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 and poorly understood. 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 200,000 poor female microcredit customers and show that demand increased by 59 to 74 percent when customers were allowed to pay in weekly installments instead of in a lump sum, even though doing so was more costly for them. The finding is not explained by price or income, which do not change. We describe the possible roles of liquidity constraints and other explanations, and relate the result to discussions of demand for microinsurance and other products, including merit goods, in similar contexts.

Keywords

Discount rates; present bias; liquidity constraints; saving constraints; Mexico; merit goods.

JEL codes

D9; D12; O12; G21; G22

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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. 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 59 to 74 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. The argument is that liquidity constraints makes buying in small pieces more attractive, although it leads to paying higher unit costs. 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 (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. The product is generally popular: 62 percent of customers purchase the policy at the given price when they have the option to pay in small weekly installments.[1] The sample includes 200,000 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 of them 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).

Existing studies of payment modalities use relatively small samples to analyze randomized experiments, artefactual field studies, and observed behaviors with no intervention (e.g., Feinberg, 1990; Tarozzi et al., 2014; Thornton et al., 2010). The present paper instead exploits a large-scale 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 too large and are split in two. The branch splits happen at an administrative level and affect back-office operations, not customers' experience: the lending process, the location and nature of meetings, membership in groups, and the nature of engagements with the bank remain unchanged.[2] But customers are affected by the assignment to a new branch in one specific way: those served by the new branch are required to pay the (US$4.50) insurance premium upfront for

[1] Take up rates of life microinsurance are higher than those of most other microinsurance products, which are frequently in the single digits (Cole, 2015; Eling et al., 2014).

[2] One difference is that the new 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.

one loan cycle/insurance coverage period.[3] 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. A limitation of the bank's computer software causes customers assigned to the newly-created branches to be marked as borrowing from newly-created groups in the lender's management information system, although these customers' groups did not change. 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.[4]

Because the assignment of customers to branches after a split is driven by the bank's administrative needs and should be 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. The causal interpretation of the natural experiment hinges on the case that, apart from the assignment to the new branch, customers are unaffected by the branch split since their borrowing, repayment, and insurance purchase experiences have not changed. 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) compare to choices of customers who remain in the branches to which the treatment group had previously belonged (the control group).

[3] 57 Mexican pesos; USD1~MXP12.75 in 2011, the date of our data.

[4] 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 62,042 customers were assigned to a new branch, so manually overriding the system was not feasible.

We show that demand falls by 37 to 42 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, the same rate applicable to customers' loans). Demand falls to a take-up rate of about 35-40 percent when customers are required to pay through upfront lump sum payments, a level comparable to that of other life microinsurance products, for which take-up rates range between about 25 percent and 50 percent (Arun, Bendig, & Arun, 2012; Collins, Morduch, Rutherford, & Ruthven, 2009; Giesbert, Steiner, & Bendig, 2011; Huber, 2012). Demand then rises back to previous levels, increasing by 59-74 percent from the lower base in the first cycle after the branch split, when customers regain the option to pay in installments.

Because neither the product price nor customers' incomes change, these two factors cannot explain the demand response. The result is consistent with binding liquidity and savings constraints, among other factors. In the conclusion we place the results in the context of the welfare implications of encouraging take-up of a product with questionable actuarial value for most customers, and 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 (MIX Market, 2016). The life insurance product studied is a term policy that lasts just 19 weeks.[5] 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. 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.[6]

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 repayment. All group-lending customers are women. Groups can include up to 50 customers, with an average of 18 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.[7] Each additional unit of insurance increases total coverage by 15,000 pesos (about US$1,175) 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

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[5] 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.

[6] 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.

[7] Field observations suggest that customers are well aware of the voluntary nature of the life insurance product (beyond the free, automatically-provided module). Bauchet, Chakravarty, and Hunter (2018) provide more information on the voluntary nature of the insurance purchase (the paper shows how customers, absent a branch split, use the purchase of life insurance as a signal of creditworthiness).

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 before the branch split).

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 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, 91 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 upon a limitation of Compartamos's software system. Compartamos requires that all customers new to the institution and customers in newly-created borrowing groups (even if they are not new themselves) pay for insurance upfront in a lump sum for their first loan cycle. In all other loan cycles, 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 to be too large to manage, it is split in two by Compartamos, and some customers in the existing branch are assigned to be serviced by a newly-created branch.[8] In 2011, the year of our data, 50 existing branches were split and 50 new branches were created. The newly-created branches, and all the groups they serve, are marked as new in the software, including existing groups of existing customers who were part of the original branch but were re-assigned by Compartamos to be serviced by the new branch.

The choice of which group to keep in the original branch and which to move into a newly-created branch depends mainly 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. In particular, the two groups are equally likely to purchase insurance before the branch split.

[8] One external validity concern is that branches that split may operate in an environment that is different from branches that do not, for example in terms of business growth or returns to capital. The data, however, reveal that while splitting branches are larger than non-splitting branches on average just before they are split (Appendix Table 1), they are not growing faster than non-splitting branches (Appendix Table 2) and are geographically spread throughout the country (Appendix Figure 1).

The assignment to remain in the original branch or to be serviced by the new branch does not effectively change 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 groups and their members 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 original 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 including 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.[9] 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 694,846 loans taken by 200,545 unique customers. These customers were members of 24,654 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 in the loan cycle before the branch split 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 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

[9] This feature implies that possible customers who drop out of borrowing from Compartamos between the loan cycle before the branch split and the loan cycle immediately after the split are not included in our sample. As a result, possible differential dropout based on branch assignment cannot bias our coefficient estimates. When re-analyzing the full dataset including dropouts, we find that dropout rates were slightly lower among customers assigned to the new branch (19.2%) than customers remaining in the same branch (21.8%), which is counter to the hypothesis that the assignment to a new branch leads customers to pause or stop their borrowing. The difference is statistically significant in a t-test ($p<0.001$), but the standardized difference is small: 0.065 standard deviations. Differential dropout rates therefore do not seem to be in a position to bias our results.

cycles of 16 weeks each), and the average loan size is about 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 62.5 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 200,545 customers in our sample, 176 died in 2011 (0.088 percent). Because the sample is constructed to include a sub-set of clients who take multiple loans and are served by specific branches, this is not representative of death rates of Compartamos customers. Analyzing a larger sample of customers of the same loan program of Compartamos 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.[10] The regression equation is specified as:

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

[10] 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 3), although the magnitude of the coefficients increases.

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).[11] P_{ic} is a binary variable that takes the value one for the first loan cycle post-branch split and zero for all other loan cycles. T_i is a binary variable equal to one if the customer belongs to a group assigned to be serviced by a new branch created in 2011 and zero if she belongs to a group 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 along several characteristics (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 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

[11] 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 4).

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. The reason for and mechanisms of branch splits suggest it is the case, 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.

Most of the differences in means between customers who remain in the same branch and are assigned to be serviced by the new branch are statistically significant at the five percent level. However, three results increase our confidence that the statistically significant differences may be due to the large sample size, and that the assumption of exogeneity in the branch assignment holds. First the average values for the two sub-groups are very similar in magnitude. Standardized differences in mean characteristics of customers who remain in the same branch and are assigned to be serviced by the new branch, and their loans, are very small. Of the 13 variables shown in Table 2, 11 of the standardized differences are smaller than 0.06 standard deviations. Two variables, customers' and groups' history with Compartamos, show differences of 0.13 and 0.16 standard deviations, which remain small (for example, smaller than Jacob Cohen (1988)'s definition of a small effect size).

Second, the key variable of interest, the propensity of customers to purchase insurance, is not statistically significantly different in the loan cycle before the branch split: 62.3 percent of customers who remain in the original branch bought additional insurance coverage before the branch split, compared to 62.8 percent of customers later assigned to be serviced by a new branch (p=0.092).

Finally, regressions coefficients indicating the demand response to the assignment to the new branch are very close in specifications with and without a full set of controls for customers' characteristics. (Estimating with fixed effects also removes unobserved heterogeneity.) As a result, we believe that the assumption of exogenous assignment to a new branch holds; we acknowledge, however, that our causal interpretation of the results is based on this unproven assumption.

4. Results

Figure 1 shows the main finding. The percentage of customers who purchase one or more modules of insurance is similar one and two loan cycles before the branch split.[12] The insurance take-up rate in the first loan cycle after the branch split, when customers in the new branch must

[12] Appendix Table 5 shows that insurance take-up rates were not statistically significantly different by branch assignment one and two loan cycles before the branch split when controlling for customer and loan characteristics. We find a statistically significant difference three cycles before the split, which is not easily explained by characteristics of borrowers and their loans in that cycle (Appendix Table 6).

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.

Table 3 extends the results in Figure 1 with results from the difference-in-difference analysis of Equation 1. Coefficients indicate that requiring upfront payment decreases take-up by 23 to 27 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 40 percent from the base of 62.5 percent. Requiring upfront payment also reduces the average number of modules purchased by 0.24 to 0.27 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.[13] First-stage regression coefficients are presented in the first two columns. The Sanderson-Windmeijer multivariate F tests of excluded instruments are larger than 690,000, 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).

[13] 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.

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 26 percentage points ($p<0.001$).

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, 638 of the 1,585 loan officers (40 percent) managing groups in their first cycle after the branch split were new employees hired for the new branch.

Table 5 confirms that the presence of new loan officers has little impact. The likelihood of purchasing life insurance decreases by 22 to 27 percentage points when customers of new loan officers are excluded from the sample ($p<0.001$), versus 23 to 27 percentage points when these customers are included (Table 3). The average number of modules of insurance purchased decreases by 0.23-0.28 modules ($p<0.001$) instead of by 0.24-0.27 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 show that requiring upfront payment leads to a 26 to 28 percentage point decrease in insurance take-up ($p<0.001$), and a decrease in the number of insurance modules purchased by 0.27 to 0.29 modules ($p<0.001$).

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 23 to 27 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 37 and 42 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 59 and 74 percent.

5. Discussion

When customers move to new branches, neither prices nor incomes change. Other factors are thus needed to explain the demand response to the restriction on paying in installments, and liquidity constraints are a primary candidate. Paying by installments is effectively like taking a loan (as noted above, the associated interest rate is about 70 percent), and the sample is composed of women who already borrow at high interest rates from Compartamos, indicating limited financial slack. Liquidity constraints have been shown to have a large impact on microinsurance take-up in other settings (Casaburi & Willis, 2018; Cole et al., 2013). Similarly, allowing customers to borrow to purchase merit goods increases demand by allowing payments to be spread out and moved to a later time (e.g., Tarozzi et al. (2014)). Relatedly, liquidity constraints due to underlying saving constraints mean that having (and holding onto) lump sums may be especially valuable and the installment mechanism can be seen as a useful contractual saving device (Afzal, d'Adda, Fafchamps, Quinn, & Said, 2017; Casaburi & Macchiavello, 2016; Dizon & Lybbert, 2017; Herskowitz, 2016; Rutherford, 2000).

Still, the price of insurance is relatively low: nearly all Compartamos customers who purchase insurance buy just one unit, and the upfront cost (57 pesos) is roughly equivalent to the cost of three cans of soda.[14] In relative terms, the 57-peso insurance premium is roughly one percent of estimated average monthly income (5,801 pesos) for Compartamos customers, or 0.25 percent when considering the four-month coverage period.[15]

Nevertheless, customers may consider the cost relative to their daily income rather than monthly income. Taking the average daily income of 193 pesos in Angelucci et al. (2015), the four-peso weekly installment may not seem like much (4/193, or two percent of daily income), but a 57-peso upfront payment would be framed as a much larger sum (57/193, or 30 percent) and that framing could induce a large drop in demand. (See Hershfield, Shu, and Benartzi (2018), for a related experimental finding on the re-framing of the costs of retirement saving.) Similarly, the results are consistent with concentration bias (Dertwinkel-Kalt, Gerhardt, Riener, Schwerter, & Strang, 2017; Kőszegi & Szeidl, 2013). Experiments show that, all else the same, dispersed costs (in this case, paying over time in installments) tend to be viewed as less costly than concentrated costs (a single upfront payment), even when total costs over time are equivalent.

[14] 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 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. Still, the loan may not fully satisfy liquidity needs and thus may not be able to stretch to cover the purchase of the insurance.

[15] The Compartamos administrative data lack average monthly income. We instead use data from in Angelucci, Karlan, and Zinman (2015). Angelucci et al. (2015) collect data on Compartamos customers in the North-Central Sonora region, near the border with Arizona, showing a control group mean income of 5,801 pesos per month (so average daily income would be roughly 193 pesos). Total monthly income is calculated from their 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 of borrowing on income in their treatment group (customers of Compartamos), so treatment and control income data can be treated as comparable at endline (2011).

Psychological re-framing of the costs may contribute to overcoming an unfavorable actuarial value of the product. Optimizing customers weigh their perception of the insurance product's costs against expected benefits. Death rates are generally low, especially in the context of the product's premium; (Bauchet et al., forthcoming, note 4) calculate that the policy is actuarially fair only for customers aged 65 years and above. Deciding to purchase will then depend on the strength of younger customers' risk aversion and the broad costs of purchasing (convenience, etc.). Reductions in the perception of the product's cost (by spreading it out and facilitating its financing), may matter especially when the product is not clearly a good deal. The insurance may not offer them much protection, but when split into installments it costs little on a weekly basis.

In Appendix A we describe other potential factors, including the convenience of paying in installments, trust, discount rates, present bias, and the probability of mortality during the insurance term.

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 the option to pay in weekly installments, led to a 23 to 27 percentage point decrease in take-up of the product. The effect size is equivalent to a 37 to 42 percent drop in insurance demand when the choice of payment modality is eliminated. (In the subsequent shift from requiring upfront lump-sum payments to allowing a choice of payment modality comparison, demand rises by 59 to 74 percent.)

This result is notable given that paying in installments is more expensive for customers than paying upfront (an effective annualized interest rate of 70 percent is charged on the premium when paid in installments). Liquidity and savings constraints are possible explanations for the result, but we cannot rule out that other factors also play a role (e.g. convenience of paying in installments bundled with weekly loan repayments, high discount rates, and present bias).

The fact that demand falls so sharply with a small change in the payment modality echoes findings from the literature on merit goods (Ahuja, Kremer, & Zwane, 2010; Jessica 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).[16] 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). Similar to merit goods, the willingness to pay for

[16] Merit goods are broadly defined as goods that are valued by society according to criteria other than the individual preferences of consumers (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). As noted above, given that mortality rates in our sample are very low, the particular life insurance product we investigate may, in this case, be over-purchased relative to a (paternalistic) social optimum.

microinsurance is surprising low overall. The growing body of evidence underscores the importance of payment modalities alongside conventional elements like price.

The welfare implications of the product we study depend on the benefits and costs of the insurance product. The product is not clearly a good investment for younger customers unless they are highly risk averse. If younger customers are not making optimal choices, making it easier to purchase the product is not necessarily welfare-increasing from the vantage of a paternalistic social planner. This is an important concern. Our larger interest, however, has been to document the role of the payment modality on demand, holding price and other important variables constant, with an eye to other markets.

The customers of Compartamos are particular in some important ways. First, they are customers of a microfinance institution, and thus all want loans and willingly pay for them. Compartamos's loans are relatively expensive (about 70 percent on an annualized basis), so it is unsurprising that the sample would face liquidity constraints. Similarly, the customers are relatively poor women, and their options to borrow (or their savings to tap) are limited. These features push toward preferring paying in installments. In contexts with greater liquidity, the demand response when paying in a single lump sum payment versus paying in installments would likely be attenuated. Also, customers at Compartamos meet regularly to transact loan repayments, so paying for insurance in installments is logistically convenient (both for the financial institution and the customers), an arrangement that may not be feasible in other settings.

At the same time, the sample represents a large population in Mexico: Compartamos serves nearly three million women (MIX Market, 2016) and is by far the largest microfinance institution in Latin America. Moreover, the incidence of liquidity constraints is broadly experienced in poor communities globally. Especially with the spread of mobile banking platforms, transacting in small, regular payments is getting far easier and cheaper, opening possibilities for expanding the set of feasible payment modalities in many different settings.

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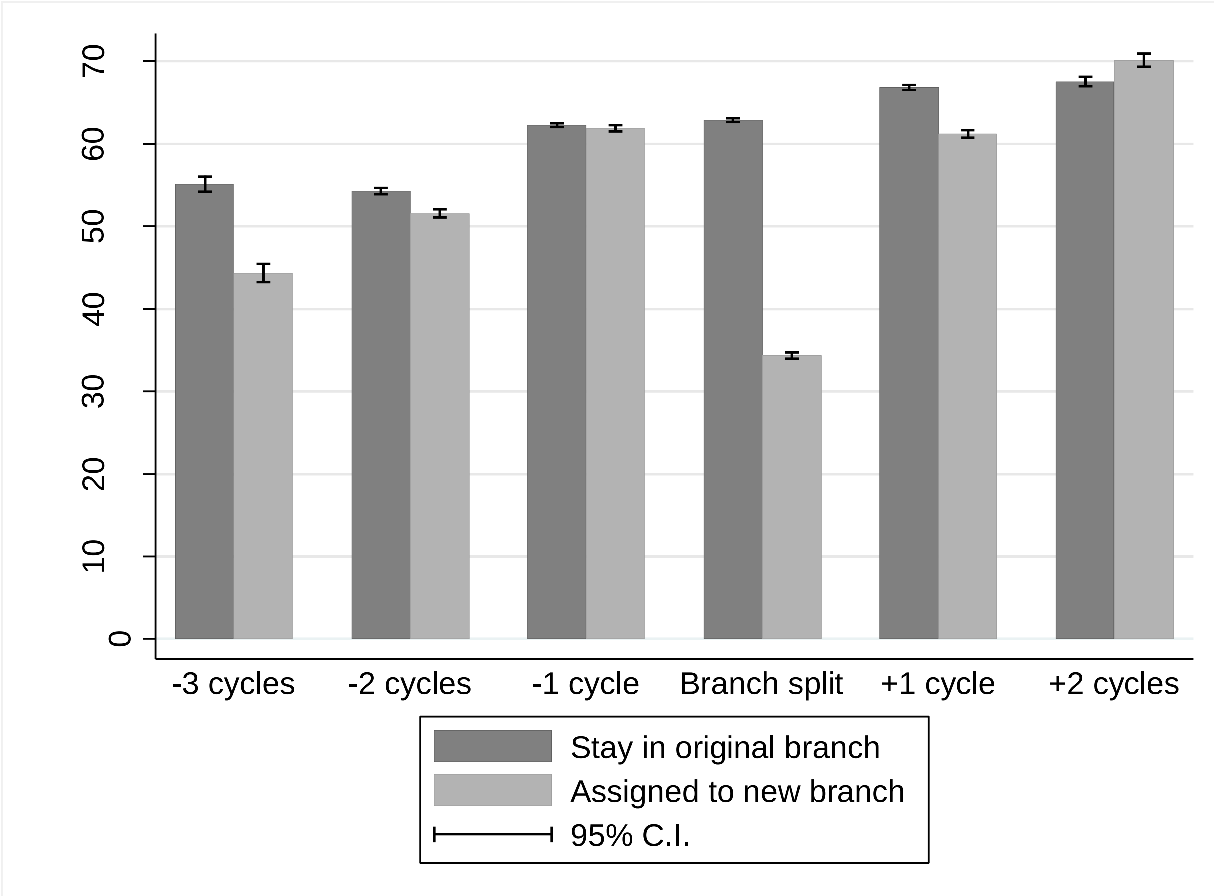
Figure 1. Take-up of insurance by branch split status.



Sample size: 18,443 to 200,545 customers depending on loan cycle (200,545 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. Standard errors are from regressions of the insurance take-up dummy on a constant, for each sub-sample; Appendix Table 5 shows that insurance take-up rates were not statistically significantly different by branch assignment one and two loan cycles before the branch split when controlling for customer and loan characteristics. We find a statistically significant difference three cycles before the split, which is not easily explained by characteristics of borrowers and their loans in that cycle (Appendix Table 6).

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	18,443	50.3	11,409	55.1	*7,034*	42.4
-2 cycles	106,960	53.3	73,914	54.3	*33,046*	51.1
-1 cycle	200,545	62.5	138,503	62.3	*62,042*	62.8
Branch split	200,545	54.3	138,503	62.9	62,042	35.1
+1 cycle	129,346	65.6	90,075	66.8	39,271	62.9
+2 cycles	39,007	68.2	26,727	67.5	12,280	69.8

Notes: The 102,122 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 200,545.

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

	(1)	(2)	(3)	(4)	(5)	(6)
	All customers (n=200,545)		Customers remaining in same branch (n=138,503)	Customers assigned to new branch (n=62,042)	Standardized difference	p-value
	Mean	Std. deviation				
Part A: Demographic characteristics						
Age (years)	40.8	12.2	40.9	40.6	0.027	<0.001
Number of children	3.11	1.96	3.10	3.13	-0.014	0.047
Marital status: married (%)	61	49	60.1	62.9	-0.057	<0.001
Education level: Secondary or higher (%)	42	49	42.3	39.8	0.051	<0.001
Customer owns her home, mortgage is fully paid (%)	70	46	69.2	71.5	-0.051	<0.001
Part B: Loan characteristics						
Customer loan cycle number	7.6	5.1	7.8	7.1	0.134	<0.001
Loan size (pesos)	9,626	6,738	9,679	9,507	0.026	0.092
Group loan cycle number	10.0	6.8	10.3	9.2	0.163	<0.001
Group size	20.90	7.24	20.89	20.93	-0.005	0.011
Part C: Insurance characteristics						
Purchased any additional insurance (%)	62.5	48.4	62.3	62.8	-0.012	0.092
Paid insurance in installments, if bought insurance (%)	90.2	29.7	89.7	91.4	-0.058	<0.001[a]
Average number of insurance modules purchased	0.634	0.527	0.633	0.636	-0.005	0.255
Purchased 1 module, if bought insurance (%)	99.3	8.5	99.2	99.4	-0.018	<0.001[a]

Notes: Data in columns 3 and 4 are means. The standardized differences are calculated as [(mean of remaining customers – mean of customers assigned to new branch)/standard deviation of the entire sample]. P-values are those of coefficients in a regression of being assigned to the new branch on all variables included in the table (with two exceptions indicated below) with standard errors clustered at the group level (following (McKenzie, 2015)). The exceptions are denoted with the superscript [a]: the two p-values are from t-tests of the difference in means for remaining customers (column 3) and customers assigned to the new branch (column 4), because the sample for these variables is restricted to insurance buyers.

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	-0.265***	-0.232***	-0.273***	-0.237***
	(0.007)	(0.008)	(0.007)	(0.008)
1 if loan cycle is post branch split	0.026***	0.007*	0.031***	0.010**
	(0.004)	(0.004)	(0.004)	(0.004)
Customer age		0.099***		0.099***
		(0.026)		(0.026)
Customer age, squared		-0.001***		-0.001***
		(0.000)		(0.000)
Number of children		-0.003**		-0.003**
		(0.002)		(0.002)
Marital status: Married		0.017***		0.016***
		(0.004)		(0.005)
Education level: Secondary or higher		-0.011***		-0.012***
		(0.004)		(0.004)
Customer owns her house		0.004		0.004
		(0.004)		(0.004)
Customer loan cycle		0.032***		0.035***
		(0.001)		(0.001)
Group loan cycle		0.005***		0.005***
		(0.001)		(0.001)
Group size		0.008***		0.008***
		(0.001)		(0.001)
Constant	0.609***	-2.124***	0.619***	-2.157***
	(0.001)	(0.576)	(0.001)	(0.582)
Observations	694,846	694,846	694,846	694,846
R-squared	0.027	0.038	0.024	0.035
Number of unique customers	200,545	200,545	200,545	200,545
Mean of dep. var. in cycle before branch split	0.625		0.634	

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)	0.912***	0.884***		
	(0.001)	(0.001)		
Insurance payment *must* be upfront			-0.262***	-0.255***
			(0.002)	(0.003)
Customer age		0.004		0.100***
		(0.008)		(0.029)
Customer age, squared		-0.000		-0.001***
		(0.000)		(0.000)
Number of children		0.002***		-0.003*
		(0.001)		(0.001)
Marital status: Married		-0.001		0.016***
		(0.002)		(0.004)
Education level: Secondary or higher		0.004**		-0.010**
		(0.002)		(0.004)
Customer owns her house		-0.000		0.004
		(0.001)		(0.003)
Customer loan cycle		-0.037***		0.023***
		(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	694,846	694,846	694,846	694,846
Number of unique customers	200,545	200,545	200,545	200,545
Sanderson-Windmeijer multivariate F test of excluded instruments:	9.4e+05***	6.9e+05***	9.4e+05***	6.9e+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	-0.271***	-0.220***	-0.282***	-0.228***
	(0.009)	(0.011)	(0.009)	(0.011)
1 if loan cycle is post branch split	0.034***	0.004	0.041***	0.008*
	(0.004)	(0.004)	(0.004)	(0.004)
Customer age		0.074		0.067
		(0.077)		(0.075)
Customer age, squared		-0.001		-0.001
		(0.001)		(0.001)
Number of children		-0.004**		-0.005**
		(0.002)		(0.002)
Marital status: Married		0.018***		0.018***
		(0.005)		(0.006)
Education level: Secondary or higher		-0.010**		-0.013**
		(0.005)		(0.005)
Customer owns her house		0.003		0.003
		(0.005)		(0.005)
Customer loan cycle		0.035***		0.038***
		(0.002)		(0.002)
Group loan cycle		0.008***		0.008***
		(0.001)		(0.001)
Group size		0.008***		0.009***
		(0.001)		(0.001)
Constant	0.606***	-1.566	0.616***	-1.464
	(0.001)	(1.451)	(0.001)	(1.422)
Observations	570,209	570,209	570,209	570,209
R-squared	0.019	0.033	0.017	0.031
Number of unique customers	200,545	200,545	200,545	200,545
Mean of dep. var. in cycle before branch split	0.625		0.634	

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	-0.278***	-0.259***	-0.289***	-0.270***
	(0.007)	(0.009)	(0.008)	(0.009)
Customer age		0.004***		0.006***
		(0.001)		(0.001)
Customer age, squared		-0.000***		-0.000***
		(0.000)		(0.000)
Number of children		-0.004***		-0.005***
		(0.001)		(0.001)
Marital status: Married		0.009***		0.007**
		(0.003)		(0.003)
Education level: Secondary or higher		0.024***		0.032***
		(0.003)		(0.003)
Customer owns her house		-0.019***		-0.016***
		(0.004)		(0.004)
Customer loan cycle		0.003***		0.003***
		(0.000)		(0.000)
Group loan cycle		0.001***		0.001**
		(0.001)		(0.001)
Group size		0.003***		0.002***
		(0.001)		(0.001)
Constant	0.629***	0.400***	0.645***	0.378***
	(0.004)	(0.016)	(0.004)	(0.016)
Observations	200,545	200,545	200,545	200,545
R-squared	0.066	0.074	0.059	0.066
Mean of dep. var. in cycle before branch split	0.625		0.634	

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

Supplemental Material for Online Appendix

Appendix A. Potential factors explaining the finding other than liquidity constraints.

In this appendix, we discuss other possible factors explaining the drop in insurance demand as a result of the loss of the option to pay the premium in installments, including convenience, trust, discount rates, present bias, and the probability of mortality during the insurance term. Given our data, we cannot provide evidence in support or against these factors.

Convenience of the payment in installments. Paying in installments could be more convenient for customers. Paying upfront requires purchasers to bring the full insurance premium in cash to the next group meeting, while those who pay in installments skip this step. Schultz, Metcalfe, and Gray (2013) and Thornton et al. (2010) show that making sign-up processes more convenient increases take-up of health insurance, while (Asuming, 2013) does not. Chemin (2018) also does not find strong demand responses to offering payments in installments and through mobile money platforms for a weakly-demanded health insurance product. In this setting, the convenience gains appear too small to fully explain the large demand response.

Convenience, concentration bias, and liquidity constraints also relate to evidence showing 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).

Trust (or breach of trust). Trust often arises as a factor limiting insurance demand (Cai, Chen, Fang, & Zhou, 2009; Cole et al., 2013; Giné, Townsend, & Vickery, 2008; Zhang, Wang, Wang, & Hsiao, 2006), but here insurance customers already had an ongoing relationship with Compartamos. On average customers had completed more than seven loan cycles by the time of the branch split, and, as noted, 62 percent of customers typically purchase insurance. Still, we cannot dismiss the role of a breach of trust perceived by customers who had been paying for insurance in installments and who were (somewhat arbitrarily) forced to pay in an upfront lump sum for a cycle. The demand response may be one way that customers signal anger or disappointment with Compartamos.

Discount rates. In principle, high discount rates could explain the reduction in take-up of insurance when paying over time is not possible. 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). Here, however, we calculate that the discount rate must be very high—at least 106 percent per year—such that the sum of installments (16 weekly installments of four pesos) is lower in expected value than the upfront cost (57 pesos).

Individual discount rates, particularly in developing countries, are difficult to assess precisely. 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. 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.

Present Bias. A different kind of commitment mechanism might appeal to time-inconsistent customers who are aware of their inconsistency (e.g., sophisticated hyperbolic discounters) and who desire to purchase insurance. Present-biased customers 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). For these individuals, pre-committing to paying in installments could be a way to reconcile their present impatience with their longer-term desire to purchase insurance (Cole, 2015; Eling, Pradhan, & Schmit, 2014).

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. Bauchet, Damon, and Hunter (forthcoming) also analyze a similar but larger dataset of Compartamos customers than the one used in this paper, finding customers who die during a loan cycle were not more likely to have purchased insurance, indicating that customers do not seem to make purchase decisions based on their mortality risk.

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Appendix Figure 1. Geographic distribution of branches that split in 2011.

Appendix Table 1. Size of branches that split and do not split.

	All branches	Branches that do not split in 2011	Branches that split in 2011 (Feb-Sep)
Number of customers	4,970	4,665	7,090
Number of groups	295	279	408
Loan portfolio	37.2	34.2	56.9

Notes: Data are as of January 31, 2011 (i.e. pre-split), and exclude branches that split in January 2011. Loan portfolio is in millions of Mexican pesos.

Appendix Table 2. Rates of growth in branches that split and branches that did not split.

	(1)	(2)	(3)	(4)	(5)	(6)
	Growth rate in the number of:					
	Borrowers		Groups		Portfolio	
1 if splitting branch; 0 if non-splitting branch	-1.569	-1.136	-1.081*	-0.722	-2.865	-2.175
	(1.056)	(1.192)	(0.576)	(0.627)	(2.161)	(2.464)
Constant	1.608	-26.94	1.143**	-13.39	2.922	-57.24
	(1.056)	(28.28)	(0.576)	(14.71)	(2.161)	(58.79)
Observations	346	346	346	346	346	346
R-squared	0.001	0.486	0.002	0.520	0.001	0.478
State dummies	No	Yes	No	Yes	No	Yes
Month dummies	No	Yes	No	Yes	No	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Heteroscedasticity-robust standard errors in parentheses. Each observation is one branch; branches that were created in 2011 were excluded from the sample. The growth rate calculation depends on whether a particular branch split in 2011: (a) for non-splitting branches, growth = (Dec. 2011 value – Jan. 2011 value)/Jan. 2011 value; (b) for splitting branches, growth = (Value in month before split – Jan. 2011 value)/Jan. 2011 value.

Appendix Table 3. 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	-0.283***	-0.281***	-0.29***	-0.29***
	(0.007)	(0.009)	(0.01)	(0.01)
1 if loan cycle is post branch split	0.006	0.007*	0.01**	0.01***
	(0.004)	(0.004)	(0.00)	(0.00)
Customer age		-0.304		-0.30
		(0.277)		(0.28)
Customer age, squared		0.004		0.00
		(0.003)		(0.00)
Number of children		-0.006***		-0.01**
		(0.002)		(0.00)
Marital status: Married		0.021***		0.02***
		(0.006)		(0.01)
Education level: Secondary or higher		-0.009		-0.01*
		(0.006)		(0.01)
Customer owns her house		0.007		0.01
		(0.006)		(0.01)
Group loan cycle		-0.000		0.00
		(0.001)		(0.00)
Group size		0.006***		0.01***
		(0.001)		(0.00)
Constant	0.625***	5.942	0.63***	5.84
	(0.002)	(5.907)	(0.00)	(5.88)
Observations	401,090	401,090	401,090	401,090
R-squared	0.061	0.063	0.054	0.056
Number of unique customers	200,545	200,545	200,545	200,545
Mean of dep. var. in cycle before branch split	0.625		0.634	

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 4. 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	-0.564***	-0.500***		
	(0.006)	(0.007)		
1 if loan cycle is post branch split	0.049***	0.018***		
	(0.002)	(0.002)		
1 if customer assigned to a new branch			-0.595***	-0.569***
			(0.019)	(0.021)
Customer age		0.155**		0.011***
		(0.060)		(0.001)
Customer age, squared		-0.002**		-0.000***
		(0.001)		(0.000)
Number of children		-0.006**		-0.009***
		(0.003)		(0.002)
Marital status: Married		0.030***		0.013**
		(0.008)		(0.006)
Education level: Secondary or higher		-0.020***		0.058***
		(0.008)		(0.006)
Customer owns her house		0.011*		-0.030***
		(0.006)		(0.007)
Customer loan cycle		0.052***		0.005***
		(0.001)		(0.001)
Group loan cycle		0.009***		0.002*
		(0.000)		(0.001)
Group size		0.013***		0.004***
		(0.000)		(0.001)
Constant			-0.439***	-0.931***
			(0.006)	(0.030)
Observations	612,087	612,087	200,545	200,545
Number of unique customers	173,961	173,961	200,545	200,545
Mean of dep. var. in cycle before branch split	0.634			

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.

Appendix Table 5. Tests of the differences in take-up in loan cycles before the branch split.

	(1)	(2)	(3)	(4)
Dependent variable:	Dummy = 1 if customer purchased insurance			
Sample:	All cycles before split	3 cycles before split	2 cycles before split	1 cycle before split
1 if assigned to new branch in cycle of split; 0 if stays in same branch	-0.004	-0.103***	-0.007	0.010
	(0.006)	(0.019)	(0.009)	(0.007)
Customer age	0.005***	0.004**	0.006***	0.004***
	(0.000)	(0.002)	(0.001)	(0.001)
Customer age, squared	-0.000***	-0.000	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Number of children	-0.002**	0.000	-0.003**	-0.001
	(0.001)	(0.002)	(0.001)	(0.001)
Marital status: Married	0.010***	-0.014	0.006*	0.013***
	(0.002)	(0.009)	(0.004)	(0.003)
Education level: Secondary or higher	0.033***	0.031***	0.033***	0.033***
	(0.003)	(0.009)	(0.004)	(0.003)
Customer owns her house	-0.030***	-0.036***	-0.026***	-0.029***
	(0.003)	(0.010)	(0.005)	(0.004)
Customer loan cycle	0.010***	0.017***	0.017***	0.005***
	(0.000)	(0.001)	(0.000)	(0.000)
Group loan cycle	0.001**	0.004**	0.003***	-0.000
	(0.000)	(0.002)	(0.001)	(0.000)
Group size	0.002***	0.004***	0.003***	0.001
	(0.000)	(0.001)	(0.001)	(0.001)
Constant	0.328***	0.173***	0.154***	0.438***
	(0.013)	(0.047)	(0.020)	(0.015)
Observations	325,948	18,443	106,960	200,545
R-squared	0.021	0.071	0.056	0.008

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered by group in parentheses. Column 1 is estimated by ordinary least squares even though the data form a panel because the variable indicating the assignment to the new branch would be absorbed into the fixed effects.

Appendix Table 6. Characteristics of customers who took loans 3 cycles before the branch split and their loans.

	(1) Customers without loan 3 cycles before split	(2) Customers with loan 3 cycles before split	(3) Standardized difference	(4) p-value
Part A: Demographic characteristics	**(n=182,102 customers)**	**(n=18,443 customers)**		
Age (years)	40.8	41.0	-0.016	0.036
Number of children	3.1	3.2	-0.063	<0.001
Marital status: married (%)	60.9	62.6	-0.034	<0.001
Education level: Secondary or higher (%)	41.5	41.0	0.011	0.145
Customer owns her home, mortgage is fully paid (%)	69	72	-0.056	<0.001
Part B: Loan characteristics	**(n=676,403 loans)**	**(n=18,443 loans)**		
Customer loan cycle number	8.4	7.0	0.251	<0.001
Loan size (pesos)	9,995	9,835	0.023	0.002
Group loan cycle number	9.1	9.6	-0.057	<0.001
Group size	20.8	22.6	-0.244	<0.001
Part C: Insurance characteristics	**(n=676,403 loans)**	**(n=18,443 loans)**		
Purchased any additional insurance (%)	59.5	50.3	0.189	<0.001
Paid insurance in installments, if bought insurance (%)	60.6	51.2	0.175	<0.001
Average number of insurance modules purchased	85.7	91.2	-0.155	<0.001
Purchased 1 module, if bought insurance (%)	99.1	99.2	-0.010	0.352

Notes: Data in columns 1 and 2 are means. The standardized differences are calculated as [(mean in column 1 – mean in column 2)/standard deviation of the entire sample]. P-values are from t-tests of the difference in the means in columns 1 and 2.