Paying in pieces:

A natural experiment on demand for life insurance under different payment schemes

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Abstract

Risk is pervasive in low-income economies, but insurance markets tend to be under-developed and demand for existing products is often low. Usually, customers must buy insurance by making a single lump-sum payment. We study a popular life insurance product sold by Mexico's leading microfinance institution. We exploit a large-scale natural experiment involving 207,000 poor female microcredit customers and show that demand increases by 38 to 44 percent when customers are allowed to pay in weekly installments instead of in a lump sum, even though doing so is more costly for them. The finding is not easily explained by price, income, information, trust, or convenience. We describe the possible roles of liquidity constraints, discount rates, and three behavioral explanations: framing effects, present bias, and difficulties constituting lump sums. We relate the result to discussions of low demand for microinsurance and other products, including merit goods, in similar contexts.

Keywords

Microinsurance; present bias; liquidity constraints; saving constraints; Mexico; merit goods.

JEL codes

D9; D12; O12; G21; G22

Highlights

- Customers of a Mexican micro-lender voluntarily purchase a term life insurance product.
- Due to a software limit, sometimes premiums must be paid in full upfront rather than over time.
- When upfront payment is required, demand for insurance drops by 27 to 31 percent.
- When installments are again allowed, demand rises to previous levels by 38 to 44 percent.
- Demand is strongly influenced by the payment modality, not just price.

1. Introduction

Insurance demand is often much lower than predicted by the frequency of risks faced by poor households in developing countries (Cole, 2015; Eling, Pradhan, & Schmit, 2014). Standard economic models emphasize the roles of price relative to risk, but behavioral economics and concerns about trust and social networks are expanding ways to understand demand for insurance and other consumer choices. We take advantage of a large-scale natural experiment in Mexico to show how demand for a life insurance product is highly sensitive to payment modality, and we review factors that may explain the finding. Insurance premiums are usually paid in lump sum payments before the term of the insurance starts (Casaburi & Willis, 2018), and we find that shifting from requiring upfront lump-sum payments to allowing payment in weekly installments increases insurance demand by 38 to 44 percent.

Facilitating payments is central to business models for "bottom of the pyramid" commerce. Prahalad (2004), for example, describes Procter and Gamble's success when selling shampoo in India in single-serve sachets rather than just in large bottles. Purchasing sachets allowed customers to break purchases into amounts consistent with their week-to-week cash flows, although at higher unit costs. The argument is that liquidity constraints makes buying in small pieces more attractive. Payment modalities get much less attention than price in studies of consumer demand, however, partly because payment modes are difficult to study. Few payment options are typically available, although the number of modalities is increasing (e.g., payment via mobile money systems). When several modalities exist, the choice of which one to use is typically left to individuals, opening the door to selection bias (e.g., Burt et al., 2017).

Our setting is well-suited to testing the impact of payment modalities on demand. The term-life insurance product that we study was designed to be simple and is well understood by customers. Unlike many microinsurance products, the product is relatively popular: 62 percent of customers purchase the policy at the given price when they have the option to pay in small weekly installments. The sample includes 207,000 low-income women served by a large microfinance institution in Mexico. All potential insurance buyers are also customers in a joint-liability microcredit group, which allows most customers to easily bundle the insurance premium payments with their weekly loan installments (the 16-week loan cycle coincides with the 19-week insurance coverage period).

This paper makes two contributions to understanding the importance of payment modalities in the demand for microinsurance, with implications for the adoption of other products in developing countries including merit goods.[1] The first contribution is the use of a large-scale natural experiment to establish the causal impact of payment modality on the demand for microinsurance. Existing studies on payment modalities use relatively small samples to analyze randomized experiments, artefactual field studies, and observed behaviors with no intervention. The present paper instead exploits a natural experiment that permits the analysis of actual purchase decisions by a large sample of customers, showing results that are big in size for a small change in payment modality.

The natural experiment emerges when branches of the microfinance institution grow large and are split in two. The branch splits happen at an administrative level and affect back-office operations. A limitation of the bank's computer software, however, causes customers assigned to newly-created branches to be exogenously marked as borrowing from newly-created

[1] Merit goods are broadly defined as goods that are valued by society according to criteria other than the individual preferences of consumers. They may have positive external benefits, but not necessarily: merit goods may simply be goods that a (paternalistic) social planner deems valuable for people to consume, such as education and basic healthcare (Musgrave, 2008). An important quality of merit goods is that they tend to be under-purchased relative to the social optimum (thus merit goods are candidates for subsidy, nudges, and other steps to increase demand).

groups in the lender's management information system, although these customers' groups did not change.[2] Customers in the newly-created branches are unaffected in most important ways: the lending process, the location and nature of meetings, membership in groups, and the nature of engagements with the bank remain unchanged.[3]

A consequence is that these customers are required to pay the (US$4.50) insurance premium upfront for one loan cycle/insurance coverage period.[4] This happens because the bank requires that all new customers and customers in newly-created groups (including existing customers who join such groups) must pay the insurance premium upfront for one cycle if they choose to purchase insurance. The institution acknowledges that applying this requirement to existing customers assigned to a new branch is illogical from a business point of view, but its management found it easier to require all customers in new branches to abide by the rule rather than to selectively override the software system.[5]

Because the assignment of customers to branches after a split is independent of customer and group characteristics, the insurance purchase decision in the cycle after a split can be used to estimate the causal impact of the payment modality. We identify a natural experiment rather than a randomized trial, but the language of the lab remains helpful: the empirical focus is on how purchase decisions of customers in newly-created branches (the treatment group) change before and after the creation of the new branches, compared to choices of a control group comprised of

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[2] Customers are allowed to switch group between loan cycles, but this decision is endogenous, so we cannot use variation from movers to estimate the causal impact of the upfront payment requirement on the demand for the product. The natural experiment relies on customers whose "new" status is determined exogenously and who are not in fact moving to newly-formed groups.

[3] One difference is that the newly-split branches are often staffed by newly-hired personnel. We use data on staff tenure to show that the presence of new personnel does not drive the estimated changes in insurance demand.

[4] 57 Mexican pesos; USD1~MXP12.75 in 2011, the date of our data.

[5] This limitation applied as of 2011, the year of the data analyzed in this paper. A modification of the computer system was in the works, but had not yet taken effect. In 2011, 50 branches were split and 68,645 customers were assigned to a new branch.

customers who remain in the "mother branches" – branches to which the treatment group had previously belonged – and kept the option to pay the premium in installments.

We show that demand falls by 27 to 31 percent (from the 62 percent base) when, holding all else constant, customers who used to have a choice of payment modality are required to pay the premium as a one-time lump-sum payment. This is notable since paying with a lump sum is considerably cheaper (paying in installments carries an effective annualized interest rate of about 70 percent). Demand then rises back to previous levels, increasing by 38-44 percent from the lower base in the first cycle after the branch split, when customers regain the option to pay in installments.

Our second contribution is the identification of possible explanations for the drop in demand when customers are required to pay the insurance premium upfront. Because neither the product price nor customers' incomes change, these two factors cannot explain the demand response. As we detail in Section 5, the drop is also not easily explained by strategic behavior based on expected mortality, convenience of paying in installments, information, and trust in the insurer.

We identify five possible explanations. First, high discount rates could lead customers to view the discounted sum of installment payments as cheaper than upfront payments. Second, liquidity constraints may be binding, so customers who regularly borrow at high interest rates could see buying insurance in installments as equivalent to taking a similarly expensive (but much smaller) loan. We show, however, that to explain the demand response discount rates would have to be far higher than are typically found in similar economies. We also describe possible mitigating factors for liquidity constraints.

The demand response is also consistent with three behavioral explanations (which cannot be distinguished in the data). First, consistent with recent experimental evidence (Hershfield, Shu, & Benartzi, 2018), customers may reframe the cost of the insurance; the upfront cost of 57 pesos may seem much larger than the cost of four pesos per weekly installment. Second, if customers are saving constrained, having (and holding onto) lump sums may be especially valuable (Afzal, d'Adda, Fafchamps, Quinn, & Said, 2017; Rutherford, 2000). Third, present-biased customers may be reluctant to purchase the insurance upfront yet still see the value of insurance; pre-committing to the payment in installments can be a way to reconcile their present impatience with their longer-term desire to purchase insurance, along the lines of Laibson (1997).

In the conclusion we draw parallels and implications for the demand of other financial and non-financial products, including merit goods.

2. Field setup

The research was conducted in partnership with Compartamos, the largest microfinance institution in Mexico with nearly three million customers in 2016 (MixMarket, 2016). The life insurance product studied is a term policy that lasts just 19 weeks.[6] The insurance policy pays 100 percent of its face value to the beneficiary. (It is not a "credit life" insurance policy that pays off any outstanding debt owed by the deceased; instead, any outstanding loan balances due to Compartamos are automatically forgiven in the case of a customer's death.) The microfinance institution acts as an intermediary between the insured (its customers) and a large private insurer.

[6] If a customer takes a new loan at the next loan cycle, a new policy comes into effect at the time of the new loan disbursement and cancels the previous policy three weeks before expiration. If a customer chooses not to borrow at the next loan cycle, the policy remains in effect for three weeks after the end of the last loan cycle.

Compartamos markets the insurance, collects premiums for the insurer, and receives claims. The policy is available to all active customers regardless of age and medical condition (no medical certificate is asked), and covers natural and accidental death of the customer only.[7]

Compartamos offers loans under joint-liability contracts with group lending, as well as individual loan contracts. The sample here includes only individuals borrowing under the group methodology. Loan cycles are standardized to 16 weeks, with weekly member meetings and weekly repayment. All group-lending customers are women. Groups can include up to 50 customers, with an average of 21 members in our sample.

All customers in the group lending methodology are provided one module of coverage at no cost to them, paid for by Compartamos, and they have the option to purchase additional modules of coverage. Each additional unit of insurance increases total coverage by 15,000 pesos (about US$1,175 in 2011) for 57 pesos (about US$4.50). For comparison, a bottle of soda costs around 20 pesos in 2011, the year of the study. New customers and customers aged 70 years and older are limited to one additional module while other customers can buy up to seven additional modules for a total coverage of about US$9,400. In practice, however, nearly all customers who purchase insurance only purchase one module (99.3 percent).

To make the policy easier to understand and more attractive to low-income customers, paperwork is limited, both at the times of purchasing a policy and claiming benefits. Signing up consists of paying the premium and providing a photocopy of the beneficiary's official identification document. In case of a claim, the payoff is disbursed to the beneficiary upon

[7] This specific policy is not available to individuals who do not borrow from Compartamos, although the underwriting insurer offers similar policies to the general population. The insurance does not cover death because of suicide or illegal action of the insured or beneficiary; these cases are very rare.

presentation of the insured's death certificate and the beneficiary's national identification document. Claims are paid even if the insured was in default on her loan at the time of her death.

Most customers have a choice of two ways to pay the insurance policy: pay the full 57-peso premium at the beginning of the loan cycle, or pay the premium in 16 weekly installments bundled with their loan repayment installments. The weekly installments of four pesos per module of insurance add to a total cost of 64 pesos per module. Paying in installments therefore implies an increase of 12.3 percent in the total premium amount, or an annualized interest rate of about 70 percent. Upfront payment requires customers to bring the full premium amount at the first weekly group meeting after the loan was disbursed, i.e. one week after having signed the paperwork to purchase insurance. Payments by installments do not require additional action by the customers after having signed the purchase form, as premiums are collected as part of the weekly loan installment. In practice, 90 percent of insurance purchasers with a choice of payment method choose to pay in installments.

3. Methods

3.1. Research design

The identification strategy builds from a limitation of Compartamos's software system. Compartamos requires that all customers new to the institution pay for insurance upfront in a lump sum for their first loan cycle. Customers in new borrowing groups must also pay premiums upfront for one cycle. In loan cycles after that, customers have the option to pay by installment.

A computer software quirk means that a third group of customers is also required to pay insurance premiums upfront—and they are our focus. These are members of branches newly created after branch splits. When a branch gets too large to manage, it is split in two by

Compartamos, and some customers in the existing branch are assigned to a newly-created branch. In 2011, the year of our data, 50 existing branches were split and 50 new branches were created. The newly-created branches (and all their customers) are marked as new in the software, including existing customers and groups who were part of the "mother branch" but were re-assigned by Compartamos to be serviced by the new branch.

The choice of who to keep and who to move into a newly-created branch depends on customers' geographic proximity to the existing branch office. (We show in Section 3.4 below that customers assigned to new branches are similar in observable characteristics to customers remaining in the original branches.) The assignment to remain in the original branch or to be serviced by the new branch does not effectively change the customers' experience with Compartamos. Branches only fulfill back-office functions and are not organized as a point of service for customers of the lender's group-lending program. Groups meet at the home of one of the members, not in the branch. Loan officers travel to the groups' meeting place to oversee loan applications and repayment. The lender operates a cashless business, so customers receive their loan proceeds and make their payments in a local bank rather than in a lender's branch.

Beneficiaries of the life insurance policies also do not need to go to a branch. If a customer who purchased a life insurance policy dies, the policy's beneficiary can provide the necessary paperwork to the loan officer during one of the weekly group meetings, and later receives from the loan officer a payment order cashable in a local bank. As a result, customers almost never go to the lender's branch, and the geographical location of the branch office does not play any role in their borrowing, repayment, or insurance purchase and claim.

In addition to the change in payment modality for insurance purchases, there is one other important change when branches split. New branches are more likely to be staffed with new loan officers, and these staff members face special financial incentives (their guaranteed pay is higher and their productivity bonuses lower). In our sample of split branches, 40 percent of loan officers are new, and we show in section 4 that results are robust to excluding branches served by new loan officers.

The research design focuses on split branches. We compare the insurance take-up rates of current customers who remain in current branches (who have a choice of premium payment modality) to take-up rates of current customers in newly-created branches (who must pay the premium upfront). Comparing the broader set of customers with no payment choice to the broader set with choice would likely introduce bias. This is because customers who are required to pay upfront are generally different from those who have a choice. They are either genuinely new customers, with no history with the lender and with the insurance product it offers, or repeat customers who move to a newly-created group, for a variety of possible reasons that are not available in our data. Because the differences between customers in these two groups are likely both observable and unobservable, the net impact of the premium payment modality is impossible to identify from the simple comparison, even when controlling for confounding factors with statistical analyses.

3.2. Data and sample

Data were obtained from the administrative records of Compartamos. Since loans are the joint responsibility of the customers in a group, Compartamos does not need full information on its customers to underwrite loans, and gathers only limited information. It collects demographic and household indicators include age, marital status, education level, number of children, and home ownership status. It does not collect data on income, occupation, uses of the loans, levels of risk aversion, or time preferences. The administrative records do provide credit history data including the name of the customer's group, the number of loan cycles completed by the group and by the customer (as explained above, they may differ), and the customer's loan size for every cycle. The database also includes insurance indicators such as the number of modules of additional insurance purchased and whether a claim was made during a loan cycle (that is, the customer died).

The sample is comprised of active customers of Compartamos who belonged to one of the 50 branches that split in 2011 and meet three criteria. First, they must have borrowed for at least two consecutive loan cycles: immediately before and after the branch split. Second, the research design relies on customers having a choice of method of premium payment before the branch split, and losing it in the new branch. New customers and customers in new groups in the last loan cycle before the branch split were therefore dropped from the analysis sample. Third, only customers who remain members of the same group in the loan cycles immediately before and after the branch split are included in the sample, because the identification strategy relies on their exogenously losing the choice of premium payment modality.

The analysis sample, described in Table 1, includes all customers who meet the three inclusion criteria described above. The customers' data include all loans taken in 2011. Because the credit program that we study is only open to women, our findings may not generalize to other subjects. On the other hand, the sample is large, including 717,286 loans taken by 207,187 unique customers. These customers were members of 25,597 distinct borrowing groups. The data for the main analysis include information on two to four loan cycles per customer, with an average of 3.5 cycles.

Characteristics of the customers, their loans, and their insurance purchase decisions are shown in Table 2. The typical customer in the sample is a middle-aged married woman living in a family of five. About 40 percent of the customers reached the secondary school level or higher, and about 70 percent own their home. The average length of time that customers have been borrowing from Compartamos is just over two years (7.6 loan cycles of 16 weeks each), and the average loan size is almost US$750. Informal discussions with customers reveal that many of them have a small economic activity such as buying and reselling clothes or running a small shop, often in complement to their husband's salaried employment.

As noted earlier, the average insurance take-up rate before the branch splits is high, with 62 percent of customers purchasing some insurance. The large majority of customers who have a choice of payment method prefer to pay their premium in weekly installments (about 90 percent). Customers purchase 0.6 modules on average, but nearly all customers who purchase insurance (99.3 percent) buy only one module. The death rate is very low. Of the 207,187 customers in our sample, 181 died in 2011 (0.087 percent). Because the sample is constructed to include a sub-set of clients who take multiple loans, we cannot calculate a meaningful proportion of customers who die during a contract. Analyzing a larger sample of Compartamos clients in the same year, Bauchet, Damon, and Hunter (forthcoming) report a probability that a customer dies during a loan cycle of 0.039 percent, or a roughly four-in-10,000 chance.

3.3. Empirical strategy

The main empirical strategy relies on a difference-in-difference approach, implemented on an unbalanced panel dataset with customer fixed effects.[8] The regression equation is specified as:

$$I_{ic} = \alpha + \delta * P_{ic} + \beta * P_{ic} * T_i + \theta * X_{ic} + \lambda_i + \varepsilon_{ic} \tag{1}$$

where i indexes customers and c indexes loan cycles. I_{ic} is one of two measures of insurance purchase. We analyze the impact of required upfront payment on (i) a binary variable equal to one if a customer purchases any module of insurance and zero if she decides not to buy insurance, and (ii) the number of modules of insurance purchased (range: 0-7).[9] P_{ic} is a binary variable that takes the value one for all loan cycles post-branch split and zero for all loan cycles before the branch split. T_i is a binary variable equal to one if the customer is assigned to be serviced by a new branch created in 2011 and zero if she is assigned to remain serviced by the same branch. X_{ic} is a vector of customer and group characteristics including age, age square, number of children, marital status, education, home ownership, customers' number of previous loan cycles, groups' number of previous loan cycles, and group size. We present two versions of all regressions, excluding vector X and including it, to verify that our results are robust to controlling for observable customer and group characteristics, and because the samples of customers who remain in the original branch and are assigned to the new branch are statistically significantly different (Table 2). These variables remain in the fixed effects regression because values change for a few customers over the year for which we have data. λ_i are customer fixed

[8] Results are similar when analyzing a balanced panel including two loan cycles per customer (the cycles immediately before and after the branch split; Appendix Table 1), although the magnitude of the coefficients increases.
[9] In our main tables we analyze the number of modules of insurance purchased using ordinary least squares regressions; results are similar when using Poisson regressions for count data (Appendix Table 2).

effects, which control for observable and unobservable time-invariant characteristics of customers We also present cross-sectional estimates, which align with our main findings. ε is the error term. Standard errors are clustered at the group level.

We also estimate the local average treatment effect of the assignment to the new branch using a panel instrumental variable specification. The instrument is a binary variable equal to one for customers who are in a newly-created branch and in a loan cycle during which they are required to pay the insurance premium as an upfront lump sum. In other loan cycles and for other customers, the variable equals zero.

3.4. Tests of the exogeneity of the branch assignment

The identification strategy relies on the assumption that customers and groups are exogenously assigned to the new branch. This is the case a priori, as described in Section 3.1 above. The new branch is typically created in a new part of town, and groups are distributed among new and old branches depending on their distance from each branch office. Nonetheless, this system could allow some level of endogeneity if the socio-economic status of Compartamos customers is unequally distributed between neighborhoods of a city.

To investigate that possibility, Table 2 reports customers' characteristics in their last loan cycle before their branch is split. It shows that, before the split, customers who will remain in the original branch are very similar to customers who will be serviced by the new branch in terms of demographic characteristics, length of their relationship with the lender, loan size, and insurance purchase decisions. The differences between the means are statistically significant at the five percent level for all variables but one, so we present all regressions with and without a full set of controls for customers' characteristics. (Estimating with fixed effects also removes unobserved heterogeneity.)

Despite the statistically significant differences, the average values for the two sub-groups are very similar in magnitude. Importantly, the difference in insurance purchase rate between customers who remain in the same branch and customers who are assigned to the new branch is not statistically significant: 62.3 percent of customers who remain in the original branch bought additional insurance coverage before the branch split, compared to 61.9 percent of customers later assigned to be serviced by a new branch (p=0.105).

4. Results

Figure 1 shows the main finding. The percentage of customers who purchase one or more modules of insurance is roughly similar in all loan cycles except for the one immediately after the branch split, and is not statistically significantly different in the last loan cycle before the branch split (also shown in Table 2, Part C). The insurance take-up rate in the first loan cycle after the branch split, when customers in the new branch must pay the premium upfront, is about 30 percentage points lower among customers assigned to be serviced by the new branch than among customers remaining in the original branch. Figure 1 depicts the purchase behavior of the 207,187 customers who participated in the loan cycles immediately preceding and following the split; the number of observations in earlier and later cycles is lower since these customers may not have been consistently borrowing over time.

Table 3 reports results from the difference-in-difference analysis of Equation 1. Coefficients indicate that requiring upfront payment decreases take-up by 17 to 19 percentage points ($p<0.001$), depending on whether control variables are included in the model. The result corresponds to a drop in take-up by about 30 percent and is slightly smaller in magnitude than the raw averages in Figure 1 indicated. Requiring upfront payment also reduces the average number of modules purchased by 0.17 to 0.20 modules ($p<0.001$), but this analysis of the intensive margin is only indicative since less than one percent of insurance buyers purchase more than one module.

Table 4 presents a panel instrumental variable specification to estimate the local average treatment effect of the assignment to the new branch rather than the intent-to-treat estimate obtained from Equation 1. We instrument for the obligation to pay the insurance premium upfront with a binary variable equal to one for the first loan cycle in the new branch for customers assigned to a new branch, and equal to zero in all other loan cycles and for all cycles of customers remaining in the original branch.[10] First-stage regression coefficients are presented in the first two columns. The Sanderson-Windmeijer multivariate F tests of excluded instruments are larger than 770,000, indicating that the new branch assignment is a strong excluded instrument. In this analysis, standard errors are heteroscedasticity-robust instead of clustered by borrowing group because we cannot estimate a panel IV regression with clustered standard errors. We estimate linear probability models even though the dependent variables in both equations are binary variables, following Angrist and Pischke (2009).

Coefficients from the second-stage regressions are in the third and fourth column of Table 4. They again show that requiring upfront payment of the premium leads to a large drop in insurance take-up: requiring upfront payment decreases take-up by about 25 percentage points ($p<0.001$).

[10] The instrumented and instrument variables differ in that some customers in our sample are obliged to pay upfront for reasons other than the assignment to the new branch, as explained in Section 2.

As noted in section 3.1, the findings could be influenced by the fact that new branches tend to be staffed with new loan officers. In addition to being less experienced, newly-hired loan officers have a higher guaranteed pay and lower productivity bonuses for their first three months of employment. As a result, their incentive to sell insurance is reduced. In the sample, 645 of the 1,608 loan officers (40 percent) managing groups in their first cycle after the branch split were new employees hired for the new branch.

Figure 2 augments the data presented in Figure 1 by adding the average insurance take-up rates excluding customers in groups managed by new loan officers post-split (the third column in the last three cycles). The impact of the modified incentive structure for new loan officers does not markedly influence take-up. Note that five new branches were staffed entirely with new loan officers, reducing the number of branches post-split to 95 in the analysis reported in this section.

Table 5 confirms that the presence of new loan officers had little impact. The likelihood of purchasing life insurance decreases by 20 to 24 percentage points when customers of new loan officers are excluded from the sample ($p<0.001$), versus 17 to 19 percentage points when these customers are included (Table 3). The average number of modules of insurance purchased decreases by 0.21-0.24 modules ($p<0.001$) instead of by 0.17-0.20 modules (Table 3).

Table 6 presents results from a cross-sectional analysis of data for the loan cycle after the branch split (in which customers in the new branch do not have a choice of payment modality), comparing take-up rates among customers serviced by the new branch to take-up rates among customers who remained in the original branch. This analysis loses the benefit of controlling for time-invariant characteristics of customers with through fixed effects estimation, but it has the advantage of incorporating information from customers who do not change their insurance purchase decisions (i.e., those who always purchase or never purchase insurance). These estimates are closer to the univariate comparison of average take up rates (shown in Figure 1), and show that requiring upfront payment leads to a 27 to 29 percentage point decrease in insurance take-up ($p<0.001$), and a decrease in the number of insurance modules purchased by 0.28 to 0.30 modules ($p<0.001$). This is the largest demand response we estimate.

In sum, our main estimates (which are the most conservative) show that the requirement to pay insurance upfront led to a reduction in demand by 17 to 19 percentage points. From a base take-up rate of 62 percent (when choice to pay by installments is available), the estimates correspond to a demand reduction between 27 and 31 percent. If the shift is viewed in the other direction (from a base of upfront lump-sum payments to a context involving choice to pay by installment), the percent increase in demand is between 38 and 44 percent.

5. Discussion

The demand response can potentially be explained by both neoclassical and behavioral theories. Neither price nor income changes in the assignment to new branches, so we turn elsewhere for explanations. We first describe why adverse selection, convenience, information, and trust are unlikely to explain the demand response. We then consider five alternative explanations: high discount rates, liquidity constraints, framing effects, present bias, and difficulties constituting lump sums.

5.1. Adverse selection, convenience, information and trust

Lower total insurance cost in case of premature death. Customers could prefer the payment in installments because it allows them, if they die before the end of the cycle, to pay less than the full cost of coverage but transfer the full payout to their beneficiary. This argument is unlikely to explain our findings for two reasons. First, customers' choice of modality of payment of the insurance premium is not correlated with their likelihood of dying. Table 7 shows that, on average, customers who purchased life insurance coverage, had a choice of premium payment modality, and eventually died during a loan cycle were not notably more likely to have chosen to pay the insurance premium in installments than upfront (coefficient=0.004, p=0.869).

Second, and more generally, indirect evidence indicates that customers do not make life insurance purchase decisions based on their risk of death. The observed overall purchase rate of 62 percent contrasts with the very low death rate and low actuarial value of the product (the policy is actuarially fair for customers aged 65 years and older (Bauchet et al., forthcoming)). Bauchet et al. (forthcoming) also analyze a similar but larger dataset of Compartamos customers than the one used in this paper, finding no evidence of adverse selection in customers' insurance purchasing behavior.

Convenience of the payment in installments. Upfront buyers need to bring the full insurance premium amount in cash at the next group meeting, while those who pay in installments skip this step. Thus remembering to bring an extra 57 pesos one week later may be more cognitively demanding than simply bringing a slightly higher amount to each week's meeting, and might drive customers' preference for the installment option. The evidence on the role of convenience of purchasing a policy on microinsurance demand is ambiguous. Schultz, Metcalfe, and Gray (2013) and Thornton et al. (2010) show that making sign-up processes more convenient increases take-up of health insurance. Other studies, however, do not find an impact of increasing the convenience of signing up for the product (Asuming, 2013), including when offering payments in installments and though mobile money platforms (Chemin, 2018). In our setting, the convenience gains from paying in installment appear to be too small to explain the large drop in demand. In sum, convenience alone seems unlikely to sway the purchase decision of existing customers who value the product, although we cannot dismiss the possibility entirely.

Lack of information and lack of trust in the insurance provider. Lack of trust in the insurance provider has been shown to decrease take-up rates of microinsurance (Cai, Chen, Fang, & Zhou, 2009; Cole et al., 2013; Giné, Townsend, & Vickery, 2008; Zhang, Wang, Wang, & Hsiao, 2006). The concern, however, is greatest for insurers entering new markets. Here instead the insurance customers have had an ongoing relationship with Compartamos, and, as noted, 62 percent of customers typically purchase insurance. In addition, all customers automatically receive one module of coverage at no cost to them as long as they borrow in a Compartamos group. Given that on average customers have completed ten loan cycles by the time of the branch split, they have considerable information about and experience with the financial institution and the insurance product. They likely also have direct experience or indirect knowledge of the death of a customer and the subsequent prompt insurance payment. Lack of trust in the product and in Compartamos's ability to fulfill the insurance's promise is unlikely to play an important role in the choice of insurance payment modality for customers who have already chosen to trust Compartamos and the insurer by purchasing the product.

5.2. Discount rates and liquidity constraints

High discount rates. In principle, the take-up of the insurance product when upfront payment is required is influenced by customers' discount rates. Paying the insurance premium in installments over time, rather than upfront, would be appealing to customers who have a high discount rate as it decreases the perceived total premium amount, even though the payment in installments carries a positive interest rate.[11]

The rate of discount that sets the sum of installments (16 weekly installments of four pesos) equal to the upfront cost (57 pesos) is 1.4 percent per week, or about 106 percent per year. Individual discount rates, particularly in developing countries, are difficult to precisely assess. Some studies find individual annual discount rates in the low single-digits in India (between 3.2 and 4.5 percent among microfinance customers (Bauer & Chytilová, 2010)), Vietnam and Russia (between 0.7 and 4.2 percent (Anderson & Gugerty, 2009)), and the United States (Gourinchas & Parker, 2002; Laibson, Repetto, & Tobacman, 2007). Other estimates are much higher, ranging from 26 percent in Nepal (Carvalho, Prina, & Sydnor, 2016) to 43 percent in Chile (Barr & Packard, 2000) and up to 117 percent in Madagascar (Nielsen, 2001). Except for the Madagascar estimates, these estimated discount rates are not high enough to explain the demand response by themselves.

Close to our setting, Carvalho (2010) uses data from Mexico's national conditional cash transfer program PROGRESA (now called *Prospera*) to calculate a discount rate for individuals similar to those served by Compartamos. He finds a lower-bound estimate of an annual discount rate of 43 percent, which is again too low to explain the demand response by itself. The fact that 62 percent of customers purchase insurance at the start suggests that discount rates are not in fact unusually high, since very high discount rates would undermine baseline demand for insurance.

[11] A high discount rate also diminishes the perceived value of the insurance payout, but the exogenous assignment to paying upfront induced by the branch split implies that this does not bias our estimates. With respect to merit goods more broadly, lower discount rates are associated with increased probabilities that individuals adopt merit goods and connected practices such as treating water, washing hands, cooking with clean fuels, and owning a bed net (Atmadja, Sills, Pattanayak, Yang, & Patil, 2017).

Yet, Carvalho (2010) finds that generally people in his Mexican sample are "very impatient" (p. 4), so we cannot fully preclude discount rates as a factor.

Liquidity constraints. The findings are also consistent with liquidity constraints: paying by installments is effectively like taking a loan (as noted above, the associated interest rate is about 70 percent). As Casaburi and Willis (2018) note, insurance contracts with upfront payments transfer income through time – possibly to a time with low liquidity. In an experiment with crop insurance in Kenya, they find that requiring farmers to pay insurance premiums at harvest-time leads to 72 percent take-up versus just five percent when payments must be made pre-harvest. Similarly, combining loans or other forms of financing over time can help boost the demand for merit goods by overcoming liquidity constraints (e.g., Tarozzi et al. (2014)).

Two mitigating factors make liquidity constraints somewhat less likely in our context. Most important, the price of insurance is relatively low: nearly all those who purchase insurance buy just one unit, and the upfront cost (57 pesos) is roughly equivalent to the cost of three cans of soda. In informal discussions with researchers, Compartamos customers indicated that they do not view the premium as prohibitively expensive, and described being confident in their ability to come up with such a lump sum if necessary. In relative terms, the 57-peso insurance premium is roughly one percent of average monthly income (5,801 pesos) in Angelucci et al. (2015), or 0.25 percent when considering the four-month coverage period.

In addition, one week before the lump-sum insurance premium payment is due (for those paying in a single, upfront payment), the customers receive microcredit loans from Compartamos with an average size of 9,593 pesos, providing substantial liquidity. The insurance premium due represents just 0.6 percent of that amount. If customers have even minimal slack, they should be able to carve out enough funds from the loan to finance the purchase of the insurance. While we expect that the role of liquidity constraints is thus small on its own, the data do not allow us to directly test the extent to which individuals are liquidity constrained and how it relates to the impact of insurance payment modalities.

5.3. Hypotheses from behavioral economics

The results above are also consistent with ideas emerging in behavioral economics. We highlight three behavioral mechanisms: (1) reframing of costs; (2) responding to saving constraints and privileging lump sums; and (3) paying by installments as a commitment device deployed by (sophisticated) customers with time-inconsistent preferences. These explanations cannot be distinguished in the data.

Reframing costs. Customers may reframe the cost of the insurance when viewed per installment. Specifically, Compartamos customers may think little of paying an installment of four pesos a week but think twice about making the upfront payment of 57 pesos. In a field experiment on saving for retirement, for example, Hershfield et al. (2018) find that enrollment in a saving plan quadrupled when deposits were framed as requiring a deposit of $5 per day rather than $150 per month (even though deposit requirements were identical in both cases). We rely on administrative data that do not include information on incomes, but we can put the costs in context using a survey of potential customers of the same microfinance institution in the same year (2011). Angelucci et al. (2015) restrict attention to the North-Central Sonora region, near the border with Arizona, showing a control group mean income of 5,801 pesos per month.[12] The

[12] Total monthly income is calculated from Angelucci et al. (2015) Table 4 as the sum of household business income (840 pesos), labor income (4,541 pesos), remittances and transfer income (327 pesos) and government subsidies or aid (93 pesos). Their regression estimates find no significant impact on income in their treatment group (customers of Compartamos), so treatment and control income data can be treated as comparable at endline (endline survey was conducted in 2011).

figure implies that average daily income would be roughly 193 pesos. Against this benchmark of daily income, a four-peso installment may not seem like much (4/193, or two percent), but a 57-peso upfront payment is framed as a much larger sum (57/193, or 30 percent).[13]

Saving constraints and lump sums. Customers may face difficulties saving, so having (and holding onto) lump sums may be especially valuable. Unlike the liquidity constraints explanation, the behavioral constraint here centers on the particular challenges of accumulating lump sums, rather than issues around timing. In this context, devoting the 57 pesos of an existing lump sum to the insurance premium may impose a large opportunity cost relative to other uses for the lump sum. Instead, the four-peso installment payment is relatively small, and the payment structure allows customers to pay the premium with small sums of money that might otherwise slip through their hands (Rutherford, 2000). The value of lump sums has been the focus of recent literature. Afzal et al. (2017), for example, construct a series of artefactual field experiments that show how people are willing to pay for installment structures that provide a mechanism to transform a stream of small cash flows into a larger sum, concluding that whether the structure looks like a loan or a saving product is less important than the function of aggregation. Similarly, Casaburi and Macchiavello (2016) show that Kenyan dairy farmers willingly sacrifice earnings in exchange for being paid in (larger) monthly sums rather than (smaller) weekly payments, effectively paying their buyers for a financial aggregation service. Other research shows how betting is used by individuals in developing countries as a costly lump-sum generation strategy, particularly by individuals who report difficulties saving (Dizon & Lybbert, 2017; Herskowitz,

[13] This explanation is also consistent with evidence that individuals are willing to pay a higher price, and/or to spend more money, when they are primed or instructed to use a credit card rather than cash, which permits (among other differences) the ability to pay over time (Feinberg, 1990; Raghubir & Srivastava, 2008). The credit card effect is "unlikely" to be due to liquidity constraints (Prelec & Simester, 2001), but has been attributed to mobile payment systems and credit cards reducing the "pain of paying" (Zellermayer, 1996) compared to checks and cash (Soman, 2003).

2016). As in the examples above, accumulating lump sums may be particularly difficult for the individuals in our sample, and, correspondingly, parting with lump sums would be particularly costly. Customers are therefore willing to pay extra for the installment arrangement and the freedom from having to pay a lump sum.

Present Bias and Delayed Purchase. Time-inconsistent customers who are aware of their inconsistency (e.g., sophisticated hyperbolic discounters) may see the wisdom of purchasing insurance but could be reluctant to commit themselves to purchasing a policy when the full premium must be paid upfront in the present moment (or close to the present), along the lines of Laibson (1997). "Present-biased" individuals, who over-value present consumption but regret their impatience later on, could be swayed by the upfront cost of the insurance into not purchasing a policy even though they value the product. For present-biased individuals, pre-committing to the payment in installments can be a way to reconcile their present impatience with their longer-term desire to purchase insurance. In line with this, Cole (2015) identifies self-control as one of the behavioral biases that reduces take-up of microinsurance (also see the review by Eling et al. (2014)).

6. Conclusion

Microinsurance has great potential to help poor households manage the risks they face, although it has yet to achieve large market penetration. This paper shows that a small change in the modality of payment of a term life microinsurance premium had a big impact on the demand for the product. Requiring upfront payment, rather than giving a choice between the upfront payment and a payment in weekly installment bundled with a loan repayment, led to a 17 to 19 percentage point decrease in take-up of the product. The effect size is equivalent to a 27 to 31 percent drop in insurance demand when the choice of payment modality is eliminated. In the shift from requiring upfront lump-sum payments to allowing a choice of payment modality comparison, demand rises by 38 to 44 percent.

This result is puzzling from the vantage of standard economic theory, especially given that paying in installments is more expensive than paying upfront (an effective annualized interest rate of 70 percent is charged on the premium when paid in installments). Adverse selection, convenience in purchasing, and lack of trust in the insurance provider are unlikely to explain the result.

Discount rates would need to be very high (we calculate a threshold of 106%) to explain the demand response, a figure that is higher than found in similar contexts but which we can't rule out with the available data. Liquidity constraints could also play a role, but they are likely to be mitigated since the upfront premium is low and customers receive a loan one week prior to the premium due date. Other mechanisms that might explain the result include (i) reframing of the price as a cost per week or per month; (ii) saving constraints that raise the effective opportunity cost of spending lump sums; and (iii) customer self-control issues, which may make the payment in installments more attractive to present-biased individuals. We cannot distinguish between these possibilities in the data.

The fact that demand falls so sharply with a small change in the payment modality echoes findings from the literature on merit goods, which shows that important elements are missing from standard models of consumer demand, particularly the assumptions that price is the main barrier to purchase (holding income fixed) and that products are well-understood by potential purchasers (Ahuja, Kremer, & Zwane, 2010; Cohen & Dupas, 2010; Cropper, Haile, Lampietti, Poulos, & Whittington, 2004; Grimm, Lenz, Peters, & Sievert, 2017; Kremer & Miguel, 2007;

Meredith, Robinson, Walker, & Wydick, 2013; Mobarak, Dwivedi, Bailis, Hildemann, & Miller, 2012). The chance to pay in multiple smaller installments has been shown to increase adoption rates for a variety of products, including bed nets, improved woodstoves, and water filters (Beltramo, Blalock, Levine, & Simons, 2015; Devoto, Duflo, Dupas, Parienté, & Pons, 2012; Fink & Masiye, 2012; Grimm et al., 2017; Guiteras, Levine, Polley, & Quistorff, 2016; Levine, Beltramo, Blalock, Cotterman, & Simons, 2016; Tarozzi et al., 2014).

While not a traditional merit good, insurance is an important asset in poor communities as the costs of healthcare, funerals, crop losses, property damage, and other shocks often quickly exhaust savings and negatively affect future decisions (Karlan, Osei, Osei-Akoto, & Udry, 2014; Kazianga & Udry, 2006; Morduch, 1995). Yet, similar to merit goods, the willingness to pay for microinsurance is surprising low overall. The growing body of evidence underscores the importance of payment modalities alongside conventional elements like price.

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References

Afzal, U., d'Adda, G., Fafchamps, M., Quinn, S., & Said, F. (2017). Two Sides of the Same Rupee? Comparing Demand for Microcredit and Microsaving in a Framed Field Experiment in Rural Pakistan. *The Economic Journal*. doi:10.1111/ecoj.12512

Ahuja, A., Kremer, M., & Zwane, A. P. (2010). Providing Safe Water: Evidence from Randomized Evaluations. *Annual Review of Resource Economics, 2*(1), 237-256. doi:10.1146/annurev.resource.012809.103919

Anderson, C. L., & Gugerty, M. K. (2009). Intertemporal choice and development policy: New evidence on the time-varying discount rates from Vietnam and Russia. *The Developing Economies, 47*(2), 123-146. doi:10.1111/j.1746-1049.2009.00080.x

Angelucci, M., Karlan, D., & Zinman, J. (2015). Microcredit Impacts: Evidence from a Randomized Microcredit Program Placement Experiment by Compartamos Banco. *American Economic Journal: Applied Economics, 7*(1), 151-182. doi:doi: 10.1257/app.20130537

Angrist, J. D., & Pischke, J.-S. (2009). *Mostly harmless econometrics: An empiricist's companion*. Princeton, NJ: Princeton University Press.

Asuming, P. (2013). *Getting the poor to enroll in health insurance, and its effects on their health: Evidence from a field experiment in Ghana.* Mimeo.

Atmadja, S. S., Sills, E. O., Pattanayak, S. K., Yang, J.-C., & Patil, S. (2017). Explaining environmental health behaviors: evidence from rural India on the influence of discount rates. *Environment and Development Economics, 22*(3), 229-248. doi:10.1017/S1355770X17000018

Barr, A., & Packard, T. (2000). *Revealed and concealed preferences in the Chilean pension system: An experimental investigation*. Discussion Paper Series No. 53, Department of Economics, University of Oxford.

Bauchet, J., Damon, A., & Hunter, B. (forthcoming). Asymmetric information in microinsurance markets: Experimental evidence from Mexico. *Economic Development and Cultural Change*.

Bauer, M., & Chytilová, J. (2010). The Impact of Education on Subjective Discount Rate in Ugandan Villages. *Economic Development and Cultural Change, 58*(4), 643-669. doi:10.1086/652475

Beltramo, T., Blalock, G., Levine, D. I., & Simons, A. M. (2015). The effect of marketing messages and payment over time on willingness to pay for fuel-efficient cookstoves. *Journal of Economic Behavior & Organization, 118*(Supplement C), 333-345. doi:10.1016/j.jebo.2015.04.025

Burt, Z., Njee, R. M., Mbatia, Y., Msimbe, V., Brown, J., Clasen, T. F., Malebo, H. M., & Ray, I. (2017). User preferences and willingness to pay for safe drinking water: Experimental evidence from rural Tanzania. *Social Science & Medicine, 173*(Supplement C), 63-71. doi:10.1016/j.socscimed.2016.11.031

Cai, H., Chen, Y., Fang, H., & Zhou, L.-A. (2009). *Microinsurance, Trust and Economic Development: Evidence from a Randomized Natural Field Experiment*. NBER Working Paper Series No. 15396. Retrieved from http://www.nber.org/papers/w15396

Carvalho, L. S. (2010). *Poverty and time preference*. RAND Labor and Population Working Paper WR-759. Retrieved from http://dx.doi.org/10.2139/ssrn.1625524

Carvalho, L. S., Prina, S., & Sydnor, J. (2016). The effect of saving on risk attitudes and intertemporal choices. *Journal of Development Economics, 120*(Supplement C), 41-52. doi:10.1016/j.jdeveco.2016.01.001

Casaburi, L., & Macchiavello, R. (2016). *Firm and Market Response to Saving Constraints: Evidence from the Kenyan Dairy Industry*. CEPR Discussion Paper No. DP10952. Retrieved from https://ssrn.com/abstract=2697565

Casaburi, L., & Willis, J. (2018). *Time vs. State in Insurance: Experimental Evidence from Contract Farming in Kenya*. University of Zurich and Columbia University. Retrieved from https://scholar.harvard.edu/jwillis/publications/time-vs-state-insurance-experimental-evidence-contract-farming-kenya

Chemin, M. (2018). Informal Groups and Health Insurance Take-up Evidence from a Field Experiment. *World Development, 101*(Supplement C), 54-72. doi:10.1016/j.worlddev.2017.08.001

Cohen, J., & Dupas, P. (2010). Free Distribution or Cost-Sharing? Evidence from a Randomized Malaria Prevention Experiment. *Quarterly Journal of Economics, 125*(1), 1.

Cole, S. (2015). Overcoming Barriers to Microinsurance Adoption: Evidence from the Field. *The Geneva Papers on Risk and Insurance-Issues and Practice, 40*(4), 720-740.

Cole, S., Giné, X., Tobacman, J., Townsend, R. M., Topalova, P., & Vickery, J. I. (2013). Barriers to Household Risk Management: Evidence from India. *American Economic Journal: Applied Economics, 5*(1), 104-135. doi:10.1257/app.5.1.104

Cropper, M. L., Haile, M., Lampietti, J., Poulos, C., & Whittington, D. (2004). The demand for a malaria vaccine: evidence from Ethiopia. *Journal of Development Economics, 75*(1), 303-318. doi:10.1016/j.jdeveco.2003.02.006

Devoto, F., Duflo, E., Dupas, P., Parienté, W., & Pons, V. (2012). Happiness on Tap: Piped Water Adoption in Urban Morocco. *American Economic Journal: Economic Policy, 4*(4), 68-99. doi:doi: 10.1257/pol.4.4.68

Dizon, F., & Lybbert, T. J. (2017). *Leveraging the Lottery for Financial Inclusion: Lotto-Linked Savings Accounts in Haiti*. Retrieved from http://economics.ucr.edu/pacdev/pacdev-papers/leveraging_the_lottery.pdf

Eling, M., Pradhan, S., & Schmit, J. T. (2014). The determinants of microinsurance demand. *The Geneva Papers on Risk and Insurance-Issues and Practice, 39*(2), 224-263.

Feinberg, R. A. (1990). The Social Nature of the Classical Conditioning Phenomena in People: A Comment on Hunt, Florsheim, Chatterjee, and Kernan. *Psychological Reports, 67*(1), 331-334. doi:10.2466/pr0.1990.67.1.331

Fink, G., & Masiye, F. (2012). Assessing the impact of scaling-up bednet coverage through agricultural loan programmes: evidence from a cluster randomised controlled trial in Katete, Zambia. *Transactions of The Royal Society of Tropical Medicine and Hygiene, 106*(11), 660-667. doi:10.1016/j.trstmh.2012.07.013

Giné, X., Townsend, R. M., & Vickery, J. (2008). Patterns of rainfall insurance participation in rural India. *The World Bank Economic Review, 22*(3), 539-566.

Gourinchas, P. O., & Parker, J. A. (2002). Consumption over the life cycle. *Econometrica, 70*(1), 47-89.

Grimm, M., Lenz, L., Peters, J., & Sievert, M. (2017). *Demand for off-grid solar electricity – Experimental evidence from Rwanda*. ZEF-Discussion Papers on Development Policy No. 232. Center for Development Research, Bonn.

Guiteras, R. P., Levine, D. I., Polley, T., & Quistorff, B. (2016). *Credit Constraints, Discounting and Investment in Health: Evidence from Micropayments for Clean Water in Dhaka*. Working Paper. Retrieved from http://go.ncsu.edu/rpguiter.dhaka-water-wtp.pdf

Hershfield, H., Shu, S., & Benartzi, S. (2018). *Temporal Reframing and Savings: A Field Experiment*. Retrieved from https://ssrn.com/abstract=3097468

Herskowitz, S. (2016). *Gambling, Saving, and Lumpy Expenditures: Sports Betting in Uganda.* (Ph.D.), University of California, Berkeley. Retrieved from https://www.sylvanherskowitz.com/jmp.html

Karlan, D., Osei, R., Osei-Akoto, I., & Udry, C. (2014). Agricultural Decisions after Relaxing Credit and Risk Constraints. *The Quarterly Journal of Economics, 129*(2), 597-652. doi:10.1093/qje/qju002

Kazianga, H., & Udry, C. (2006). Consumption smoothing? Livestock, insurance and drought in rural Burkina Faso. *Journal of Development Economics, 79*(2), 413-446.

Kremer, M., & Miguel, E. (2007). The illusion of sustainability. *The Quarterly Journal of Economics, 122*(3), 1007-1065.

Laibson, D. (1997). Golden Eggs and Hyperbolic Discounting. *The Quarterly Journal of Economics, 112*(2), 443-478. doi:10.1162/003355397555253

Laibson, D., Repetto, A., & Tobacman, J. (2007). *Estimating discount functions with consumption choices over the lifecycle*. NBER Working Paper No. 13314.

Levine, D., Beltramo, T., Blalock, G., Cotterman, C., & Simons, A. M. (2016). *What Impedes Efficient Adoption of Products?* CEGA Working Paper Series No. WPS-059. Center for Effective Global Action. University of California, Berkeley.

Meredith, J., Robinson, J., Walker, S., & Wydick, B. (2013). Keeping the doctor away: Experimental evidence on investment in preventative health products. *Journal of Development Economics, 105*(Supplement C), 196-210. doi:10.1016/j.jdeveco.2013.08.003

MixMarket. (2016). Compartamos Banco Profile. Retrieved 24 October 2017 https://www.themix.org/mixmarket/profiles/compartamos-banco

Mobarak, A. M., Dwivedi, P., Bailis, R., Hildemann, L., & Miller, G. (2012). Low demand for nontraditional cookstove technologies. *Proceedings of the national Academy of sciences, 109*(27), 10815-10820. doi:10.1073/pnas.1115571109

Morduch, J. (1995). Income smoothing and consumption smoothing. *The Journal of Economic Perspectives, 9*(3), 103-114.

Musgrave, R. A. (2008). Merit Goods. In S. N. Durlauf & L. E. Blume (Eds.), *The New Palgrave Dictionary of Economics: Volume 1 – 8* (pp. 4173-4176). London: Palgrave Macmillan UK.

Nielsen, U. (2001). *Poverty and Attitudes towards Time and Risk - Experimental Evidence from Madagascar*. Royal Veterinary and Agricultural University of Denmark.

Prahalad, C. K. (2004). *The fortune at the bottom of the pyramid: Eradicating Poverty through Profits*. Upper Saddle River, NJ: Wharton School Publishing.

Prelec, D., & Simester, D. (2001). Always Leave Home Without It: A Further Investigation of the Credit-Card Effect on Willingness to Pay. *Marketing Letters, 12*(1), 5-12. doi:10.1023/a:1008196717017

Raghubir, P., & Srivastava, J. (2008). Monopoly money: the effect of payment coupling and form on spending behavior. *Journal of Experimental Psychology: Applied, 14*(3), 213-225. doi:10.1037/1076-898x.14.3.213

Rutherford, S. (2000). *The poor and their money*. New Delhi: Oxford University Press.

Schultz, E., Metcalfe, M., & Gray, B. (2013). *The impact of health insurance education on enrollment of microfinance institution clients in the Ghana National Health Insurance Scheme, Norther region of Ghana*. ILO MicroInsurance Facility Research Paper No. 33.

Soman, D. (2003). The Effect of Payment Transparency on Consumption: Quasi-Experiments from the Field. *Marketing Letters, 14*(3), 173-183.

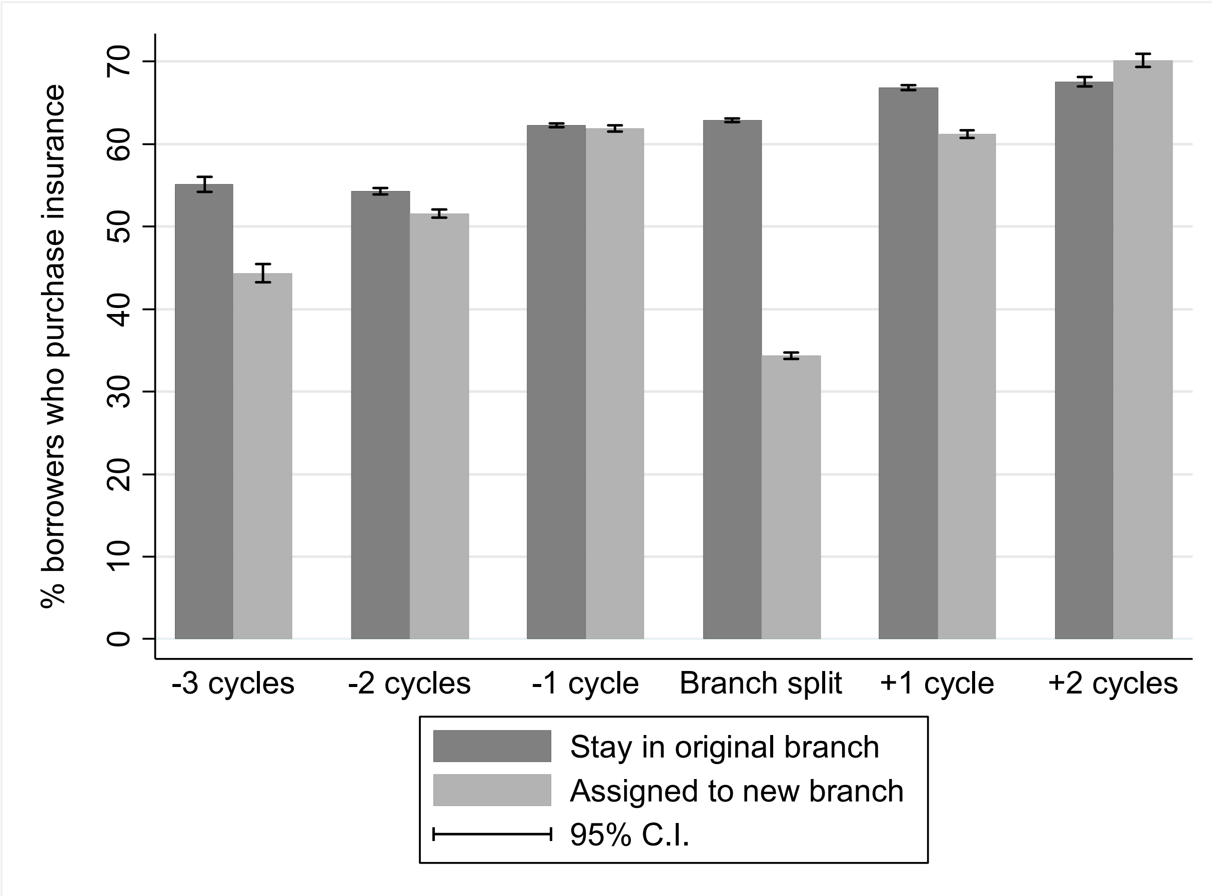
Tarozzi, A., Mahajan, A., Blackburn, B., Kopf, D., Krishnan, L., & Yoong, J. (2014). Micro-loans, insecticide-treated bednets, and malaria: evidence from a randomized controlled trial in Orissa, India. *The American Economic Review, 104*(7), 1909-1941.

Thornton, R. L., Hatt, L. E., Field, E. M., Islam, M., Solís Diaz, F., & González, M. A. (2010). Social security health insurance for the informal sector in Nicaragua: a randomized evaluation. *Health Economics, 19*(S1), 181-206.

Zellermayer, O. (1996). *The pain of paying.* (PhD), Carnegie Mellon University, Pittsburgh, PA.

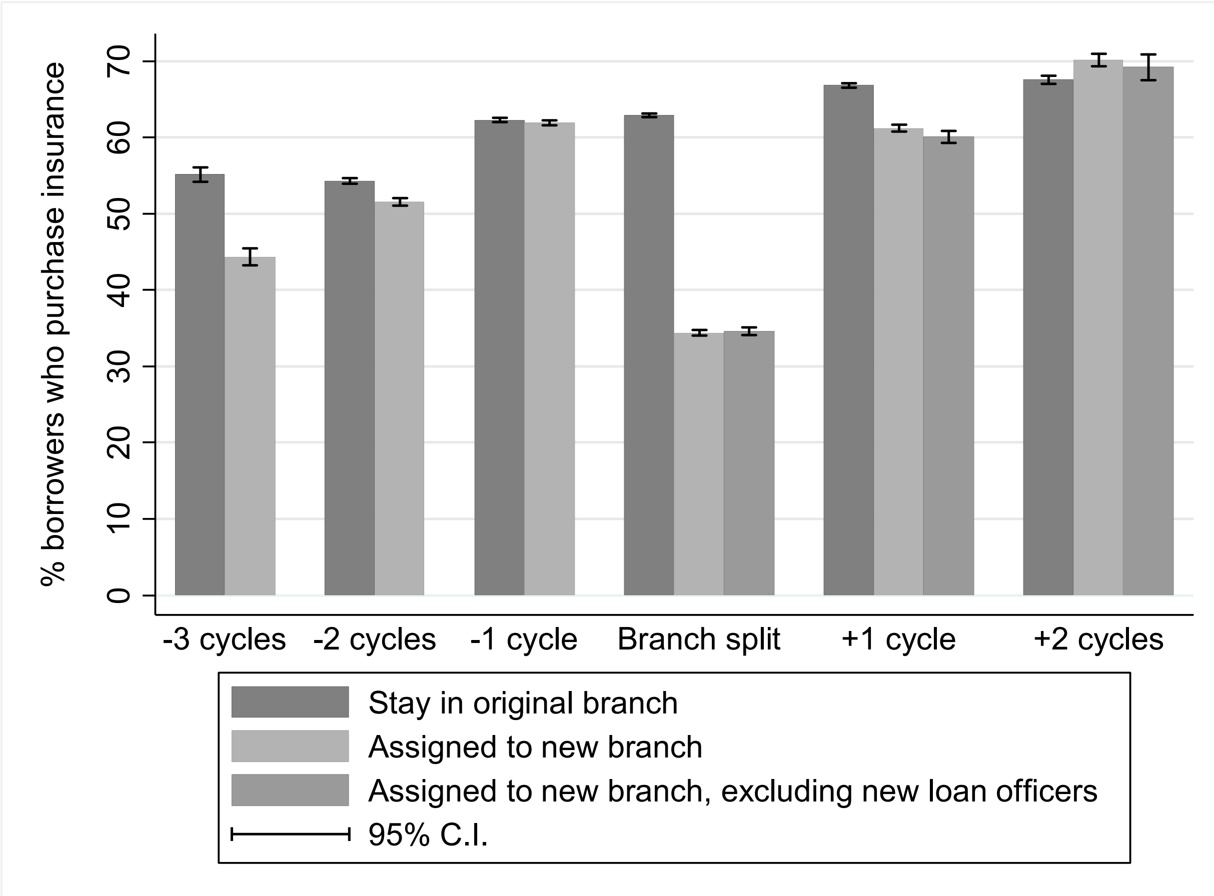
Zhang, L., Wang, H., Wang, L., & Hsiao, W. (2006). Social capital and farmer's willingness-to-join a newly established community-based health insurance in rural China. *Health Policy, 76*(2), 233-242. doi:10.1016/j.healthpol.2005.06.001

Figure 1. Take-up of insurance by branch split status.



Sample size: 19,195 to 207,187 customers depending on loan cycle (207,187 customers each in cycles -1 and split). No customer in the data has consistently borrowed over all 6 loan cycles shown, but some customers borrowed up to three cycles before the split. The maximum number of loan cycles observed for a single customer is four.

Figure 2. Take-up of insurance by branch split status, excluding new loan officers.



Sample size: 19,195 to 207,187 customers depending on loan cycle (207,187 customers each in cycles -1 and split). No customer in the data has consistently borrowed over all 6 loan cycles shown, but some customers borrowed up to three cycles before the split. The maximum number of loan cycles observed for a single customer is four.

Table 1. Sample size and insurance take-up rates by loan cycle.

Loan cycle	(1)	(2)	(3)	(4)	(5)	(6)
	Full sample		Stay in original branch		Assigned to new branch	
	N	Take-up	N	Take-up	N	Take-up
-3 cycles	19,195	50.7	11,409	55.1	*7,786*	44.3
-2 cycles	112,372	53.3	73,918	54.3	*38,454*	51.6
-1 cycle	207,187	62.1	138,542	62.3	*68,645*	61.9
Branch split	207,187	53.4	138,542	62.9	68,645	34.4
+1 cycle	132,371	65.0	90,095	66.8	42,276	61.2
+2 cycles	38,975	68.4	26,730	67.5	12,245	70.1

Notes: The 114,885 loans indicated in italic in column 5 were taken in the original branch by customers who later are assigned to be serviced by the new branch. Take-up is the percentage of loans (N) that were accompanied by a life insurance policy. The number of unique customers is 207,187.

Table 2. Characteristics of customers and their loans, in the last loan cycle before branch splits.

	(1)	(2)	(3)	(4)
	All customers (n=207,187)	Customers remaining in same branch (n=138,542)	Customers assigned to new branch (n=68,645)	p-value
Part A: Demographic characteristics				
Age (years)	40.8	40.9	40.6	<0.001
Number of children	3.11	3.10	3.13	<0.001
Marital status: married (%)	60.9	60.1	62.4	<0.001
Education level: Secondary or higher (%)	41.6	42.3	40.2	<0.001
Customer owns her home, mortgage is fully paid (%)	69.7	69.2	70.8	<0.001
Part B: Loan characteristics				
Customer loan cycle number	7.6	7.8	7.3	<0.001
Loan size (pesos)	9,594	9,679	9,421	<0.001
Group loan cycle number	10.0	10.3	9.5	<0.001
Group size	20.92	20.89	20.97	0.022
Part C: Insurance characteristics				
Purchased any additional insurance (%)	62.1	62.3	61.9	0.105
Paid insurance in installments, if bought insurance (%)	90.3	89.7	91.7	<0.001
Average number of insurance modules purchased	0.631	0.633	0.626	0.004
Purchased 1 module, if bought insurance (%)	99.3	99.2	99.4	
Purchased 2 modules, if bought insurance (%)	0.48	0.51	0.42	
Purchased 3 modules, if bought insurance (%)	0.07	0.08	0.05	
Purchased 4 modules, if bought insurance (%)	0.03	0.03	0.02	0.007
Purchased 5 modules, if bought insurance (%)	0.01	0.01	0.01	
Purchased 6 modules, if bought insurance (%)	0.01	0.01	<0.01	
Purchased 7 modules, if bought insurance (%)	0.12	0.14	0.08	

Notes: Data in columns 1-3 are means. P-values are from t-tests of the difference in the means for customers remaining in the same branch (column 2) and customers assigned to the new branch (column 3); the exception is the number of modules purchased, for which the p-value is from a Pearson's chi-square test.

Table 3. Impact on insurance purchases of requiring upfront payment of the insurance premium.

	(1)	(2)	(3)	(4)
Dependent variable:	1 if customer purchased any module of insurance		Number of modules of insurance purchased (0-7)	
Post * Customer assigned to new branch	-0.192***	-0.167***	-0.20***	-0.17***
	(0.006)	(0.007)	(0.01)	(0.01)
1 if loan cycle is post branch split	0.051***	-0.095***	0.06***	-0.09***
	(0.004)	(0.006)	(0.00)	(0.01)
Customer age		0.100***		0.10***
		(0.024)		(0.02)
Customer age, squared		-0.001***		-0.00***
		(0.000)		(0.00)
Number of children		-0.004**		-0.00**
		(0.001)		(0.00)
Marital status: Married		0.017***		0.02***
		(0.004)		(0.00)
Education level: Secondary or higher		-0.010***		-0.01***
		(0.004)		(0.00)
Customer owns her house		0.001		0.00
		(0.004)		(0.00)
Customer loan cycle		0.080***		0.08***
		(0.003)		(0.00)
Group loan cycle		0.002***		0.00***
		(0.001)		(0.00)
Group size		0.008***		0.01***
		(0.001)		(0.00)
Constant	0.594***	-2.496***	0.60***	-2.52***
	(0.002)	(0.550)	(0.00)	(0.56)
Observations	717,286	717,286	717,286	717,286
R-squared	0.014	0.033	0.012	0.030
Number of unique customers	207,187	207,187	207,187	207,187
Mean of dep. var. in cycle before branch split	0.620		0.629	

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered by customer group in parentheses. All regressions include customer fixed effects.

Table 4. Impact on insurance purchases of requiring upfront payment of the insurance premium, panel instrumental variable specification.

	(1)	(2)	(3)	(4)
	First stage		Second stage	
Dependent variable:	1 if insurance payment must be upfront; 0 if customer has a choice of payment		1 if customer purchased any module of insurance	
Customers' first loan in new branch (binary variable)	0.913***	0.888***		
	(0.001)	(0.001)		
Insurance payment *must* be upfront			-0.261***	-0.252***
			(0.002)	(0.003)
Customer age		0.003		0.104***
		(0.008)		(0.029)
Customer age, squared		-0.000		-0.001***
		(0.000)		(0.000)
Number of children		0.003***		-0.002*
		(0.001)		(0.001)
Marital status: Married		-0.001		0.016***
		(0.002)		(0.004)
Education level: Secondary or higher		0.004**		-0.009**
		(0.002)		(0.004)
Customer owns her house		-0.000		0.002
		(0.001)		(0.003)
Customer loan cycle		-0.038***		0.022***
		(0.000)		(0.001)
Group loan cycle		-0.008***		0.003***
		(0.000)		(0.000)
Group size		-0.005***		0.006***
		(0.000)		(0.000)
Observations	717,286	717,286	717,286	717,286
Number of unique customers	207,187	207,187	207,187	207,187
Sanderson-Windmeijer multivariate F test of excluded instruments:	1.1e+06***	7.7e+05***	1.1e+06***	7.7e+05***

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. All regressions include customer fixed effects. The sample consists of two observations per customer: one for the loan cycle immediately before the branch split, and one for the first loan cycle after the branch split.

Table 5. Impact of requiring upfront payment of the insurance premium on insurance purchases, excluding customers of new loan officers post-branch split.

	(1)	(2)	(3)	(4)
Dependent variable:	1 if customer purchased any module of insurance		Number of modules of insurance purchased (0-7)	
Post * Customer assigned to new branch	-0.236***	-0.201***	-0.24***	-0.21***
	(0.007)	(0.009)	(0.01)	(0.01)
1 if loan cycle is post branch split	0.055***	-0.076***	0.06***	-0.07***
	(0.004)	(0.006)	(0.00)	(0.01)
Customer age		0.067		0.06
		(0.073)		(0.07)
Customer age, squared		-0.001		-0.00
		(0.001)		(0.00)
Number of children		-0.004**		-0.00**
		(0.002)		(0.00)
Marital status: Married		0.019***		0.02***
		(0.005)		(0.01)
Education level: Secondary or higher		-0.008*		-0.01**
		(0.005)		(0.01)
Customer owns her house		0.003		0.00
		(0.005)		(0.00)
Customer loan cycle		0.073***		0.08***
		(0.003)		(0.00)
Group loan cycle		0.003***		0.00***
		(0.001)		(0.00)
Group size		0.009***		0.01***
		(0.001)		(0.00)
Constant	0.595***	-1.688	0.60***	-1.56
	(0.001)	(1.377)	(0.00)	(1.35)
Observations	587,247	587,247	587,247	587,247
R-squared	0.016	0.034	0.015	0.031
Number of unique customers	207,187	207,187	207,187	207,187
Mean of dep. var. in cycle before branch split	0.620		0.629	

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered by customer group in parentheses. All regressions include customer fixed effects.

Table 6. Impact of requiring upfront payment of the insurance premium on insurance purchases, cross-sectional analysis of data from the first loan cycle after the branch split.

	(1)	(2)	(3)	(4)
Dependent variable:	1 if customer purchased any module of insurance		Number of modules of insurance purchased (0-7)	
1 if customer assigned to a new branch	-0.285***	-0.267***	-0.30***	-0.28***
	(0.007)	(0.008)	(0.01)	(0.01)
Customer age		0.005***		0.01***
		(0.001)		(0.00)
Customer age, squared		-0.000***		-0.00***
		(0.000)		(0.00)
Number of children		-0.004***		-0.00***
		(0.001)		(0.00)
Marital status: Married		0.009***		0.01**
		(0.003)		(0.00)
Education level: Secondary or higher		0.023***		0.03***
		(0.003)		(0.00)
Customer owns her house		-0.019***		-0.02***
		(0.004)		(0.00)
Customer loan cycle		0.003***		0.00***
		(0.000)		(0.00)
Group loan cycle		0.001***		0.00**
		(0.001)		(0.00)
Group size		0.003***		0.00***
		(0.001)		(0.00)
Constant	0.629***	0.397***	0.64***	0.38***
	(0.004)	(0.015)	(0.00)	(0.02)
Observations	207,187	207,187	207,187	207,187
R-squared	0.072	0.080	0.064	0.072
Mean of dep. var. in cycle before branch split	0.620		0.629	

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered by customer group in parentheses.

Table 7. Customer death as a determinant of choice of insurance premium payment modality.

	(1)	(2)
Dependent variable:	1 if customer chooses to pay premium in installments; 0 if customer chooses to pay upfront	
Customers died during that loan cycle	0.026	0.004
	(0.023)	(0.023)
Customer age		-0.006
		(0.012)
Customer age, squared		0.000
		(0.000)
Number of children		0.000
		(0.001)
Marital status: Married		0.001
		(0.003)
Education level: Secondary or higher		0.003
		(0.003)
Customer owns her house		0.006**
		(0.003)
Customer loan cycle		0.013***
		(0.001)
Group loan cycle		0.006***
		(0.001)
Group size		-0.001
		(0.000)
Constant	0.910***	0.830***
	(0.000)	(0.240)
Observations	396,843	396,843
R-squared	0.000	0.015
Number of unique customers	176,052	176,052

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered by customer group in parentheses. All regressions include customer fixed effects. The sample consists of all loan cycles of customers in which they purchased additional life insurance coverage, and had a choice of premium payment modality (i.e. customer loan cycle>1 and group cycle>1); by construction, the first loan of customers assigned to a new branch is excluded.

Supplemental Material for Online Appendix

Appendix Table 1. Impact of requiring upfront payment of the insurance premium on insurance purchases, balanced panel dataset.

	(1)	(2)	(3)	(4)
Dependent variable:	1 if customer purchased any module of insurance		Number of modules of insurance purchased (0-7)	
Post * Customer assigned to new branch	-0.282***	-0.287***	-0.29***	-0.29***
	(0.007)	(0.009)	(0.01)	(0.01)
1 if loan cycle is post branch split	0.006	0.008*	0.01**	0.01***
	(0.004)	(0.004)	(0.00)	(0.00)
Customer age		-0.206		-0.20
		(0.304)		(0.30)
Customer age, squared		0.003		0.00
		(0.003)		(0.00)
Number of children		-0.005**		-0.00**
		(0.002)		(0.00)
Marital status: Married		0.020***		0.02***
		(0.006)		(0.01)
Education level: Secondary or higher		-0.009		-0.01*
		(0.006)		(0.01)
Customer owns her house		0.003		0.00
		(0.006)		(0.01)
Group loan cycle		-0.001		-0.00
		(0.001)		(0.00)
Group size		0.006***		0.01***
		(0.001)		(0.00)
Constant	0.621***	3.786	0.63***	3.70
	(0.002)	(6.486)	(0.00)	(6.46)
Observations	414,374	414,374	414,374	414,374
R-squared	0.064	0.066	0.057	0.059
Number of unique customers	207,187	207,187	207,187	207,187
Mean of dep. var. in cycle before branch split	0.620		0.629	

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered by customer group in parentheses. All regressions include customer fixed effects. The sample consists of two observations per customer: one for the loan cycle immediately before the branch split, and one for the first loan cycle after the branch split.

Appendix Table 2. Poisson regressions.

	(1)	(2)	(3)	(4)
Dependent variable:	Number of modules of insurance purchased (0-7)			
Regression mirrors:	Table 3, column 3	Table 3, column 4	Table 6, column 3	Table 6, column 4
Sample:	All loan cycles		Cycle of branch split only	
Customer fixed effects included:	Yes		No	
Post * Customer assigned to new branch	-0.361***	-0.315***		
	(0.005)	(0.008)		
1 if loan cycle is post branch split	-0.947***	-0.158***		
	(0.002)	(0.004)		
1 if customer assigned to a new branch			-0.617***	-0.593***
			(0.019)	(0.020)
Customer age		0.157***		0.012***
		(0.060)		(0.001)
Customer age, squared		-0.002**		-0.000***
		(0.001)		(0.000)
Number of children		-0.007***		-0.009***
		(0.003)		(0.002)
Marital status: Married		0.032***		0.014**
		(0.008)		(0.006)
Education level: Secondary or higher		-0.018**		0.057***
		(0.008)		(0.006)
Customer owns her house		0.005		-0.030***
		(0.006)		(0.007)
Customer loan cycle		0.134***		0.005***
		(0.002)		(0.001)
Group loan cycle		0.004***		0.002*
		(0.001)		(0.001)
Group size		0.014***		0.004***
		(0.000)		(0.001)
Constant			-0.439***	0.004***
			(0.006)	(0.001)
Observations	628,725	628,725	207,187	207,187
Number of unique customers	178,774	178,774	207,187	207,187
Mean of dep. var. in cycle before branch split	0.629			

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are heteroscedasticity-robust in columns 1 and 2, and clustered by customer group in parentheses in columns 3 and 4. The number of customers is lower in columns 1 and 2 than in columns 3 and 4 because 88,562 observations were dropped from the conditional fixed-effects Poisson regression because of all zero outcomes.