(0.022)	(0.015)	(0.051)	(0.038)	(0.134)	(0.098)
IIP	-0.004	-0.001	0.002	0.026	-0.036	0.019	0.142	0.114
	(0.014)	(0.020)	(0.016)	(0.022)	(0.038)	(0.051)	(0.092)	(0.117)
X	0.022	0.010	0.011	0.039	0.004	0.065	0.089	0.053
	(0.022)	(0.024)	(0.021)	(0.024)	(0.055)	(0.059)	(0.145)	(0.139)
Flex*X	-0.030		-0.003		-0.014		-0.004	
	(0.028)		(0.031)		(0.076)		(0.190)	
IIP*X		-0.005		-0.052*		-0.122		0.062
		(0.029)		(0.031)		(0.076)		(0.169)
Observations	727	727	727	727	727	727	727	727

Notes: All specifications are OLS estimates and include controls, salesperson, enumerators and tehsils fixed effects. Controls include individual characteristics: respondent age, literacy, access to credit, savings, the proportion of household members with regular income, if system is installed in business or home; contract characteristics: average daily rate, dummies for whether at least one fan, tv, light and mobile charger is installed, perpetual rental vs rent-to-own contract. The reference group in each regression are individuals in the fixed rate and no-IIP group. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table D2: Impact of actual frequency of payments on repayment performance, LATE in cross-section

	(1) First stage	(2) At least one inactive day over the period	(3) Inactive days as a share of contract duration	(4) Cancelled, system repossesed
Avg n. of top-ups per month		-0.092	-0.024	-0.440***
		(0.082)	(0.071)	(0.171)
Flex	-0.135			
	(0.124)			
IIP	0.017			
	(0.121)			
Flex*IIP	0.283			
	(0.172)			
Observations	727	727	727	727
R-squared	0.152	-0.211	0.175	0.098
F stat first stage	1.736			

Notes: The table reports LATE estimates of the actual frequency of top-ups on repayment. Estimations are obtained via IV where "Avg n. of top-ups per month" is instrumented by the IIP treatment dummy, the flexible schedule treatment dummy and their interaction. Column 1 reports the main coefficients in the first stage. Columns 2 to 4 report the second stage results. Each cell shows the impact of the endogenous regressor on the outcome reported in the column heading. All specifications include salespersons, enumerators, and tehsil fixed effects. Controls include individual characteristics: respondent age, literacy, access to credit, savings, the proportion of household members with regular income, if system is installed in business or home; contract characteristics: average daily rate, dummies for whether at least one fan, tv, light and mobile charger is installed, perpetual rental vs rent-to-own contract. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table D3: Impact of flexibility and IIP on inactivity, lasso controls

	(1)	(2)	(3)	(4)	(5)
	Cross-secion		Months 1 - 3	Months 4 - 6	Months 7 - 12
Panel A: Extensive - At least one inactive day					
Flex	0.004	0.038*	0.025	-0.009	0.034
	(0.014)	(0.020)	(0.033)	(0.047)	(0.055)
IIP	0.001	0.030	-0.007	0.012	0.084*
	(0.014)	(0.019)	(0.029)	(0.044)	(0.047)
Flex*IIP		-0.060**	-0.061	0.012	-0.045
		(0.030)	(0.043)	(0.064)	(0.071)
Fixed no IIP group mean	0.950	0.950	0.351	0.628	0.567
P-val of Flex + IIP + Flex*IIP		0.745	0.181	0.742	0.143
Panel B: Intensive - Share of inactive days					
Flex	0.024	0.037	0.012	0.008	0.016
	(0.015)	(0.023)	(0.016)	(0.033)	(0.035)
IIP	0.002	0.014	0.006	0.025	0.029
	(0.015)	(0.020)	(0.015)	(0.028)	(0.031)
Flex*IIP		-0.023	-0.045**	-0.023	-0.029
		(0.030)	(0.022)	(0.044)	(0.045)
Fixed no IIP group mean	0.239	0.239	0.102	0.231	0.205
P-val of Flex + IIP + Flex*IIP		0.200	0.0919	0.756	0.629
Observations	727	727	2,134	1,720	2,477

Notes: Columns 1 and 2 report cross-section estimates. The dependent variables are calculated over the entire period, i.e. at least one inactive day over contract duration and the share of inactive days over contract duration. Specifications include individual controls listed below, salespersons, enumerators and tehsil fixed effects. Columns 3 to 5 report monthly panel estimates for different time horizons: 1 - 3 months, 4 - 6 months, and 7 - 12 months the contract activation, respectively. The dependent variables are calculated over each month, i.e. at least one inactive day in the month and number of inactive days in the month. The reference group in each regression are individuals in the fixed payment schedule and no-IIP group. 'Fixed no IIP group mean' refers to the average outcome over corresponding time period for the reference group. 'P-value of Flex + IPP + Flex*IIP' is the p-value from joint significance of coefficients on Flex, IIP and FLEX*IPP. Controls are selected using post-double selection LASSO (Belloni et al., 2014a,b). Robust standard errors clustered at the individual level in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table D4: Impact of flexibility and IIP on frequency of top-ups, lasso controls

	(1)	(2)	(3)	(4)	(5)
	Cross-section		Months 1 - 3	Months 4 - 6	Months 7 - 12
Flex	0.031	-0.123	0.005	-0.119	-0.291
	(0.097)	(0.121)	(0.074)	(0.154)	(0.206)
IIP	0.152*	0.019	-0.033	0.164	0.018
	(0.083)	(0.117)	(0.067)	(0.152)	(0.188)
Flex*IIP		0.278*	0.122	0.082	0.328
		(0.167)	(0.105)	(0.214)	(0.291)
Fixed no IIP group mean	0.964	0.964	1.069	1.258	1.614
P-val of Flex + IIP + Flex*IIP		0.241	0.342	0.437	0.817
Observations	727	727	2,134	1,720	2,477

Notes: Columns 1 and 2 report cross-section estimates. The dependent variables are calculated over the entire period, i.e. average number of tops ups per month over the contract period. Columns 3 to 5 report monthly panel estimates for different time horizons: 1 - 3 months, 4 - 6 months, and 7 - 12 months since the contract activation, respectively. In the panel analysis, the dependent variable is for each month i.e. the number of top-ups in that month. The reference group in each regression are individuals in the fixed payment schedule and no-IIP group. 'Fixed no IIP group mean' refers to the average outcome over corresponding time period for the reference group. 'P-value of Flex + IPP + Flex*IIP' is the p-value from joint significance of coefficients on Flex, IIP and FLEX*IPP. Controls are selected using post-double selection LASSO (Belloni et al., 2014a,b). Robust standard errors clustered at the individual level in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table D5: Impact of flexibility and IIP on contract cancellation, lasso controls

	(1)	(2)	(3)	(4)	(5)
	Cross section		Months 1 - 3	Months 4 - 6	Months 7 - 12
Flex	-0.015	0.087*	0.028**	0.017	0.003
	(0.035)	(0.052)	(0.014)	(0.023)	(0.016)
IIP	-0.039	0.048	0.026**	0.007	0.003
	(0.036)	(0.048)	(0.012)	(0.018)	(0.014)
Flex*IIP		-0.183***	-0.053***	-0.036	-0.032
		(0.070)	(0.018)	(0.029)	(0.020)
Fixed no IIP group mean	0.528	0.528	0.0293	0.0769	0.0724
P-val of Flex + IIP + Flex*IIP		0.360	0.896	0.587	0.0782
Observations	727	727	2134	1720	2477

Notes: Columns 1 and 2 report cross-section estimates. Columns 3 to 5 report monthly panel estimates for different time horizons: 1 - 3 months, 4 - 6 months, and 7 - 12 months since the contract activation, respectively. The dependent variable is an indicator for if contract was cancelled. In the panel analysis, the dependent variable is cumulative i.e. at month 2 it takes a value of 1 if the contract was cancelled any time in the last 2 months, at month 3, if it was cancelled in the last 3 months and so on. The reference group in each regression are individuals in the fixed payment schedule and no-IIP group. 'Fixed no IIP group mean' refers to the average outcome over corresponding time period for the reference group. 'P-value of Flex + IPP + Flex*IIP' is the p-value from joint significance of coefficients on Flex, IIP and FLEX*IPP. Controls are selected using post-double selection LASSO (Belloni et al., 2014a,b). Robust standard errors clustered at the individual level in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table D6: Impact of flexibility and IIP on number of inactivity cycles, cross-section analysis

	(1)	(2)	(3)	(4)
Flex	-0.468	-0.877	-0.984*	-1.439
	(0.539)	(0.899)	(0.571)	(0.988)
IIP	0.639	0.287	0.256	-0.134
	(0.567)	(0.886)	(0.602)	(0.966)
Flex*IIP		0.735		0.805
		(1.132)		(1.192)
Observations	727	727	728	728
Fixed no IIP group mean	7.671	7.671	7.671	7.671
P-val: Flex+IIP+Flex*IIP=0		0.863		0.410

Notes: Columns 1 and 2 include individual controls, salespersons, enumerators and tehsil fixed effects. The reference group in each regression are individuals in the fixed payment schedule and no-IIP group. 'Fixed no IIP group mean' refers to the average outcome over corresponding time period for the reference group. 'P-value of Flex + IPP + Flex*IIP' is the p-value from joint significance of coefficients on Flex, IIP and FLEX*IPP. Controls include individual characteristics: respondent age, literacy, access to credit, savings, the proportion of household members with regular income, if system is installed in business or home; contract characteristics: average daily rate, dummies for whether at least one fan, tv, light and mobile charger is installed, perpetual rental vs rent-to-own contract. Columns 3 and 4 include no fixed effects and controls. Standard errors clustered at the individual level in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

5 Pre-Analysis Plan

Fieldwork locations: Pakistan
Fieldwork dates: March 2017 to December 2017
Date of Pre-Analysis Plan: October 18, 2017

1 Introduction

This study specifically involves a set of products that are relevant to the needs of the poor in rural-off grid areas. These solar products are comparable in cost to what local villagers currently spend on their lighting needs and allow access to lighting, fans, chargers and TV. The system is suitable to serve off-grid areas, as well as on-grid areas as a backup option. This document outlines our experiment and our plan of analyzing the data.

We collaborate with EcoEnergy (EE), a for-profit company supplying sustainable and efficient solar energy solutions (e.g. lights, fans, mobile chargers, TV) to small businesses and households in rural Pakistan, to evaluate an innovative market solution. The product relieves credit constraints to adoption and has strong enforcement features: customers access energy through a pay-as-you-go monthly scheme and are disconnected when their credit expires. Since there is at the moment no financial penalty for late payments, these represent a pure loss for EE. Therefore, timely and quality repayments are crucial for business sustainability. The solar system can be customized to match consumer needs and allows the monthly fee, which can range from USD 8 to 30, to match what they may be currently spending on energy alternatives. The experiment will run in Southern Sindh, Pakistan from March to December, 2017. At the time of writing this pre-analysis, we had access to administrative client data and baseline interviews of 350 clients. We have run an initial check for missing values and data entry errors but have not run substantive analysis on this data.

The research provides contributions both research and policy-wise. First, we investigate key determinants of the sustainability of the business model and of product take-up, by looking at the trade-off between discipline and flexibility in repayment schedule, which is a debated issue in the microfinance literature (see Labie et al., 2016 for a review). Second, we push the frontier of the behavioural and microfinance literatures, looking at individual constraints to repayment. The experimental design tests implementation intentions, that have been found to be effective soft ways to increase the salience of actions towards goals in other settings (Milkman et al., 2011, 2013; Nickerson and Rogers, 2010). Our study is the first to test

this behavioural tool in the setting of product repayment, and could contribute not only to the issue of ensuring financial sustainability of off-grid solar solutions, but also to the wider debate on flexibility in microfinance, by providing cheap and scalable solutions to ensure quality repayments.
We intend to submit this Pre-Analysis Plan to the AEA RCT Registry.

2 Experimental design

EE conducts product demonstrations at the village or bazar level. Interested individuals and businesses are met individually and applicants that fulfill the eligibility criteria are then offered the product.
The experimental design varies the terms of the product offered to treatment group clients along two dimensions: the flexibility of the repayment schedule, and the presence of tools to reduce inattention and commitment problems in repayment.

- **Flexibility of payment.** In order to compare the effect of flexibility in the monthly instalment payment, we compare two types of contracts:
  - A fixed contract, close to EE's existing one under which clients will be required to make their entire payments on a monthly basis.
  - A flexible contract, under which clients can decide when and at what frequency within each month they want to pay the instalment. Clients in this group will essentially be free to plan how they want to make payments within each month: at take-up, we will inform them of the daily rate and give examples of payments at different frequencies (e.g., weekly, bi-weekly, monthly, bi-monthly).
- **Implementation Intention Plan (IIP).** The specific screening protocol used by EE makes credit constraints an unlikely explanation for late or non-repayment. We thus focus on inattention and lack of salience as main factors behind default in this setting. To test their role, and assess the effectiveness of cheap and scalable solutions to contrast them, the proposed design randomises the offer of a planning tool to clients based on implementation plans. Drawing from literature in psychology on the use of implementation plans (Gollwitzer and Sheeran, 2006), we ask customers to formulate a plan for his next payments and circle the payment dates on a calendar, delivered by the enumerator, which can then be displayed at his work place or house. This process should help the subject anticipate possible issues in repayment and the strategies to overcome them.

The level of randomization for both treatments is at the individual level, which results in a 2x2 factorial design. A random generator number leading to either one or the other contract version has been incorporated in the software used by the salespersons to register new customers. The implementation intention

plan intervention is delivered by the enumerator at the time of survey administration, some days after the contract is signed. The treatment is randomised by the research team via the survey software.
The study sample is expected to be formed by about 650 individuals who signed a contract with EE and installed a solar system. Customers are categorized as small business owners or households, depending on the place where the system is installed. All surveys are administered via tablets using SurveyCTO.

3 Research questions and identification strategy

The project aims to provide empirical evidence aimed at testing the following research questions:

- **RQ1:** *What is the average effect of flexibility on repayment performance?*

  There is not a clear prediction on the expected effect of a flexible contract on the quality of payment. We will estimate:

  $$y_i = \alpha + \beta_1 Flex_i + X\gamma + \varepsilon_i \tag{8}$$

  where β_1 is the effect of being assigned to the flexible contract with respect to a fixed one. One has to notice that the decision over the actual frequency of payment represents an endogenous decision, therefore 1 should be considered as ITT, i.e. the effect of the possibility to choose the schedule of payments, not of a particular frequency per se.

- **RQ2:** *What are the sources of heterogeneity of the effects of flexibility?*

  Allowing for flexibility of payments reduces poor quality payments for individuals for whom consumption smoothing is harder (seasonal income, irregular income sources, low assets); and for sophisticates; but worsens repayment outcomes for individuals who face self-control or commitment issues. We will investigate these predictions by estimating:

  $$y_i = \alpha + \beta_1 Flex_i + \beta_2 Flex_i \times H_i + X\gamma + \varepsilon_i \tag{9}$$

  where the vector H contains variables which are proxy for the ability to smooth consumption, for sophistication and for mental constraints. They are further detailed in the next session. We expect β_2 to be negative when interacted with the ability to smooth consumption and mental constraints; and positive when interacted with sophistication. We expect that effects may vary along the distance from the bazar where payments can be made (as a proxy for transaction costs), since the literature shows how even small practical barriers can have large effects on behavior when commitment problems are at work. We explore this heterogeneity by running 2 on the subsample of people living above and below the median distance from the bazar.

- **RQ3:** *What is the average effect of the IIP intervention on repayment performance?*

  On average the IIP intervention, if sufficiently effective and relevant for the target population, is expected to improve the quality of repayments. We will estimate:

$$y_i = \alpha + \beta_1 IIP_i + X\gamma + \varepsilon_i \tag{10}$$

- **RQ4:** *What are the sources of heterogeneity of the effects of IIP?*

  The effect of IIP is stronger for subjects who face higher mental constraints (self-control, cognitive capacity, self efficacy); and lower for sophisticates. This will be estimated with the following model:

$$y_i = \alpha + \beta_1 IIP_i + \beta_2 IIP_i \times H_i + X\gamma + \varepsilon_i \tag{11}$$

  The effect of IIP is higher for individuals who are assigned to the flexibility contract, because the latter represent a simple way to operationalize one's intentions to pay in a way closer to their needs. We then estimate:

$$y_i = \alpha + \beta_1 Flex_i + \beta_2 IIP_i + \beta_3 IIP_i \times Flex_i + X\gamma + \varepsilon_i \tag{12}$$

  and we expect β_3 to be positive and significant.

- **RQ5:** *Are IIPs effective in mitigating the negative effects of the flexible payment schedule on people with higher mental constraints?*

  We estimate:

$$y_i = \alpha + (\beta_1 Flex_i + \beta_2 IIP_i + \beta_3 IIP_i \times Flex_i) \times (1 + \mu H_i) + X\gamma + \varepsilon_i \tag{13}$$

  in RQ2 we hypothesized that flexible contracts would yield negative effects on individuals with higher mental constraints. By introducing IIP, we argue that such negative effect could be mitigated. We therefore expect that the coefficient of the triple interaction ($\beta_3 \times \mu$ in equation 6) is non-negative.

- **RQ6:** *What are the determinants of repayment frequency? What is the effect of the actual repayment schedule on repayment performance?*

  We explore the determinants of repayment frequency by running 6 on the average number of payments in a month over the study period.

  We estimate the effect of the actual repayment schedule using Local Average Treatment Effects (LATE). We will use the contractual feature treatment as an instrument for the actual repayment frequency (equation 7) and we expect a positive relationship between the flexible treatment and higher repayment frequencies (first step in equation 8). We estimate:

$$y_i = \alpha_1 + \beta_1 Freq_i + X\gamma + \varepsilon_i \tag{14}$$

$$Freq_i = \alpha_2 + \beta_2 Flex_i + X\gamma + \epsilon_i \tag{15}$$

- **RQ7:** *Are there differential treatment effects for customers who installed the system for their household vs for their business activity?*

  The research question is addressed by running the previous analysis on the different sub-samples of customer types. However, this will be done only conditional on the presence of sufficient power in the sample of business customers, which are expected to be a smaller share of the overall sample.

- **RQ8:** *Are the repayment contractual features (fix vs flex) affecting customers' dropout?*

  The research question is addressed by estimating regression 1 with dropout over the evaluation period as a dependent variable. We anticipate two types of dropout. The first type pertains to people who change their mind before making any experience of the system. The second type pertains to people who decide to drop out after actually trying the product.

4 Data and variables

Two sources provide data for the analysis. The first is EE administrative records on customers' subscription, type of system installed, all dues, deadlines and flows of payments made by customers. This allows to timely monitor late payments, non-payments and defaults. The second source is surveys. The baseline survey is administered few days after the contract with EE is signed and is conducted by an independent NGO. Baseline data collection takes place between March and November 2017, following EE's commercial expansion in new areas.

4.1 Outcomes

The main outcome of the analysis pertain to the sphere of quality of payments to EE and defaults by customers. For each dimension, we will assess both the extensive and intensive margin. The following family of outcomes will be considered for the time windows between the installation date and the end of the monitoring period, expected by June 2018:

Table 4.1: Outcome variables

Variable	Name; Family	Description	Source	Hypothesis
Y_{i1}	Probability of delayed payments; extensive margin	A dummy variable for whether individual i experienced at least one delayed payment	EE admin data	RQ1-7
Y_{i2}	Probability of switch-off; extensive margi	A dummy variable for whether individual i has been switched-off because of missed payments	EE admin data	RQ1-7
Y_{i3}	Probability of default; extensive margin	A dummy variable for whether individual i is considered as defaulter. Default occurs after a long non-payment period and implies that,the system is pull back	EE admin data	RQ1-7
Y_{i4}	Share of delayed payments; intensive margin	Number of delayed payments episodes over the total number of months of the contract	EE admin data	RQ1-7
Y_{i5}	N. of switch-offs; intensive margin	Number of switching-off episodes over the monitoring period	EE admin data	RQ1-7
Y_{i6}	Share of days of delay; extensive margin	Total number of days of delay in payment over the monitoring period	EE admin data	RQ1-7
Y_{i7}	Actual frequency of payments	The average number of payments in a month over the study period	EE admin data	RQ6
Y_{i8}	Dropout before installation	A dummy variable for whether individual i drops out, before being installed the system	EE admin data	RQ8
Y_{i9}	Dropout after installation	A dummy variable for whether individual i drops out, after being installed the system	EE admin data	RQ8

4.2 Treatments

Table 4.2: Treatment variables

Variable	Name; Family	Description	Source	Hypothesis
$Flex_i$	Flexible repayment schedule	A dummy variable which is equal to one if the individual is assigned a flexible repayment schedule and to 0 for fixed schedule	EE admin data	RQ1-2; RQ5-8
IIP_i	Intention Implementation Plan	A dummy variable which is equal to one if the individual received the IIP treatment and 0 otherwise	Question naire	RQ3-8

4.3 Dimensions of heterogeneity

Table 4.3: Variables for analysis of heterogeneity (1)

Variable	Name; Family	Description	Source	Hypothesis
H_{i1}	Seasonality of income sources	Seasonality of income sources/ ability to smooth consumption is given by an index constructed through PCA, including the following variables. It is calculated on the sample of household customers. i. The share of household active members who earn on an irregular basis. ii. Dummy variables for availability of savings (both formal and informal) and access to credit (at least one,formal credit in the past) iii. Index for assets owned (using PCA)	Q2.5; Q2.6; Q8.9; Q8.15; Q2.9	RQ2
H_{i2}	Cognitive capacity; mental constraints	Index aggregating answers to three calculus questions, each coded as dummy variable for correct answer. The index is the sum of correct answers	Q7.4; Q7.5; Q7.6	RQ 2, 4, 5
H_{i3}	Cognitive capacity; mental constraints	Performance index in a memory task consisting in repeating a series of numbers which increase as the task gets more difficult. Each series is coded as a dummy equal to 1 when the individual correctly repeats the series. The index is the sum of correct answers	Q7.7a - Q7.7g	RQ 2, 4, 5
H_{i4}	Ability to pay bill on time	Index given by the mean of answers to self-reported ability to perform all the steps required to pay a bill on time.	Q7.8.1 - Q7.8.5	RQ 2, 4, 5
H_{i5}	Main constraint to paying bill on time	Variable indicating the behavior corresponding to the lowest mean of answers to the questions on self-reported ability to perform the steps required to pay a bill on time. Specifically, this is a set of dummy variables indicating whether each specific constraint to paying on time is the main one (the one with the lowest mean).	Q7.8.1 - Q7.8.5	RQ 2, 4, 5

Table 4.4: Variables for analysis of heterogeneity (2)

Variable	Name; Family	Description	Source	Hypothesis
H_{i6}	Resist temptation; mental constraints	Index created from the 'Implicit Theory about the Willpower to Resist Temptations scale' by Job et al. (2010). Specifically, the index is constructed by averaging the answers to the 6 questions (items 1,2 and 4 are reverse-coded).	Q7.9	RQ 2, 4, 5
H_{i7}	Self-control; mental constraints	Index created from the 10 item self-control scale from Tangney et al. (2004). Specifically, the index is constructed by adding up all the points for the checked boxes and dividing by 10. The maximum score on this scale is 5 (extremely self-controlled), and the lowest scale on this scale is 1 (not at all self-controlled).	Q7.10	RQ 2, 4, 5
H_{i8}	Locus control; mental constraints	Index given,the mean of seven items of the locus of control scale REF (ranges from 1 to 5).	Q7.11	RQ 2, 4, 5
H_{i9}	Grit; mental constraints	Index constructed from the GRIT Scale (Duckworth et al., 2007). Specifically, the index is constructed by summing 8 items, each scored on a 1 to 5 point scale (items a,b,c,d,e,f,g; b,c,d, and g are reverse-coded). Higher score means lower grit.	Q7.12	RQ 2, 4, 5
H_{i10}	Discipline with previous loans; mental constraints	Two dummy variables for whether the individual ever failed to pay back a loan or missed at least one installment due in the past.	Q8.16-Q8.17	
H_{i11}	General mental constraint index	General index of mental constraints, constructed from variables H_{i2} to H_{i10} by: 1. Reversing individual scales, so that higher values of each scale correspond to higher levels of mental constraints 2. Making an index using Anderson (2012)		RQ 2, 4, 5

Table 4.5: Variables for analysis of heterogeneity (3)

Variable	Name; Family	Description	Source	Hypothesis
H_{i12}	Time inconsistency/ present biased	A dummy variable equal to one when the individual switches to the (higher) future amount later in the short-term frame (tomorrow vs one month), than in the long-term frame (5 vs 6 months)	Q7.2	RQ 2, 4, 5
H_{i13}	Management of financial issues; sophistication	Number of 'All the time' or 'Often' answers to questions 7.15-7.19.	7.13-7.19	RQ 2, 4, 5
H_{i14}	Financial literacy	The sum of correct answers to 10 true-false questions on the consequences of missing installments on loan	8.18	RQ 2, 4, 5
H_{i15}	Customer type	A dummy variable for whether individual i installed the solar in his private house or in the business place	Q0.1	RQ7

5 Analysis

Before running regressions, sample balance tests are conducted on control variables and dimensions of heterogeneity considered in the analysis. First, we will describe whether the variables in the vectors of controls and dimensions of heterogeneity are balanced across the 4 cells in our factorial design by running:

$$X_{i0} = \alpha_1 + \beta_1 Flex_i + \beta_2 IIP_i + \beta_3 IIP_i \times Flex_i + \varepsilon_i \tag{16}$$

$$H_{i0} = \alpha_1 + \beta_1 Flex_i + \beta_2 IIP_i + \beta_3 IIP_i \times Flex_i + \varepsilon_i \tag{17}$$

we will report F-statistics from a joint test of the null hypothesis that $\beta_1 = \beta_2 = \beta_3$.

If, for a given variable, we do not reject H0 at the 90% confidence level, we will conclude that this variable is 'balanced across treatments'. If we do reject at the 90% confidence level for a given variable, we will conclude that this variable is 'unbalanced across treatments'. We will then include that variable as a control, in the robustness section.

As far as regression analysis is concerned, when outcomes are measured with binary variables, linear probability models (LPM) are calculated. Probit and logit models are estimated as a robustness check. When outcomes are measured with continuous variables, tobit models are run. Robust White standard errors are calculated.

In order to test the hypothesis related to the quality of repayment, six variables have been identified. In order to correct for multiple hypothesis testing, sharpened q-values will be calculated, based on two families of outcomes for the intensive and extensive margin, as proposed by Anderson (2012). Similarly, the analysis of heterogeneous effects will present sharpened q-values for the families of dimensions of heterogeneity depicted in the table.

5.1 Robustness checks

(i). Due to random assignment, our estimates of treatment and heterogeneous effects are expected to be unbiased. In order to account for possible imbalance that might occur in small sample, as a robustness check, we will repeat our main estimation first using all regression included in the table of controls, then using 'post-double-selection' with LASSO (Belloni et al., 2014a,b). It is possible that some customers dropout the study sample, as they abandon the service provided by EE. In such case, they would disappear from administrative data. The determinants of dropout will be analyzed, as part of research question h. We will run robustness check by excluding dropouts from the study sample.

(ii). We will estimate equation (1) with enumerator fixed effects and examine the distribution of enumerator fixed effects to see how much the treatment effects vary with people conducting the intervention. Enumerators are not randomly assigned to respondents, so this is not an experimental comparison.

(iii). RQ8 investigates the role of treatments on the probability to dropout before and after the installation of the system. Dropout represents a form of attrition, as the customers leave the sample of analysis. This may affect the analysis of RQ1 to RQ7. We therefore estimate Lee bounds (Lee and Lee, 2009).

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