Nudging Payment Behaviour: Evidence from a Field Experiment on Pay-as-You-Go Off-Grid Electricity*

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Abstract

We conduct a randomized control trial with a Pay-as-you-go (PAYG) solar system provider in Pakistan. In the default, customers are told the amount to pay every month to keep the system active. In a first treatment, customers are assisted in planning this monthly payment. In a second treatment, we disclose that payments can be made flexibly within the month. This disclosure may reduce contract cancellation by helping minimise transaction costs, but may increase contract complexity and reduce discipline. In a third treatment, we combine flexibility with assistance in planning payments. Disclosing flexibility increases contract cancellation relative to the default. Combining flexibility with planning offsets this effect. We find suggestive evidence of stronger treatment effects among users facing high mental constraints and transaction costs. Our results suggest that providers of PAYG systems may face a trade-off between disclosing complex contractual features and customer retention. Planning helps handle the added complexity.

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1 Introduction

The high costs and slow pace of grid expansion mean that developing countries must rely on off-grid solutions for basic electricity access in the short to medium run. Solar home systems dominate this sector, reaching about 20% of the off-grid population in Africa and South Asia (Lightening Global Program, 2020) and representing a market that has been growing steadily over the past decade.[1] Pay-as-you-go (PAYG) has emerged as a dominant business model for home solar systems since the flexibility allows low-income households to set their own payment schedules. Flexibility can help low-income customers tailor payments to irregular cash flows and minimize waste and transaction costs, but the literature suggests varying degrees of effectiveness under different contexts (McIntosh, 2008; Field and Pande, 2008; Labie et al., 2017; Barboni, 2017). This may be because flexibility is complex for customers to understand and can harm payment discipline (Brune et al., 2022). Therefore, from the provider's perspective, encouraging regular payments simplifies the presentation of contractual features and could reduce default.

In this paper, we conduct a Randomized Control Trial (RCT) to test the impact of two nudges on customers' product demand and payment behaviour, using administrative and survey data on 726 customers of a provider of PAYG home solar systems in rural Pakistan.[2] The first treatment arm ('Flex') discloses the possibility for customers to set a flexible payment schedule of their choosing, rather than sticking to the rigid monthly one suggested in the default condition by the provider. The second treatment (Implementation Intention Plan, 'IIP') nudges customers to formulate a plan for when and how they will make payments. Implementation plans have been found to be effective in helping users identify the schedule best suited to them and stick to commitments (Milkman et al., 2013; Nickerson and Rogers, 2010; Abel et al., 2019). When combined with flexibility in payment, implementation plans can compensate for the higher complexity and reduced commitment features of a flexible schedule: the third treatment arm ('Flex

[1] Focusing on the pre-pandemic period, GOGLA et al. (2018) reports that sales of home solar systems in 2018 have increased by 77% compared to 2017 and by 133% compared to 2016. Eight million households worldwide are estimated to have received access to electricity via solar PAYG products between 2015 - 2020 (IRENA, 2020). However, the quality of off-grid systems varies greatly.

[2] Pakistan represents a potentially very large market for PAYG solar solutions on account of its population density, relatively low proportion of the population living in absolute poverty and high costs of existing alternative energy sources (e.g. kerosene) (Lightening Global Program, 2019).

x IIP') tests this by combining the Flex and IIP treatments. All treatments are administered only once, at the start of the contract.

The extensive margin of customers' product demand, measured as the likelihood of customers cancelling their contracts, is high within our sample: more than half of the customers cancel their contracts due to default. The impact of the treatments on the extensive margin provides support for the relevance of behavioural factors in observed customer behaviour. First, disclosing flexibility leads to marginally higher contract cancellation by 9.8 percentage points - approximately 19% increase over the control group. Second, the negative effect of flexibility disclosure on cancellation is more than offset when flexibility is combined with the planning nudge, aimed at addressing its negative consequences on payment discipline. Planning in the absence of flexibility has no impact on cancellation. Third, we find suggestive evidence that cancellation is higher among individuals in the Flex treatment who report difficulties in maintaining financial discipline at baseline. Customers in the Flex treatment who face high transaction costs (proxied by the distance to the nearest payment location) are also more likely to cancel. These results suggest that flexibility on its own may increase the complexity of payment decisions and reduce payment discipline, particularly when the barriers to payment are high, and that the addition of planning may help customers better manage these challenges.

We also use administrative data on daily inactivity and payments to estimate the effect of the treatment patterns on customer payment behaviour. We find suggestive evidence of treatment effects, consistent with those on cancellation, on the likelihood of ever being inactive over the contract duration and on the number of monthly inactive days. We instead do not find any impacts on other measures of the intensive margin of product demand, such as the average duration of inactivity spells and the number of monthly payments (top-ups). Our main specification alleviates concerns that our results are due to selective attrition, but we cannot rule out the possibility that the null results are due to low statistical power from high cancellation rates.

Our paper relates to the literature studying the impact of disclosing contractual features on consumer behaviour. Customers have limited attention and tend to overlook complex information (Lang, 2022), and providers exploit this by giving limited or opaque information on product features (Chetty et al., 2009; Karlan et al., 2016; Grubb and Osborne, 2015). The evidence on the impact of information disclosure is mixed. In the field of finance, providing customers with better contract information improves their financial behaviour (Bertrand and Morse, 2011; Stango and Zinman, 2014). In the field of resource usage, Wichman (2017) finds that increasing the frequency of price and consumption information reduces resource conservation. We study households' response to the disclosure of products' contractual features in a developing country context characterized by low levels of literacy. Information disclosure widens customers' opportunities but increases the complexity of effective usage of the product. We find that in this context, providers face a trade-off between disclosure of complex contractual features and customer retention.

Contract disclosure in our setting concerns the flexibility allowed by the PAYG scheme. Existing evidence on the relative impact of rigid and flexible contracts on repayment is mostly restricted to the microfinance literature (McIntosh, 2008; Field et al., 2013; Field and Pande, 2008; Czura, 2015; Labie et al., 2017; Barboni, 2017; Barboni and Agarwal, 2019). We differ from this literature in three main respects. First, our flexibility treatment just discloses an existing feature rather than introducing and testing a new flexible feature. Second, flexibility yields different benefits in our setting compared to the microfinance one. Third, we combine flexibility disclosure and planning nudges. Implementation intentions have provided cost-effective means of increasing the likelihood of follow-through when targeted to simple and short-term behaviours and when follow-through requires overcoming an obstacle (Nickerson and Rogers, 2010; Prestwich et al., 2003; Milkman et al., 2011, 2013; Abel et al., 2019; Mazar et al., 2018).[3] Our results indicate that planning's effectiveness is detectable only when flexibility disclosure makes the formulation of plans important, and suggest that the combination of nudges can have different effects relative to the effect of each one in isolation (Banerjee et al., 2021; Muralidharan et al., 2020). Given the technological advances that lower the administrative cost of small, frequent payments, and poor customers' preference for schedules that match their irregular cash flows (Suri, 2017; Jack and Smith,

[3] 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.

2015; Afzal et al., 2018), the form of flexibility that we examine and our results are relevant in the context of microfinance, service payment, and possibly other realms.

Our study focuses on the policy-relevant domain of energy provision in developing countries (Bonan et al., 2017) and particularly on solar off-grid (Girardeau et al., 2021). Pre-paid electricity is rapidly expanding in developing countries due to technological innovations in metering and payment technologies. Existing evidence shows the advantages of pre-paid grid electricity over traditional post-paid monthly billing for liquidity-constrained users in urban contexts (Jack and Smith, 2015, 2020). The perishable nature of pre-paid electricity in PAYG solar systems introduces important distinctions with respect to pre-paid metering. The viability of these businesses is still under-researched (Guajardo, 2016, 2019; Bensch et al., 2018; Grimm et al., 2020; Groenewoudt and Romijn, 2022) and the debate is open on whether PAYG offers a viable way to cover the last mile of electricity access, particularly for the poorest (Barry and Creti, 2020; Grimm et al., 2020). In the closest study to ours, Lang (2020) focuses on the trade-off that PAYG users face between liquidity constraints and transaction costs when deciding payment frequency. In our study, we offer a broader overview of obstacles to customer retention and regular payment and assess their empirical relevance and interaction with behavioural nudges.

We acknowledge that our analysis has limitations. Our design does not allow us to address users' demand for flexibility or planning nudges. This prevents us from speaking to the literature on the demand for soft commitment devices (Bryan et al., 2010; Laibson, 2018). With survey data collected only at baseline, we cannot assess the impact of the nudges (Allcott and Kessler, 2019; Bicchieri and Dimant, 2019) and access to off-grid technology on household welfare (Grimm et al., 2017; Aklin et al., 2017; Wagner et al., 2021; Stojanovski et al., 2021).

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 offers an overview of users' behaviour. Section 6 outlines the estimation strategy, and 7 reports empirical results. Section 9 concludes.

2 Context

2.1 Setting

We collaborate with EcoEnergy (EE), a for-profit company supplying solar energy solutions in rural Pakistan. EE targets areas that are off-grid (no electricity) or have a 'bad' grid (more than 12 hours of load-shedding a day). The sample includes 726 EE customers whose systems were activated between March 2017 and December 2018. Our study followed EE's expansion in new areas in the province of Sindh, specifically the southern districts of Thatta, Badin, Sujawal, Mirpur Khas and Tando Muhammad Khan. 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.[4] Average household income in sample districts is approximately PKR 9,000 (USD 267 PPP) per month.[5] Economic activity in these districts is predominantly agrarian, employing between 50-70% of the labour force, and a small percentage of the labour force is self-employed.

Travel between villages and larger city centres is often on unclassified roads, adding to travel time and costs. The average distance to the nearest market/commercial centre in our sample is approximately 6 km, which respondents can travel to in under 20 minutes using a combination of private and public transport.

2.2 The product

The solar units provided by EE are capable of charging, depending on the model, up to a 17Ah battery and can power multiple bulbs or fans, two mobile phones via a USB charger, a radio, or a 15" TV. The systems' electricity generating capacity depends on their size and on the weather: depending on the cloud

[4] As reported in Government of Pakistan's Data for Pakistan Portal (http://www.data4pakistan.com/). The proportions of the 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.

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

cover, efficiency can drop between 10 and 25 per cent of the energy output seen on a sunny day. The system's capacity determines the daily rate charged to users, which may range between USD 0.26 and 1.7 PPP.

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. Applicants are screened twice; first, through a quick questionnaire conducted by the salesperson, to determine whether they can afford the system that meets their needs based on their current energy expenditures; and second, by the local sales manager to determine if the application should be approved.

If approved, an 'order' is created, and a visit by an operational staff member to install the system and sign the contract is scheduled. When signing the contract, customers choose between perpetual rental and rent-to-buy. The rent-to-buy contract transfers ownership of the unit after the customer has made payments roughly equivalent to its sales value and requires customers to make a down payment proportional to the system's value at the time of signing the contract. Rental customers need to make a security deposit equivalent to one month's rent and pay upfront the rent for the first month, which includes the cost of electricity.

After the installation is complete, a client profile is created in EE's billing system, providing details of customer balance and payments. This implies that the study sample does not include individuals who did not complete the installation process. Within the study area, EE has, on average, five customers per village, which are likely to have adopted systems of different capacities.

The contract involves a PAYG payment system. Customers purchase access to the electricity generated by the system through top-ups. Customers top up at mobile money (Easypaisa) agents, typically located in larger villages and market centres. Smartphone and mobile money penetration allowing direct top-up by customers was very low at the time of the study. The size of the payment, divided by the system's daily rate, determines the number of days of electricity paid for through the top-up. The daily rate gets deducted from the outstanding credit, regardless of whether or how much electricity is used or produced by the system in a day. Credit, therefore, runs down continuously, and customers cannot store their credit when they do not use electricity, or when the system's generation capacity is low due to bad weather. SMS reminders notify customers when their credit is about to expire and invite them to top up at the monthly rate. SMS are also sent to acknowledge when a payment is made and report the number of days before the next payment is due.

Once credit expires, the solar unit is remotely disconnected and does not produce any electricity. After about 30 consecutive inactive days, customers have their status turned into 'default'. At this point, EE is free to repossess the product and cancel the contract. In practice, EE's sales team contacts customers after the 30th consecutive inactive day to notify them that the system will be repossessed unless a payment is made. The possibility of negotiations between EE and the customer implies that inactivity spells longer than 30 consecutive days may not always be followed by a cancellation. Besides eventual contract cancellation, there was no financial penalty for not immediately topping up once the credit expired.

3 The experiment

3.1 Experimental design

The experimental design is articulated in two dimensions: the disclosure of the possibility to flexibly set the repayment schedule, and the administration of a planning intervention. This results in a 2x2 factorial design. Both treatments are administered once at the start of the contract.

Default contract: Under EE's default, customers are informed of the daily rate associated with their system. They are then told that they are expected to pay every month an amount corresponding to the monthly rate, computed from the daily rate under the assumption of no inactive days, and are provided with examples.[6] This forms the control group, referred to as the 'Fixed-no IIP' group in the following discussion.

[6] Specifically, the script reads: "Your plan costs a daily rate of Rs [calculated rate]. You are expected to pay the total amount of Rs XX every month. This means that, for example, if you are connected on February 3rd, you are expected to pay Rs XX by March 3rd", where XX corresponds to the monthly rate. Appendix **??** reports the script used to present the treatments to the customers.

Flexibility disclosure (Flex): In the first treatment dimension, customers are explicitly informed that the monthly payment, corresponding to their system's daily rate, can be paid in smaller and more frequent instalments within each month. These customers are still told that they are expected to pay a certain amount each month, but in addition to the information provided in the Fixed-no IIP group, they learn that they are essentially free to plan their payment schedule. For illustration purposes, these customers are given examples of payments at different frequencies (e.g., weekly, bi-weekly, monthly).[7]

Customers in both groups (Fixed-no IIP and Flex) can pay at any frequency. The flexibility disclosure treatment simply makes the possibility of setting the payment schedule autonomously clearer to the customer at the start of the contract, relative to the default.

Implementation Intention Plan (IIP): A second treatment dimension offers a planning nudge to customers, 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; identify the main obstacles they face in meeting this commitment; formulate strategies for overcoming each obstacle; and 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 workplace or house.

Combining Flex and IIP (Flex x IIP): A third treatment arm combines the Flex and IIP treatments i.e. customers are explicitly informed about flexibility in making payments and given a planning nudge.

Flexibility should help customers match their payments with their cash flow. It can also minimise transaction costs for making payments: by paying early or late, they could better exploit synergies with trips to the market centre, rather than going there solely to stick to a rigid payment schedule. In the same way, flexibility may help customers reduce waste, by keeping the system inactive when its generation capacity is low. If these were the only mechanisms through which flexibility worked, then it should affect payment and short-term inactivity without leading to higher rates of long inactivity and cancellation.

[7] Specifically, the flexibility disclosure treatment script adds to the Fixed-no IPP script the following sentences: "You can pay in different instalments. This means, for example, that you can pay Rs XX/4 every week or Rs XX/2 every two weeks. In sum, you can top up your credit as many times as you like."

However, flexibility may cause users to unwillingly become inactive and default if it increases the complexity of managing payments and reduces the commitment to making timely top-ups. Flexibility may be conducive to cancellation also if users face difficulties in resuming payment after periods of inactivity.

Planning should foster timely payments and reduce cancellations by encouraging customers to foresee and plan against the main barriers to making top-ups. Also, the planning process could encourage some ex-ante learning of the contractual terms. In these respects, planning should boost the benefits of flexibility, and potentially reduce its negative consequences in several ways. First, by helping customers identify and stick to the best payment schedule. Second, by making it easier for individuals to commit to a payment schedule of their choosing and anticipate potential barriers to adhering to it. Third, making payments easier after an inactivity spell, thus mitigating any negative effect of flexibility. However, the planning exercise, by drawing users' attention to the barriers to timely payment, may make them realize how large the costs associated with overcoming such barriers are.

Treatment effects should be stronger among users who face greater barriers to timely payment. For instance, if flexibility reduces payment discipline, its negative effects may be stronger for individuals with commitment problems or for whom making payments takes more effort due to high transaction costs. Similarly, the benefits of planning, in combination with flexibility, may be larger for these same individuals.

3.2 Implementation

The flexibility disclosure treatment was administered by EE's salespersons after all other contractual aspects - such as the set of electric items, price, and rent versus ownership - were explained, agreed upon, and accepted. The treatment assignment, therefore, occurred after the customer had accepted the general contractual conditions. This prevents our design from generating selection into contractual features. Treatment was assigned through a random number generator incorporated into the software used by the salespersons to register new customers. Hence, we stratify the flexibility disclosure treatment by the salesperson.

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

Out of the 726 customers in our sample, 155 are in the Flex treatment, 216 in the IIP treatment and 195 received both the Flex and IIP treatments. 160 customers form the control group who received the default, Fixed-no IIP contract. The slight imbalance in the number of customers assigned to each cell is due to the randomization of each treatment occurring at the individual level through two separate procedures.

4 Data

4.1 Administrative Data

We have access to EE's administrative records on customers' subscriptions, type of system installed, amount due, deadlines and flows of payments made daily. These data allow the timely monitoring of payments and system status (active, inactive, cancelled) from each customer's installation date, i.e., from March 2017 for the first customers, 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 unless they canceled their contract in less than a year.

We focus our analysis on five main outcomes. Customers' extensive and intensive product demand is measured through cancellation and inactivity, respectively. Cancellation is a binary variable indicating if the customer has cancelled their contract in the sample period. Inactivity is captured by the likelihood that a customer's balance falls to PKR 0 during the contract period, which leads to the system becoming inactive, and by the average number of days in a month when the customer's system is inactive. We set inactive days equal to one for all days following cancellation until the end of the monitoring period. In doing so, we follow the approach used in McKenzie and Puerto (2021) for firms whose decision to exit the market is influenced by a treatment: such firms are assigned profits and sales equal to zero in the post-exit period and are retained in the sample. To capture mechanisms of consumer behaviour, we explore inactive spell duration and monthly top-ups. Inactive spell duration is defined as the average number of continuous days a customer has zero balance before they make a top-up over the sample period. Since, by definition, a spell has a start and an end date, this variable is defined only over the contract period. Monthly top-ups are the average number of payments made by the customer in a month over the observation period, where we set top-ups equal to zero in the post-cancellation period. In robustness analysis, we set inactivity and top-ups as missing after cancellation.

4.2 Survey Data

The second source of data is the survey, administered within a few weeks from contract signing and conducted by an independent survey firm with the customers. The survey data provide information on customers' demographic and socioeconomic characteristics; their energy usage and other household expenditures; their performance in repaying loans in the past; and on a set of behavioural measures, including time preferences; measures of grit, locus of control, self-control, and willpower to resist temptations. Through the survey, we construct measures to use for heterogeneity analysis and as controls in the regression models.

We focus on two measures which we expect to be associated with cancellation and payment, and with heterogeneous treatment impacts. First, we construct an index for mental constraints from measures of (i) cognitive skills, (ii) self-reported ability to pay bills on time, (iii) an index for the (in)ability to resist temptations, self-control, locus of control, grit and discipline with previous loans.[8] Second, we proxy transaction costs with distance from the nearest Easypaisa agent where payments can be made.

[8] Each variable, together with its source and construction, is described in detail in Appendix **??**. The variables are first reverse-coded if needed, and then aggregated following Anderson (2008), 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.

5 Descriptive analysis

We start by providing a descriptive account of customers' characteristics and behaviour in terms of contract cancellation, inactivity and top-ups; and of the correlation between payment behaviour and cancellation. Providing these descriptive statistics is important for two reasons. First, given the novelty of these products, little is known about the characteristics and behaviour of their users. Second, detecting user behaviour patterns can inform our interpretation of the empirical results.[9]

5.1 Sample characteristics

Table 1 shows summary statistics of customers' characteristics by treatment arm. Sample characteristics are generally balanced across treatments, as shown through F-stats for joint significance of treatment groups dummies reported in column 5.[10]

Almost all (95%) of the individuals in our sample are residential customers. Customers are 36 years old on average, 82% are literate, about 25% have savings, and 17% have access to credit. Nearly a third of our respondents earn income primarily from agricultural activities; another 27% are government employees (with regular monthly salaries), while 19% are labourers, earning irregular, often weekly wages. A small percentage (13%) are self-employed. Overall, almost half of the members of respondents' households are recipients of regular income flows.

Grid connectivity is low, and the electricity quality is poor. About 20% of individuals in our sample have no access to any electric power source, 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 load-shedding daily: 33% between 1 and 6 times, 24% between 7 to 10 times and 41% more than ten times a day. Off-grid households live on average 7 Km from the closest on-grid location.

[9] The analysis which follows is conducted on the whole study sample. However, results are qualitatively similar if we use the control sample, i.e. fix and no-IIP. Results are not shown but are available upon request.

[10] We test for balance on 59 respondent and contract characteristics. The share of unbalanced variables with $p < 0.1$ is 0.086, and the share of unbalanced variables with $p < 0.05$ is 0.052. Appendix Table **??** shows the comprehensive list of contract and respondent characteristics.

As far as the home solar system is concerned, users report high levels of understanding of contract terms and mostly do not anticipate problems in making timely top-ups. The average distance between a customer and the closest Easypaisa agent is 6 km: it takes customers 17 minutes and PKR 47 (USD 1.40 PPP), on average, to cover this distance. Remembering to buy credit, putting aside money for payment, resisting the temptation to divert the money to other uses and actually making the payment are the main obstacles to timely payment anticipated by customers.

Almost all (98.3%) systems installed can power a light, while 82.8% can power a fan. Only 6.3% of customers have systems able to support a TV, while 5.6% are endowed with a mobile charger. On average, keeping systems active costs customers USD 37.6 PPP per month, i.e. about 6% of monthly household income. 67.9% of the sample choose a perpetual rental over rent-to-own contracts.

5.2 User behaviour

Overall, 56% of the customers have their contract cancelled due to default. Figure 1 shows the distribution of contract duration, inactivity and payment, overall and separately, for users who do and do not cancel over the sample period. Table **??** provides descriptive statistics for the main outcome variables of interest for the study sample.

Of the customers who cancel during the sample period, 25% and 50% cancel in the first 3 and 5 months of the contract, respectively.[11] Appendix Figure **??** shows the dynamics of cancellation over time and confirms the higher cancellation rates during the early contract months. Cancellation is almost exclusively the result of inactivity: only 4% of those who cancel do so while holding a positive balance. In the analysis, we restrict our attention to the first 18 months of the contract, given that the number of customers in our sample drops below 100 afterwards.

[11] We cannot comment on whether these cancellation rates are higher or lower than those faced by other providers. Globally, the definition of default varies, and information on client retention is not publicly available, though there is a recent push to adopt consistent performance indicators and for publishing data for greater transparency. https://www.lightingglobal.org/resource/technical-guide-for-the-kpi-framework/. EE is the only PAYG off-grid electricity provider in Pakistan. The observed cancellation rate is higher than the one estimated by EE at the time of designing the study. At that time EE was in the early stages of product expansion, and hence their estimate of customer retention was imprecise.

Payment quality is generally low: the cross-sectional data shows that 96% of customers experience at least one inactive day over the duration of the contract; and that their systems are inactive for more than a quarter of the time (26.2% of contract days). At the monthly level, this corresponds to an average of 6.1 monthly inactive days. Customers who eventually cancel report, on average, almost twice as many inactive days per month than those who do not cancel during the contract period. This is confirmed also when we look at the dynamics of inactivity over time (Appendix Figure **??**). The distribution of average monthly inactive days is also different between users who cancel and those who do not (Figure 1). The median duration of any inactivity cycle before a top-up is made is 4.6 days.

Users top up on average more than once a month (mean = 0.94, median = 0.7), and the likelihood of topping up is lower for those who eventually cancel. The average number of days paid for at top-up is 23, and the average amount is PKR 1022 (USD 31 PPP, median USD 27 PPP). The median top-up occurs on the day when the credit expires.

6 Estimation strategy

We investigate treatment effects in the cross-section dataset by estimating the following equation:

$$y_i = \alpha + \beta_1 Flex_i + \beta_2 IIP_i + \beta_3 Flex_i \times IIP_i + X_i + \gamma_t + \varepsilon_i \tag{1}$$

where y_i are the cancellation, inactivity, and payment outcomes described in Section 4 for individual i. We regress these variables on the $Flex$ and IIP treatment dummies, and their interaction $Flex \times IIP$. X_i includes location, salesperson, and enumerator fixed-effects; and individual controls, including all unbalanced covariates across treatment groups, selected using the post-double Lasso regularization approach of Belloni et al. (2011).[12]

The coefficients on the Flex and IIP dummies in equation 1 capture the main effect of each treatment

[12] Individual controls are selected among age, literacy, knowledge of contract rules and rate, availability of savings, mental constraints (index), ability to smooth consumption (index), time-inconsistent preferences, the system's daily rate, rental versus rent-to-own contract and distance from the Easypaisa agent. Appendix **??** provides variables description.

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 adopt a fully interacted model because it allows us to detect whether the combination of the Flex and IIP treatments has a different impact, relative to what we would expect from the effect of the two treatments when administered in isolation.

Equation 1 is pre-registered. The pre-analysis plan (PAP) reported additional regression specifications, omitting the interaction term. We do not report results from this estimation strategy in light of recent work that recommends estimating a saturated model with interactions between treatment cells in the presence of fully factorial experimental designs like ours. This is important both for correct inference (Muralidharan et al., 2020) and for policy implications (Banerjee et al., 2021). We report whether the marginal effect of the combined treatment is significantly different from the control (Fixed-no IIP) by displaying the p-value of a Wald test of equality of coefficients.

6.1 Departures from the pre-analysis plan

While the regression specification adheres to the pre-specified one, the analysis that we present departs from the one featured in the PAP in some respects. We summarise and motivate these departures here, and refer the reader to Appendix **??** for a detailed description.

A first set of deviations from the PAP is motivated by the desire to conform to best practices that have been established since the time of writing the PAP. The first, already mentioned, concerns the correct estimation of treatment effects from factorial designs. A second, also discussed above, concerns our treatment of attrition due to contract cancellation. We follow the literature (McKenzie and Puerto, 2021) by setting inactivity and top-ups equal to zero in the post-cancellation period.[13] This approach is preferable to the one we envisioned in the PAP, i.e., Lee bounds on treatment effects (Lee, 2009), as Lee bounds are not the correct tool to deal with selection on the extensive margin, particularly in the presence of multiple treatments with potentially non-monotonic effects. A third deviation relates to the approach we use for

[13] We thank an anonymous reviewer for encouraging us to address the issue of selective attrition through the correct definition of our variables and sample.

multiple hypothesis testing. We take a more conservative approach than specified in the PAP, by reporting sharpened q-values following Benjamini et al. (2006) across all our outcomes variables of interest, and not just within the family of extensive and intensive margin outcomes. We do the same across the dimensions of heterogeneity. Finally, while in the PAP we do not specify the control variables to be included in the regressions, in the analysis we avoid cherry-picking them and instead select them through a data-driven approach – the Post-double-selection LASSO procedure (Belloni et al., 2014).

A second source of deviation from the pre-registered analysis is due to the focus on two pre-specified dimensions of heterogeneity in the main text and showing results for the rest of the dimensions in the appendix.[14] We had pre-specified a large number of heterogeneity dimensions that we speculated ex-ante as potentially relevant. The leading view nowadays on pre-registration is that it should be used with moderation and focus only on core outcomes and heterogeneity dimensions (Banerjee et al., 2020). We present in the main text only a subset of these results, also because our ability to pursue any heterogeneity analysis is hampered by low power.

A third, large share of deviations from the PAP are due to errors or insufficient knowledge of the administrative data at the time of pre-registration. Indeed, we registered the PAP before having access to the administrative data. These deviations encompass the inclusion in the PAP of (i) outcome variables for which we have no administrative data, e.g., contract cancellation before the installation of the system; (ii) multiple variables to capture the same phenomenon, e.g., delayed payments and system deactivation due to missed payment are both inactivity; (iii) heterogeneity dimensions for which we have no data or power, such as the distinction between business and residential customers.

[14] As discussed in Appendix **??**, we we do not report results on two dimension because we do not have variability in answers.

7 Results

7.1 Treatment effects

We now examine treatment effects on pre-specified dimensions of consumer behaviour. Table 2 reports intent to treat results from the estimation of equation 1 on the extensive and intensive margins of consumer demand: cancellation, the probability of experiencing inactivity and the number of inactive days per month.

Cancellation. Disclosing flexibility marginally reduces the extensive margin of demand, increasing monthly cancellation rates by about ten percentage points, almost a 19% increase over the control means. The planning treatment alone has no significant effect on cancellation. The combination of flexibility and planning more than offsets the effect of the former, and the cancellation rates in the combined treatment do not significantly differ from those in the control treatment. This result is robust to correcting the p-values for testing for multiple hypotheses (sharpened q-values are displayed in square brackets in Table 2).

The behavioural literature on planning prompts outlines two conditions behind their effectiveness (Rogers et al., 2015). First, 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 plan. Second, planning helps when there are obstacles to overcome. In our setting, flexibility increases the complexity of payment decisions. Consistent with the greater need to make a plan in the presence of a self-imposed payment schedule, the share of customers assigned to the Flex x IIP treatment consolidating their plan on the provided calendar is significantly higher than those in the IIP treatment ($p = 0.034$).[15] Our treatment effects also support this claim: only individuals assigned to the flexible payment schedule benefit from planning, i.e., planning has an impact only when subjects have to devise their own payment schedule.

Since both treatments in our experiments were administered once at the beginning of the contract

[15] The data for this analysis comes from the survey with the customers where the enumerators took note of whether customers used the calendar, provided by the enumerators themselves, to consolidate their planned payment schedule. Note that we do not have data on the exact dates circled by customers on the calendars.

and never repeated, we may expect their effects to vary over time. Decreasing impacts over time may be expected if behavioural interventions, such as planning, have short-lived effects (Gneezy and List, 2006; Allcott, 2016); if customers learn about the flexibility built into the standard contract over time; or if selective attrition makes the individuals who are most responsive to the treatments drop out. On the contrary, we would expect persistent treatment effects if behaviour at the start of the contract informs different habits (Schaner, 2018). Though not pre-specified, in order to study treatment dynamics, we estimate equation 1 using a monthly panel over non-overlapping three-month periods with month fixed effects. The effect of the combined treatment does not appear to fade over time, both when we consider cumulative effects by retaining in the sample the customers who cancel and setting cancellation to one for the months post-cancellation (Appendix Table **??**); and when we focus on the selected sample of customers who are still active in each period (Appendix Table **??**).

Inactivity. First, we look at the intensive margin of product demand in terms of the probability of experiencing at least one inactive day over the contract period. Results in column 2 of Table 2 show that the treatment impacts on the likelihood of ever experiencing inactivity mirror those on cancellation: flexibility increases such likelihood, but combining it with planning offsets this effect. This makes sense, as inactivity is the main cause of cancellation. A possible interpretation of these results is that flexibility reduces payment discipline and increases inattention, thus causing users to miss their payment deadlines, but that planning prevents this negative consequence of flexibility by focusing users' attention on their payment deadlines. If the inactivity induced by flexibility were exclusively beneficial, i.e., a way to minimise waste and transaction costs, then we would not expect it to disappear thanks to planning. We find similar treatment effects on the average number of inactive days in a month (column 3). Flexibility increases them by two days on average, while combining it with planning restores inactivity levels to those in the fixed-non-IIP group. The results on the two measures of inactivity are not robust to the multiple hypothesis correction. This suggest taking the evidence on the treatment impacts on the intensive margin with caution.

The results on the number of monthly inactive days are also no longer statistically significant when we set to missing the days after cancellation (Appendix Table **??**). This suggests that users, whose cancellation decision is not influenced by the treatments, do not change their inactivity levels on average.[16] We find the same difference in results between the balanced and selected sample when looking at the dynamics of treatment effects over non-overlapping periods: in the balanced panel, the combined treatment has persistent negative cumulative effects on inactivity (Appendix Table **??**); while in the panel of active customers it only affects monthly inactive days in the first three months of the contract (Appendix Table **??**).

7.2 Exploring Mechanisms

We explore potential mechanisms in two ways. First, we estimate treatment effects on two outcomes that could explain consumer behaviour: the average duration of inactive spells and the number of monthly top-ups. Inactive spell duration can reveal whether the treatments allow users to use inactivity to reduce transaction costs – e.g., through short inactivity spells until the next trip to the market centre; or whether they cause customers to fall into long inactivity spells and eventual default. The number of monthly top-ups should be directly influenced by the treatments. We find null results on these two additional outcomes, except for a marginally significant increase in top-ups in the combined treatment, relative to the sum of the effects of flexibility and planning in isolation (columns 4-5 of Table 2).[17]

Second, we explore heterogeneous treatment effects on the outcomes of interest. To explore heterogeneous treatment effects, we augment equation 1 through the interaction of treatment indicators with two dimensions of heterogeneity: indicators for above-median mental constraints and transaction costs. Mental constraints is an index of various measures (detailed in Section 4) that could pose difficulties in maintaining discipline in payments. 'High' mental constraints is a dummy equal to one when the value of this index is greater than the sample median. We proxy 'high' transaction costs through a dummy equal

[16] We find null treatment effects in the cross-section for another pre-specified measure of inactivity, the average number of monthly inactivity spells, reported in column 1 of Appendix Table **??**. This variable also considers only the pre-cancellation period.

[17] In addition, though not pre-specified, we consider treatment effects on the average size of the payments. One hypothesis could be that those who are in the flexibility disclosure treatment make smaller, more frequent payments. We do not find this to be the case (column 2 of Appendix Table **??**): if anything, we find a marginally significant increase in the average payment size.

to one if a customer lives greater than 5 Km - the median distance - from the closest Easypaisa agent. The results do not survive corrections for testing multiple hypotheses, but they provide suggestive insights into the characteristics of customers who benefit the least from the product and the treatments.

The flexibility disclosure treatment increases cancellation rates more among customers with above-median than below-median mental constraints (column 1 of Table 3). This supports the hypothesis that people with high mental constraints may struggle to keep track of payments when the possibility of making them flexibly is salient. Users facing higher transaction costs are also more likely to cancel than those facing low transaction costs when exposed to the flexibility disclosure treatment, and also significantly less likely to cancel when flexibility and planning are combined (column 2 of Table 3).[18] Similarly, among users with high mental constraints and transaction costs, flexibility in isolation increases the number of monthly inactive days (columns 5-6). However, flexibility increases the likelihood of experiencing inactivity among low transaction cost users, but not among high transaction cost ones (columns 3-4). We find no significant heterogeneity on other outcome variables – the average duration of inactive spells and the number of monthly top-ups, likely due to lack of statistical power.[19]

The heterogeneity analysis presented here focuses on a subset of the potential sources of heterogeneous treatment effects that we mentioned in the PAP. Specifically, we had pre-specified the following other sources of heterogeneity: the ability to smooth consumption, financial management and time inconsistency. We find no compelling evidence of heterogeneity along these dimensions. Results are available in the online appendix Tables **??** and **??**.

8 Robustness

We now discuss factors potentially influencing the magnitude and statistical significance of our empirical results: statistical power, selective attrition and spillover effects.

Assessing statistical power is critical in experimental research, as low power increases the risk of

[18] We test and find no evidence of heterogeneous treatment effects by these dimensions on average payments.
[19] The heterogeneous effects on the average number of inactivity cycles in a month are also insignificant (Appendix Table **??**).

false negatives, but also of false positives, where non-existent effects are detected. Low statistical power may be due to the sample size or the treatment effects being relatively small (Ioannidis, 2005). Our study may suffer from both sources of low power. First, our initial sample size, which we determined through power calculations, was based on lower attrition rates due to contract cancellation than the ones we actually observed. Second, our treatments were light touch and administered only once at the start of the contract. We, therefore, report and discuss ex-post Minimum Detectable Effects (MDEs).[20]

The estimated MDEs for the average duration of inactive spells and for the number of top-ups range between 34 and 54%. These are quite high and may indicate that we could not reach statistical significance due to low power rather than due to precisely estimated null effects. If we look at the effect of broadly similar interventions on a different set of outcomes, our MDEs appear to fall short of power.[21]

Selective attrition may attenuate treatment effects if it drives the individuals who are most responsive to the treatments out of the sample. Selective attrition is a serious concern in our setting. Our results show that the treatments affect contract cancellation and that the treatment effects on cancellation are stronger for customers with certain characteristics. We address this issue in three ways. First, as already mentioned, our main definition of the outcome variables related to inactivity and top-ups retains in the sample all customers, even after they cancel their contracts. The sample of our main analysis, therefore, is not the selected sample of active customers. Second, we try to assess the potential role of selective attrition through robustness analysis, where we set to missing all outcome variables in the post-cancellation period. The comparison between the (statistically significant) results from our main analysis and the (insignificant) results from the robustness check suggests that selective attrition due to the treatments results in a sample where customers, whose inactivity and payment decisions are not significantly affected by our treatments, to be observed for longer periods. Third, we try to assess whether and how selective attrition affects the balance on observables within our sample. We show the same balance tests, displayed in Table 1 for

[20] The MDE is the effect that we would have been able to detect with 80% power at the 5% rate of significance level ex-post with the study sample. Ex-post MDEs are computed as the Standard Error(β)*2.8 and reported as a percentage of the control group mean. We follow Haushofer and Shapiro (2016) and report MDE only for non-significant parameters.

[21] 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.

the baseline sample, for customers still active after 12 months of contract (Appendix Table **??**). We find that customers in the flex treatment who cancelled within the first year are less literate, live further from Easypaisa (although non significantly) and are more subject to cognitive bias (e.g., perceiving memory issues as a constraint to pay). This is consistent with the results from the analysis of heterogeneity.

Finally, spillovers may potentially attenuate the effect of the treatments by reducing the observed differences in behaviour across customers assigned to different treatments. Customers assigned to the Flex treatment may have discussed their preferences over payment frequency and inactivity with customers in the control group, increasing the similarity in behaviour across the two groups. The concern of spillovers across customers is reduced by two features of the setting, which make learning across customers unlikely. First, the systems' daily rates vary within each village, as they are primarily driven by each customer's needs. Second, the small number of customers per village (approximately 5, amounting to less than 10% of the average number of households in a village) makes interactions between customers unlikely.

9 Conclusion

We use administrative data to study payment behaviour for a PAYG solar system, provided by a for-profit organization to individuals living in off-grid areas of rural Sindh, Pakistan. Credit runs down continuously, and the system is remotely disconnected when customer credit expires. We conduct a randomized control trial with this sample to study the impact of disclosing flexibility on customer behaviour. While flexibility should help poor households reduce waste and transaction costs, and manage payments in the presence of volatile income flows, it may hurt repayment quality if rigidity provides discipline and if the complexity of contractual terms increases the cognitive costs of adhering to them. We combine flexibility disclosure with a planning intervention to address these potentially negative behavioural consequences of flexibility.

Overall, we find support for the relevance of the negative behavioural repercussions of flexibility on the extensive margin of customer demand, measured by contract cancellation. Disclosing flexibility by itself marginally increases the likelihood of cancellation as compared to the default contract, where customers are told to make payments monthly. The planning intervention has no significant effect on any dimension of payment behaviour when added to the default contract. Combining flexibility disclosure with the planning nudge significantly reduces cancellation rates with respect to flexibility alone. We find suggestive evidence of similar treatment effects on the likelihood that a customer ever experiences inactivity and on the number of inactive days. The impact of flexibility disclosure on cancellation is more pronounced for customers with difficulties in maintaining financial discipline and living far from the payment agent.

There are no treatment effects on the average duration of inactive spells and the number of monthly payments. While our main specification should attenuate concerns of selective attrition, we may be underpowered to detect impacts on these outcomes due to high contract cancellation rates. Future research can build on these results to formulate and test a theory of change linking contractual features, behavioural outcomes in terms of inactivity and payment, and contract cancellation.

In a world where behavioural nudges are increasingly used in the public and private sectors, individuals are likely to be exposed to multiple nudges at any one time: understanding the impacts of different policy combinations is therefore important. Our results show that potential unintended consequences of nudges could be prevented by combining them with other behavioural interventions. From a methodological standpoint, these results confirm the importance of considering interactions between orthogonal treatment dimensions.

Our results on the relevance of behavioural determinants of payment also imply that providers of PAYG systems face a trade-off between providing information on complex contractual features and fostering timely payments and customer retention. Transparency of contract information may be harmful to customers if access to electricity is welfare-enhancing. Our results suggest that a potential solution to these negative effects may be complementing contractual disclosure with soft interventions that encourage making payment plans. Unfortunately, we cannot speak to the welfare effects of our treatments or of electricity access more broadly. Similarly, our design does not allow us to evaluate users' demand for flexibility or planning aids in our setting. These represent interesting and important areas for future research.

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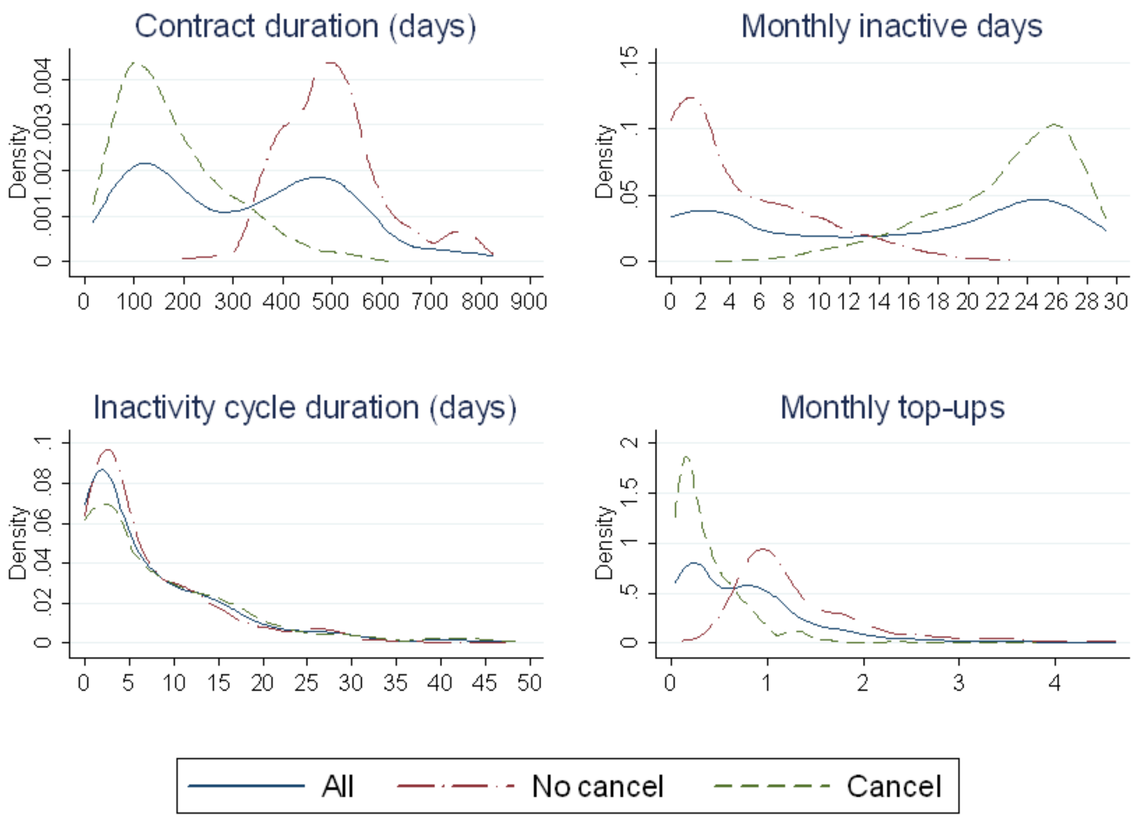
Tables and Figures

Table 1: Contract and respondent characteristics at baseline

	(1) All	(2) Flex	(3) IIP	(4) Flex x IIP	(5) F stat p
Panel A: Respondent characteristics					
Type of customer: business	0.052	0.052	0.056	0.062	0.738
Respondent age	35.566	36.110	35.194	35.503	0.702
Can read and write	0.822	0.832	0.829	0.815	0.954
Any savings	0.253	0.297	0.185	0.262	0.028
Access to credit	0.171	0.174	0.181	0.159	0.949
Share of HH members with regular income	0.457	0.495	0.462	0.442	0.541
Experiences > 10 hours loadshed/day	0.858	0.897	0.880	0.846	0.105
Understands product type	0.815	0.826	0.824	0.805	0.931
Understands payment procedure	0.912	0.897	0.903	0.913	0.512
Does not know daily rate	0.090	0.084	0.079	0.077	0.458
Distance from Easypaisa (payment) agent (Km)	6.161	6.103	6.361	6.323	0.662
Anticipate problems to repay on time	0.180	0.174	0.185	0.154	0.555
Main constraint to pay: set aside money	0.394	0.413	0.398	0.390	0.918
Main constraint to pay: keep safe from other	0.326	0.310	0.333	0.303	0.645
Main constraint to pay: resist temptations	0.394	0.458	0.417	0.338	0.108
Main constraint to pay: remember payments	0.431	0.426	0.463	0.374	0.243
Main constraint to pay: go and pay	0.366	0.374	0.370	0.328	0.555
Panel B: Contract characteristics					
Perpetual (vs. rent-to-own)	0.675	0.742	0.685	0.636	0.131
Daily rate (USD PPP)	1.258	1.199	1.221	1.293	0.077
Observations	726	155	216	195	

Notes: The table shows mean values of respondent and contract characteristics for the whole sample (column 1) and for each treatment group (columns 2 to 4). Column 5 reports the p-value of a test of joint significance (F-stat) of two treatment dummies and their interaction on the characteristic in each line.

Figure 1: Distribution of contract duration and payment behavior



Notes: The figures show kernel density plots for the whole sample ("All") and by cancellation status. The top-left panel depicts contract duration, in days. The top-right panel shows the distribution of the average number of inactive days in a month. The bottom-left panel depicts the average inactivity cycle duration (excluding the last cycle before cancellation). The bottom-right panel shows the average number of top-ups in a month. All figures are generated from the cross-section (N=726).

Table 2: Treatment effects on cancellation and payment behaviour

	(1)	(2)	(3)	(4)	(5)
	Extensive margin	Intensive margin		Mechanisms	
	Cancel	At least one inactive day	Avg. monthly inactive days	Avg. duration of inactive spells (days)	Avg. number of monthly top-ups
Flex	0.098*	0.040**	2.042*	-0.932	-0.153
	(0.052)	(0.020)	(1.094)	(1.291)	(0.120)
	[0.206]	[0.206]	[0.206]	[0.434]	[0.231]
IIP	0.064	0.030	1.310	-0.627	0.010
	(0.048)	(0.020)	(0.987)	(1.283)	(0.117)
	[0.231]	[0.221]	[0.231]	[0.442]	[0.491]
Flex*IIP	-0.208***	-0.061**	-3.324**	0.027	0.308*
	(0.070)	(0.029)	(1.456)	(1.746)	(0.170)
	[0.053]	[0.206]	[0.206]	[0.491]	[0.206]
Observations	726	726	726	726	726
Fixed no IIP group mean	0.525	0.950	13.68	9.013	0.971
P-val of Flex+IIP+Flex*IIP	0.368	0.700	0.979	0.225	0.278

Notes: The unit of analysis is a customer. The extensive margin variable, "Cancel", takes a value of one if contract cancellation occurs and zero otherwise; the intensive margin variables, "At least one inactive day" and "Avg. monthly inactive days", are dummy variables for whether customers experienced at least one inactive day and the number of inactive days in the month, respectively. "Avg. duration of inactive spells (days)" is the average duration of inactivity spells over the contract period; "Avg. number of monthly top-ups" is the average number of top-ups per month over the contract period. "Average monthly inactive days" and "Avg. number of monthly top-ups" are set equal to the total days in a month and to zero after cancellation, respectively. Estimates are obtained via OLS. All specifications include individual controls selected through LASSO between daily rate at the contract start, rental contract at start, respondent's age, respondent can read and write, any savings, knows the contract rate, knowledge of system rules, distance from Easypaisa agent, index for mental constraints, index for ability to smooth consumption, time-inconsistent preferences; month, location, enumerator and salesperson fixed-effects; robust standard errors are in parentheses. Fixed no IIP group mean refers to the control group mean. *** p<0.01, ** p<0.05, * p<0.1. Sharpened q values in square brackets control the false discovery rate for tests across pre-specified outcomes.

Table 3: Heterogenity in treatment effects on cancellation and payment behaviour

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Extensive margin		Intensive margin				Mechanisms			
	Cancel		At least one inactive day		Avg. monthly inactive days		Avg. duration of inactive spells (days)		Avg. number of monthly top-ups	
H:	High MC	High TC	High MC	High TC	High MC	High TC	High MC	High TC	High MC	High TC
Flex	-0.007	0.013	0.055*	0.072***	-0.734	0.239	-0.883	-0.765	0.029	-0.166
	(0.077)	(0.069)	(0.030)	(0.025)	(1.662)	(1.485)	(2.067)	(1.672)	(0.186)	(0.152)
IIP	0.137*	0.057	0.054*	0.053*	1.880	1.073	-2.521	1.253	0.073	-0.047
	(0.070)	(0.063)	(0.031)	(0.028)	(1.487)	(1.321)	(1.760)	(1.994)	(0.175)	(0.154)
Flex*IIP	-0.210**	-0.085	-0.087**	-0.102***	-2.101	-0.682	1.298	-1.151	0.195	0.344
	(0.102)	(0.092)	(0.042)	(0.038)	(2.142)	(1.943)	(2.571)	(2.640)	(0.250)	(0.243)
Flex*H	0.200*	0.173*	-0.028	-0.076**	5.323**	3.624*	-0.149	-0.460	-0.346	0.028
	(0.104)	(0.105)	(0.041)	(0.036)	(2.206)	(2.172)	(2.691)	(2.639)	(0.268)	(0.226)
	[0.485]	[0.485]	[0.835]	[0.485]	[0.485]	[0.485]	[1.000]	[1.000]	[0.568]	[1.000]
IIP*H	-0.148	0.011	-0.046	-0.056	-1.243	0.362	3.720	-3.853	-0.112	0.113
	(0.097)	(0.099)	(0.040)	(0.038)	(1.991)	(2.007)	(2.734)	(2.636)	(0.252)	(0.225)
	[0.485]	[1.000]	[0.65]	[0.485]	[0.835]	[1.000]	[0.533]	[0.485]	[0.945]	[0.907]
Flex*IIP*H	0.013	-0.258*	0.051	0.097*	-2.171	-5.387*	-2.521	2.159	0.207	-0.057
	(0.140)	(0.140)	(0.060)	(0.051)	(2.926)	(2.883)	(3.372)	(3.482)	(0.369)	(0.334)
	[1.000]	[0.485]	[0.825]	[0.485]	[0.835]	[0.485]	[0.835]	[0.835]	[0.871]	[1.000]
Observations	726	726	726	726	726	726	726	726	726	726

Notes: The unit of analysis is a customer. Dependent variables are as defined as in Table 2. Dimensions of heterogeneity are binary variables. The dimension is 'high mental constraint' (High MC) for odd-numbered columns, which is a binary variable = 1 if the value of the index is greater than sample median. The dimension is 'high transaction costs' (High TC) for even-numbered columns, which is a binary variable = 1 if the distance to EasyPaisa agent is greater than 5 km. All specifications include individual controls selected through LASSO between daily rate at the contract start, rental contract at start, respondent's age, respondent can read and write, any savings, knows the contract rate, knowledge of system rules, distance from Easypaisa agent, index for mental constraints, index for ability to smooth consumption, time inconsistent preferences; month, location, enumerator and salesperson fixed-effects; robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Sharpened q values in square brackets control the false discovery rate for tests across heterogeneous effects (the test only considers the two dimensions in this table).