Credit Constraints, Present Bias and Investment in Health: Evidence from Micropayments for Clean Water in Dhaka

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Abstract

Low rates of adoption of and low willingness to pay for preventative health technologies pose an ongoing puzzle. In the case of water-borne disease, the burden is high both in terms of poor health and cost of treatment. Inexpensive preventative technologies are available, but willingness to pay (WTP) for products such as chlorine treatment or ceramic filters has been observed to be low in a number of contexts.

In this paper, we investigate whether time payments (micro-loans or dedicated micro-savings) can increase WTP for a high-quality ceramic water filter among 400 households in slums of Dhaka, Bangladesh, where water quality is poor and the burden of water-borne disease high. We use a modified Becker-Degroot-Marschak mechanism to elicit WTP for the filter under a variety of payment plans. Crucially, we obtain valuations from each household across all payment plans, which (a) increases power and (b) allows us to investigate the mechanisms behind differences in WTP across plans.

We find that time payments significantly increase WTP: median WTP under a lump-sum, up-front payment is USD 9.30, versus USD 17 with a simple 6-month loan and USD 20 for an up to 12-month loan. Similarly, coverage can be greatly increased: at an unsubsidized price of USD 28 (50% subsidy price of USD 14), coverage is 12% (27%) under a lump-sum but as high as 45% (71%) given time payments.

Many explanations are consistent with these reduced-form results. In ongoing work, we use our rich within-household WTP data, the design of the payment plans, and a simple structural model of time preference to investigate the mechanisms at work behind these large differences in WTP. In particular, we measure the relative importance of credit constraints, time-preferences and the risk associated with a new technology.

JEL classifications: C93, D14, D91, G21, I15, O16, Q53, Q56

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1 Introduction

Low rates of adoption of and low willingness to pay for preventative health technologies pose an ongoing puzzle in development economics (Dupas 2011, Jameel Poverty Action Lab 2011). In the case of water-borne disease, the burden is high both in terms of poor health and cost of treatment, and inexpensive preventative technologies are available, but willingness to pay for products such as chlorine treatment or ceramic filters has been observed to be low in a number of contexts (Ahuja, Kremer, and Zwane 2010, Ashraf, Berry, and Shapiro 2010, Berry, Fischer, and Guiteras 2012, Luoto et al. 2011).

Many explanations for this puzzle have been proposed. We focus on one common characteristic of many health technologies: a relatively large up-front investment is required, while the benefits accrue over time. This is problematic for a number of interdependent reasons. First, households may find it difficult to borrow, especially for non-business purposes. Second, poor households may have high discount rates or be close to subsistence levels of consumption and therefore be unwilling to sacrifice a large amount of current consumption. Third, households may exhibit time-inconsistency in the form of present bias or hyperbolic discounting (Ashraf, Karlan, and Yin 2006). Fourth, households may be unwilling to sink a large sum into a new technology when they are unsure of its benefits. These barriers suggest a number of interventions to increase adoption and improve welfare. Consumers who face liquidity constraints or exhibit present bias may find it difficult to fund purchases even if they are willing to pay substantial amounts over time (Holla and Kremer 2009). As a result, time payments, either micro-loans or layaways (dedicated savings), may increase adoption and improve welfare (Tarozzi and Mahajan 2011, Dupas and Robinson 2013). When consumers have uncertain valuation of a new product, a free trial or money-back guarantee can allow learning at low risk (Levine and Cotterman 2012).

In this paper, we examine how time payment plans (either micro-loans or layaways) and interventions to decrease the risk incurred while learning (free trial, money-back guarantee) affect willingness to pay (WTP) and attempt to understand the mechanisms at work. Both of these are empirically challenging. First, individuals with greater access to finance may have a greater taste for health relative to consumption or more resources overall. Second, even if access to finance were randomly assigned, there are many variations possible and we would typically only observe one choice per individual, so it would require an enormous sample size to determine which policies are most attractive. Third, many of the underlying reasons for increased willingness to pay (liquidity constraints, high discount rates, present bias / hyperbolic discounting, value of low-risk learning) have similar empirical implications.

To address these questions, we measure WTP for a high-quality ceramic water filter in 400 households in slums of Dhaka, Bangladesh, where water quality is poor and the burden of water-borne disease high. We use a modified Becker-Degroot-Marschak (BDM) mechanism to elicit WTP under a variety of time payment plans, including a lump-sum paid immediately, micro-loans and dedicated micro-savings plans of varying duration. Crucially, we obtain valuations from each household across all payment plans, which (a) vastly increases power and (b) allows us to investigate the mechanisms behind differences in WTP across plans.

We find that the availability of time payments dramatically increases willingness to pay: median WTP under a lump-sum, up-front payment is approximately USD 9.30, versus USD 17 with a simple 6-month loan and USD 20 for a 12-month loan. To separate time preference from liquidity constraints, we elicited WTP from subjects given layaway (dedicated micro-savings) plans with the same payment schedule as the loans. The intuition for this approach is that, while layaway plans should be less appealing than loans to all consumers, patient consumers who are liquidity constrained will find the layaway relatively more appealing than will impatient consumers. To our surprise, we found that for almost all households, WTP with a loan is virtually identical to WTP with a layaway plan with the same payment schedule – that is, they are willing to pay the exact same amount over 6 months to receive the filter in 6 months as they are to receive the filter today. In a standard model where all forms of consumption are discounted at the same rate, this suggests that liquidity constraints are more important than time preference in explaining the large increase in WTP from time payments. Alternatively, households could discount future general consumption (i.e. money) heavily, but do not discount the use of the filter at all. In ongoing work, we estimate a simple structural model of liquidity constraints and time preference to investigate the mechanisms at work.

This paper proceeds as follows. In Section 2, we provide a brief literature review and conceptual framework. In Section 3, we describe the experimental design. In Section 4, we discuss the reduced-form evidence provided by our data. In Section 5, we propose and estimate a simple structural model of time preferences and credit constraints. Section 6 describes future refinements.

2 Literature

Under-investment in welfare-enhancing or profitable technologies is thought to be a commonplace problem in developing countries. There are a variety of products, ranging from modern fertilizer to efficient cookstoves, that many poor people do not purchase, in spite of what would appear to be large benefits. While there are many potential explanations for this seeming underinvestment, in this section we focus on research related to time preference, liquidity constraints and consumers' lack of information on the effectiveness of the new product.

Tarozzi and Mahajan (2011) (TM) and Dupas and Robinson (2013) (DR) both examine the relationship between non-standard time preferences and health investments, TM studying loans for bednet purchases in Orissa, India, and DR studying commitment savings for subject-chosen health products in Kenya. We highlight two differences between our study and these. First, we directly compare behavior under savings and borrowing. This is useful for policymakers as well as for understanding behavioral mechanisms. Second, we measure effects on WTP rather than share purchasing at a single price (TM) or total health investment or savings accumulated (DR), so our results are informative for pricing policy.

While the relationship between liquidity constraints and consumption has a long history (Deaton 1991), recent research in developing countries has focused on the production side. In addition to the large literature on microfinance, Banerjee and Duflo (2005) review estimates of returns to capital in small-scale productive activities in developing countries. de Mel, McKenzie, and Woodruff (2008) find the average real return to capital (distributed in a randomized experiment in Sri Lanka) is substantially higher than market interest rates (at least for male entrepreneurs). They interpret their results as largely consistent with liquidity constraints. Banerjee and Duflo (2012) study a change in the rules defining what firms are eligible for earmarked credit from Indian banks. They estimate very high rates of return for firms that gained easier access to credit due to the change in rules, suggesting that liquidity constraints are binding even for relatively large, formal enterprises.

Both consumers and producers are likely to be uncertain about the returns to a new technology, and experimentation can be risky (Foster and Rosenzweig 1995). Recent empirical research on the relationship between experimentation and adoption has been mixed. Dupas (2010) finds that short-run subsidies increase long-run adoption of insecticide-treated bednets in Kenya. Levine and Cotterman (2012) found that adding a free trial, time payments, and the right to return increased uptake of an efficient charcoal stove from 5 percent to 45 percent. That study showed that either the free trial or time payments increased uptake by about half the total effect, but did not identify what barriers the sales offers overcame. However, experimentation can also lead to decreased adoption if consumers find the product inconvenient or unpleasant to use (Mobarak et al. 2012, Luoto et al. 2012).

There is substantial evidence that many people have present bias, meaning that their subjective discount rate for short-term decisions today is higher than their subjective discount rate for short-term decisions in the future. The most common formulation within economics is a model that assumes there is an exponential discount rate δ for most decisions, but an additional present bias discount rate $\beta < 1$ for all future periods (Laibson, 1997; O'Donoghue and Rabin, 1999).

3 Experimental Design

The target population consists of poor households with young children in slums of Dhaka, Bangladesh. This population is of particular interest because of the low-quality piped water in these neighborhoods and high burden of water-borne disease, both generally and among young children.

The core intervention is the offer for sale of a long-lasting ceramic water filter with a retail price of approximately USD 28. We are interested in the demand for water filters because in previous research we have found a strong distaste for chlorine-based treatment (low WTP; low use even when provided free). The ceramic filter was popular in consumer testing in a similar population elsewhere in Dhaka, although few households purchased the filter at the break-even price.

We begin with a simple household survey to collect basic data on demographics, socioeconomic status, risk preferences and recent episodes of water-borne disease. We then conduct a marketing meeting to promote the filter to the subject households and explain the dangers of local water. The promotional message draws on our previous work in Dhaka with similar compounds, and combines both a positive health message as well as a message emphasizing disgust at ingesting fecal matter in unfiltered water. We inform the subject of the possible payment plans that might be offered in the sales visit and instruct her to think how much she (and possible the household) would pay for each option. We also explain the modified Becker-DeGroot-Marschak (1964) mechanism (BDM), described below, that we use to elicit WTP. To increase understanding we practice BDM using real goods and money.

Two weeks later, we return for a sales visit, in which we use BDM to obtain the households' WTP under several different payment plans, listed in Table 1 and described at greater length below. There are two basic types, loans and dedicated savings / layaway plans. The plans also differ in duration and whether the first payment is made immediately or with a one-month delay. The subject will randomly receive an offer for which she has already stated whether she would accept or reject. If she purchases a filter under non-delay plans, the filter will be delivered by the end of the next day and payments begin. Thereafter payments are collected monthly and the collections officer records at each visit if the filter has been used recently.

Willingness-to-pay data and the Becker-DeGroot-Marschak mechanism: To obtain precise data on WTP, for each offer type, we conduct a series of Becker-DeGroot-Marschak mechanism (BDM) procedures, one for each offer type. In this procedure, the subject states her maximum WTP ("bid"). If there was only one offer type the bid is then compared against a random price ("offer"). If her bid is less than the offer price, she does not purchase the filter. If her bid is greater than or equal to the offer price, she purchases the filter at the offer price. Under fairly weak assumptions, her best strategy is to bid her maximum WTP truthfully. To obtain a subject's WTP for a number of different offer types, we obtain her bid for each offer type, and then randomly select one offer type for which BDM is actually implemented. One disadvantage of our implementation was that, after extensive piloting, we found that it was necessary to provide participants with the full range of possible lottery prices, and to cap this range at the approximate break-even retail price of BDT 2100. This was necessary to improve participant understanding and to maintain a sense of fairness. However, it does mean that our WTP measure is censored, in that if a household has a very high WTP, we will observe only the top-coded value of BDT 2100. Because of this censoring, we will focus on quantile (median) estimates.

Offer types: Table 1 lists the main offer types. The simplest offer is a lump sum paid on delivery (either the same day or the next day). Next, we offer loans which begin immediately and involve 3, 7 and 12 monthly payments.[1] A parallel set of plans (3 and 7 payments) are for layaway, in which households make regular payments into a dedicated lockbox, according to the payment schedule,

[1] The prompts for BDM bids are framed in terms of the monthly payment rather than the total (e.g. "three monthly payments of TK 400," rather than "TK 1,200 over three months." However, we also provide subjects with the total amount implied by their monthly payments if they ask, as most pilot subjects have done. The BDM draw, which determines the allocation and total price paid, is in terms of the total amount, which is then converted back into monthly payments for the relevant payment plan. We conduct the BDM draw in terms of the total amount for operational simplicity – otherwise, surveyors would have to carry separate price envelopes for each offer.

until they have accumulated the offer amount. These plans are soft commitments: even though the lockbox key is held by ICDDR,B, the savings will not be confiscated if the household "defaults" by not following through on its commitment. At the time the household is scheduled to make a deposit, field staff visit to confirm that the deposit has been made. Households also have the option to "deposit" their money with the field staff in exchange for a receipt. The purpose of the layaway plans is to identify patient but liquidity-constrained consumers: while all consumers would prefer, ceteris paribus, to receive the filter immediately rather than after making several payments, a layaway arrangement (give up consumption now to receive the filter in the future) is especially unappealing to the impatient.[2]

Randomized Treatment 1: Free trial. The first treatment is a two-week free trial, giving households an opportunity to learn to use the filter and to confirm whether ease of use, taste, and other characteristics are acceptable. For risk-averse consumers one would expect the free trial to increase WTP (Levine and Cotterman 2012), although there are counterexamples (Mobarak et al. 2012, Luoto et al. 2012).

Randomized Treatment 2: Money-back guarantee or rent-to-own. One potential barrier to adoption is that households may incur income, health or consumption shocks that ex-post mean that money spent on a filter would have been better spent on something else. To test whether this is an important determinant of WTP, we randomize whether the loan offer gives the household the option to return the product for a partial or full refund. With no refund, a time payment plan is similar to a "rent-to-own" scheme, in which the subject risks losing only accumulated payments, rather than the full lump sum. With a full or partial refund, the time payment plan comes to resemble the layaway plan, but with the household receiving the flow of benefits from the product while payments are being made.

4 Reduced-Form Evidence on Willingness-to-pay and Demand

[2] An alternative approach to identifying liquidity constraints is to give the subject the good in question and perform a reverse BDM in which the subject reveals the minimum amount she is willing to accept (WTA) in exchange for the good. The idea is to remove the liquidity constraint so that any variation in minimum WTA across payment plans could be attributed to time preference. This was not successful in piloting, for two main reasons. First, a large majority of pilot subjects stated that they would not accept any amount in exchange for the filter. We interpret this as some combination of a please-the-implementer effect and an endowment effect, with the former being more likely given that subjects even refused amounts higher than the going retail price. Second, reverse time payment plans were not perceived as credible by the subjects – many were skeptical that we would return multiple times over several months to give them money.

4.1 Time Payments

The most salient result from the study is that time payments dramatically increase WTP. Figure 1 compares the share of households willing to purchase the filter given a lump-sum offer with the share using the household's maximum bid across offers. Time payments increase demand by 30 percentage points or more at all prices above BDT 700 (approximately USD 9.5). Median WTP increases from USD 9.30 to USD 20 for a 12-month loan. Figure 2 examines differences in individual household WTP. Among households that are not censored (i.e. (i) do not have all bids at the top bid amount, and (ii) express some positive WTP for any offer), WTP increases for most households, with a median increase of BDT 400 (min. 0, IQR 0-1050, max. 1900).

Even a short-term (3-month) loan significantly increases demand, which continues as the term of the loan lengthens. This can be seen in Figure 3, which plots the share of subjects willing to purchase given each loan offer.

Surprisingly, WTP given time payment layaway plans are almost identical to loans. Figure 4 shows that the demand curves lie almost on top of each other, and Figure 5 shows that nearly all households have identical WTP for loans and layaway plans of the same duration.

To summarize the puzzle identified by our reduced-form analysis:

1. We see very large increases in willingness to pay for time payments relative to lump sum. Preferences alone cannot explain this — even if consumers were hyperbolic discounters, if capital markets were complete consumers would be indifferent, in net present value terms, among loan offers of varying duration, since they could use outside financing for any purchase. Therefore, there either must be very high interest rates in the market (such that the arbitrage described above is not worthwhile) or there are binding liquidity constraints. The interest rates implied by increases in WTP given longer-duration loans are much higher than prior information on borrowing rates, which suggests that, in the context of our model, it appears that many respondents are liquidity constrained.
2. Given that liquidity constraints exist, comparing WTP across offers can provide information on preferences. However, almost all respondents had identical willingness to pay for time payments and for layaway. In a standard model where all forms of consumption are

discounted at the same rate, this requires that subjective discounting (both time preference δ and present bias β) be negligible $(\beta = \delta = 1)$.

3. However, within the class of apparently liquidity constrained consumers, many consumers have much higher WTP when payments are spread out over a longer period of time (3 months versus 7 months versus 12 months). This poses a problem: if people can save, liquidity constraints lose almost all of their bite when payments are spread out over a few months, and there should not be a large difference in WTP when spreading payments over 7 months versus 3.
4. This, in turn, implies implausible levels of curvature of utility or very high rates of subjective discounting.[3]

In our structural analysis, we explore this puzzle further.

4.2 Randomized Treatments

The results from our randomized treatments are somewhat less striking. In neither case (free trial, Figure 6; guarantee, Figure 7) do we see strong evidence for an increase in demand.

5 Structural Estimation

Our reduced-form empirical analysis provides strong evidence that micro-loans and micro-savings significantly increase WTP. To assess the relative importance of financial constraints or time preference in explaining this fact, we turn to a simple structural model that allows for time preferences and includes a flexible specification of credit constraints. Our original intent was to use differences in WTP between micro-loans and micro-savings for identification. However, because subjects almost uniformly bid the same amount for micro-loans and micro-savings plans of the same duration, we must alter our strategy. We therefore estimate time preferences over non-health related goods and assume discounting over health related goods is zero. We have evidence that both time-preference and credit constraints are important but have not yet quantified their relative importance.

[3] Assume incomes are USD 2 / person for a five-person family, or USD10/ day. Assume further the bid is USD15 over 90 days, or an average of USD0.17 per day. That payment averages less than 2% of daily income. For payments around 2% of family income, people should act almost as if they were risk neutral unless utility functions have extreme levels of curvature.

5.1 Utility

We assume that the household maximizes utility over a finite horizon. As a single filter-element usually lasts a family 12 months, we choose this as the planning horizon which we divide into monthly periods[4]. Given the data on lay-away plans, we assume there is no discounting of health-related utility, but there is discounting over other forms of utility. We assume that this discounting is exponential.

The WTP for a particular plan identifies the highest monthly price p such that the household is indifferent between purchasing at that price and not purchasing at all. Equivalently, it identifies the price such that the household's stream of lowered utilities from non-health activities is equal to the utility gain from having the filter. If the household makes payments of $\{\bar{p}_t\}_{t=0}^{11}$ over the course of 12 months (we allow for borrowing from other sources to smooth out-of-pocket payments) then

$$\sum_{i=0}^{11} \delta^t [u(y) - u(y - \bar{p}_t)] = B, \tag{1}$$

where u is the utility function over non-health activities, y is monthly income (assumed for simplicity to be constant), and B is the present-value of the filter. Taking a second-order approximation of the difference yields

$$\sum_{i=0}^{11} \delta^t \left[\bar{p}_t + \frac{1}{2} \eta \bar{p}_t^2 \right] = w, \tag{2}$$

where $\eta = -u''(y)/u'(y)$ measures utility curvature (the coefficient of absolute risk aversion) and $w = B/u'(\text{y})$ is the value of the filter normalized by the marginal utility of income.

5.2 Credit environment

Rather than build credit constraints from microfoundations, we take a reduced-form approach and model credit "constraints" as a nonlinear monthly cost-of-borrowing function $q(b)$, which for simplicity we approximate as a quadratic:

$$q(b) = R_0 + R_1 b + R_2 b^2. \tag{3}$$

[4] The 12 months is from the sales meeting. Since we assume no discounting of health benefits it doesn't matter to the model if the family receives the filter initially or later in a lay-away plan.

This extends the standard transaction-cost model of loans (as exposited in, e.g., Helms and Reille (2004)) by adding a quadratic term. Adding the quadratic term is attractive for several reasons[5]: (a) the "observed" repayment rate $q(b)/\mathrm{b}$ is not necessarily declining in b and (b) it is better able than the simple linear model to approximate situations where there are fixed limits on the amounts a household can borrow (where the borrowing costs function would be vertical). We assume that if the borrower wants to repay a loan at a different date (or via installments), then they just need to repay the lender the same net-present value as the $q(b)$ function.

We assume that each household evaluates whether to borrow through outside lenders in order to smooth consumption. We assume that if they borrow from outside lenders then they borrow from outside a fixed monthly amount while in our plan, and that after our time-payments plan is over they repay another fixed monthly amount back to their lenders till the end of the 12 months. For example, when considering how much they would pay us monthly (p) for a three-month plan, they think about borrowing possible monthly amounts b (so their consumption only drops by $p-b$) for three months and then paying back a monthly amount e for nine months (where e is determined by $q(b)$). Outside credit would be most attractive for shorter plans as there is more opportunity for smoothing.

We do not have rich enough data to estimate borrowing costs and preference parameters at the individual level. We believe that the credit environment is more similar across families than preferences (especially given that the reason for the borrowing is the same) so for now we assume that these borrowing costs are constant across the population. In future work we will attempt to look at borrowing costs of subgroups.

5.3 Estimation

As there are both individual and population level parameters, we estimate the model in an iterative two-step process. We start with initial guesses for the population-level borrowing cost parameters $R^{(0)}=\left\{R_0^{(0)},R_1^{(0)},R_2^{(0)}\right\}$. We then iterate the following two-step procedure:

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[5] Possible micro-foundations for a quadratic-shaped borrowing cost function include (a) it incorporates the idea that with multiple sources of limited funds a household will choose the cheaper options first, and (b) if lender's expect that larger loans are less likely to be paid back they will charge higher effective interest rates for larger loans.

1. Given current population level estimates $R^{(j)}$, we choose household-specific parameters $\omega_i^{(j+1)} = \{B_i, \delta_i, \eta_i\}$ to maximize the criterion function:

$$\Gamma_i\left(\omega_i \middle| R^{(j)}\right) = \sum_m \Psi_{im}(\omega_i, R^{(j)}, p_{im})$$

$$\Psi_{im}(\omega_i, R, p_{im}) = 1\{\mathrm{p}_{im} = p_{top}\}\ln\left[\frac{1}{\sigma}\phi\left(\frac{p_{im} - \hat{p}_m(\omega_i, R)}{\sigma}\right)\right] + (1 - 1\{\mathrm{p}_{im} = p_{top}\})\ln\left[1 - \Phi\left(\frac{p_{im} - \hat{p}_m(\omega_i, R)}{\sigma}\right)\right]$$

where summation is over plans m, p_{im} is the observed WTP for individual i for plan m, p_{top} is the top-coded amount, and $\hat{p}_m(\omega_i, R)$ is the predicted WTP for plan m given the parameters (i.e. the maximum WTP implied by Equation (2) given parameters $\left(\omega_i, R^{(j)}\right)$.

2. Given current individual-specific parameters for the whole sample $\omega^{(j+1)} = \left\{\omega_i^{(j+1)}\right\}_{i=1}^{N}$, we choose population level parameters $R^{(j+1)}$ to maximize the criterion function:

$$\Gamma\left(R^{(j+1)} \mid \omega^{(j+1)}\right) = \sum_i \sum_m \Psi_{im}(\omega^{(j+1)}, R^{(j+1)}, p_{im}),$$

where summation is over subjects i. We repeat steps 1-2 until convergence.

In each step we estimate the parameters of interest via maximum likelihood. With current candidate parameters and the parameters taken as given in each round, we predict the WTP for each individual. The WTP is the highest price that allows the family through some amount of borrowing to be indifferent between purchasing the filter at the price and having no filter. We solve then for the amount of borrowing that maximizes the WTP while keeping the family indifferent. We can then determine the error between predicted and observed WTPs which we assume is normally distributed. As observed WTPs are censored from above, this is a Tobit-style estimation.

5.4 Structural Results

The median values for the individual parameters are reported in Table 2, and distributions are shown for each in Figures 8-10. We see that the estimated monthly discount rate for households is quite high with a median rate of 17%. A higher discount rate over non-health utility actually increases the expected WTP for the filter as it discounts less future payments for the good. The median monetized filter value is 1008 Taka. The median absolute risk aversion is 0.0003.

The estimated parameters of the one-month borrowing cost function are shown in Table 3. The estimated function is $q(b) = 14.3 + 1.10b + .022b^2$ where the units are again Taka. All estimates were significant at the 5% level.

While the quadratic term may not appear important, Figure 11 shows this function with and without the quadratic term over a range including the market price of the filter (ie they both have the same R_0, R_1). For a loan of 2000 Taka, setting R_2 to zero would reduce the cost of the loan by close to 95%.

Given that non-health utility appears to be heavily discounted (as compared to health utility) and that the borrowing cost function is quite steep, it appears that both time preference and liquidity constraints contribute to higher WTP for time-payments.

6 Future Work

In future work, we plan to use the existing model to assess quantitatively the relative importance of the credit environment and time-preferences in filter purchases. By using estimated parameters to simulate counter-factuals we can evaluate what households would be willing to pay if borrowing costs are reduced. For example, if the government could take some action to lower the higher-order interest rate terms, how would this affect filter purchase? Similarly, what would be the effect of households being more patient over non-health goods? We also would like to see if the results differ when looking at demographic sub-groups divided by income, age of household head, and family size.

Finally, we plan to augment the model to allow hyperbolic discounting or quantity limits on borrowing.

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Table 1: Offer types

Offer type	Time of payment(s) (+months)	Filter received (month)
Lump sum	0 (same day or next day upon delivery)	0
3-month loan	0, 1, 2	0
3-month layaway	0, 1, 2	2
7-month loan	0, 1, 2, 3, 4, 5, 6	0
7-month layaway	0, 1, 2, 3, 4, 5, 6	6
12-month loan	0, 1, 2, . . . , 11	0
1-month delay	1	0
"75%, X, X"	0, 1, 2	2

In the "75%, X, X" offer, we fix the household's first payment at 75% of the maximum payment agreed to for a three-month loan, and the household then bids on the amount of the last 2 payments (X). The purpose is to provide variation between current and future payments to help identify present bias.

Table 2: Estimated Individual Preference parameters

	(1) Median
Monthly discount rate	.1690
Monetized monthly filter value	1009
Utility Curvature	.000278
Observations	255

Median values of the distribution of individual-parameters estimated in the structural model.

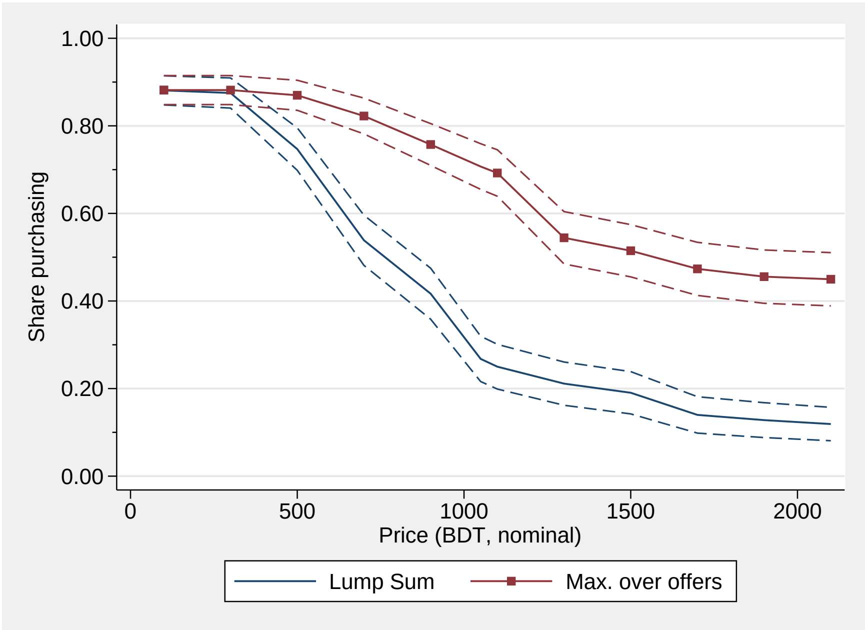
Table 3: Estimated Population 1-month Repayment Function parameters ($R_0 + R_1 b + R_2 b^2$)

	(1) Estimates
R_0	14.30
p-value ($R_0 = 0$)	.05
R_1	1.010
p-value ($R_1 = 1$)	.02
R_2	.0220
p-value ($R_2 = 0$)	.02

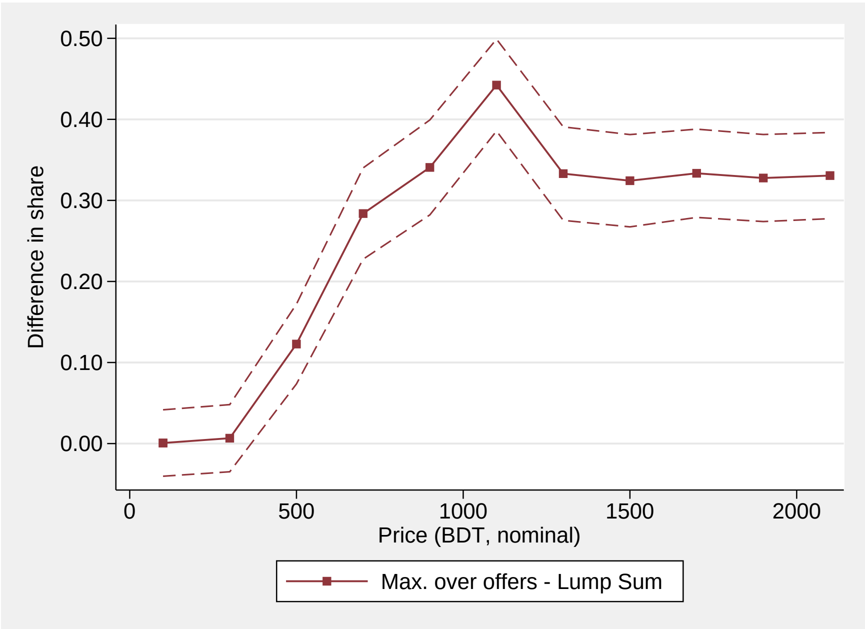
Values of population-level parameters estimated in the structural model.
P-values computed from 56 bootstrap samples.

Figure 1: Demand: Time Payments vs. Lump Sum

(a) Levels

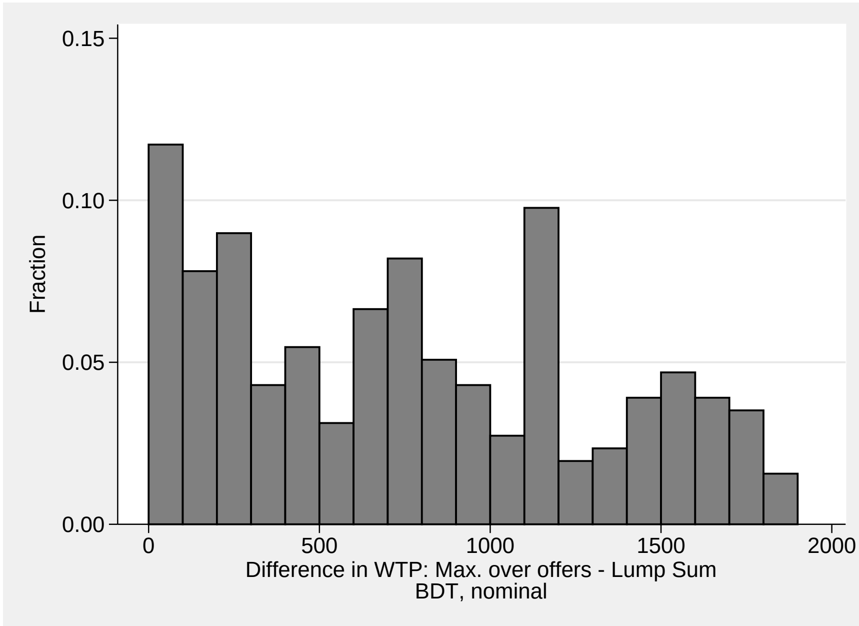


(b) Difference



Notes: the top figure plots BDM demand curves, with 90% confidence bands, using households' maximum WTP across all offers (square markers) and households' maximum WTP for an immediate lump sum (no markers). The bottom figure plots the estimated differences (max. across all offers relative to lump sum. Pointwise inference from logit regressions (at prices BDT 100, 300, 500, . . . , 2100). Standard errors clustered at the compound level. 336 observations.

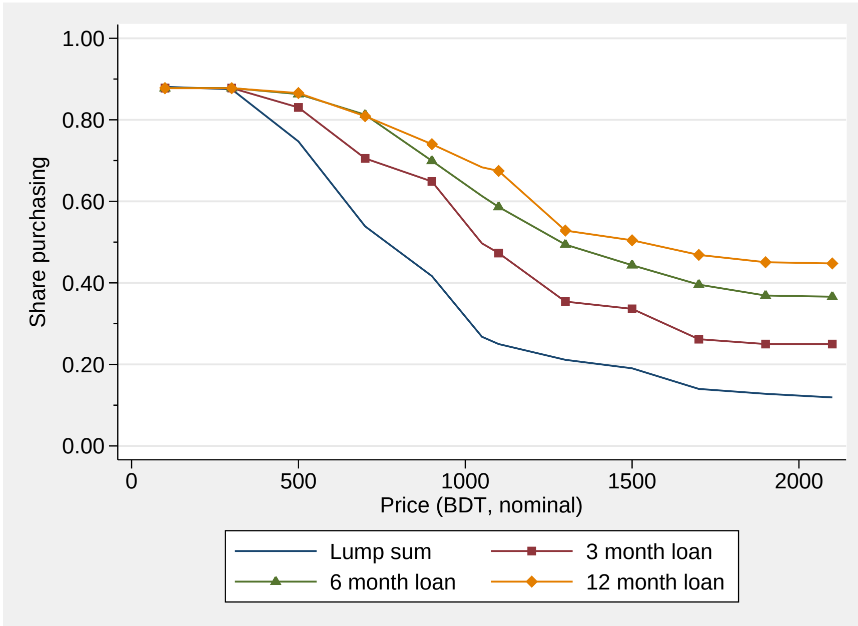
Figure 2: Distribution of household difference in WTP
Time Payments vs. Lump Sum



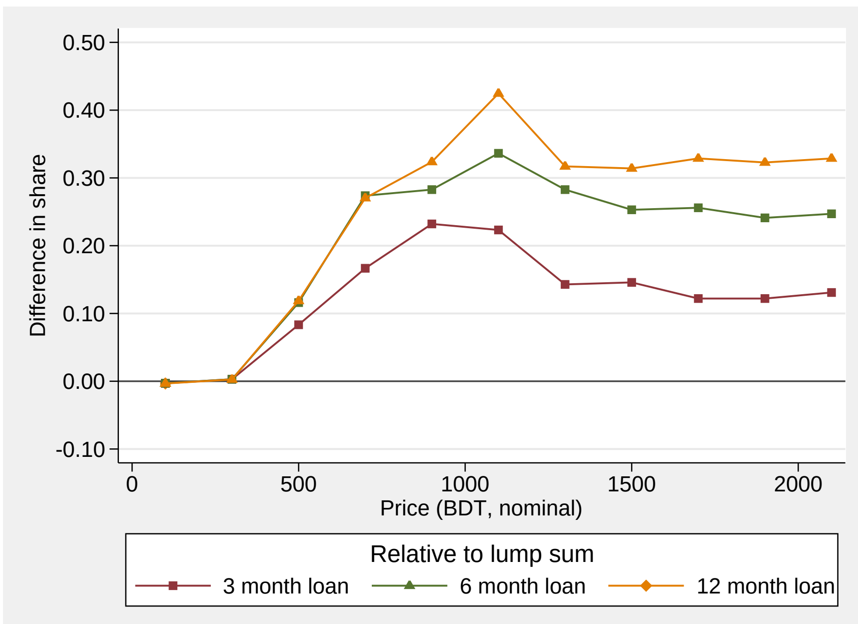
Notes: this figure plots the distribution of difference in household willingness to pay (WTP) under time payments (i.e. the maximum nominal amount across all loan and layaway offers) relative to an up-front lump-sum payment. We exclude 40 households that were top-coded, i.e. both their lump-sum and maximum time payment WTP were at the upper bound price, and the 40 households with zero WTP under all offers (including attriters and refusals), leaving 256 observations.

Figure 3: Demand Across Loan Offers

(a) Levels



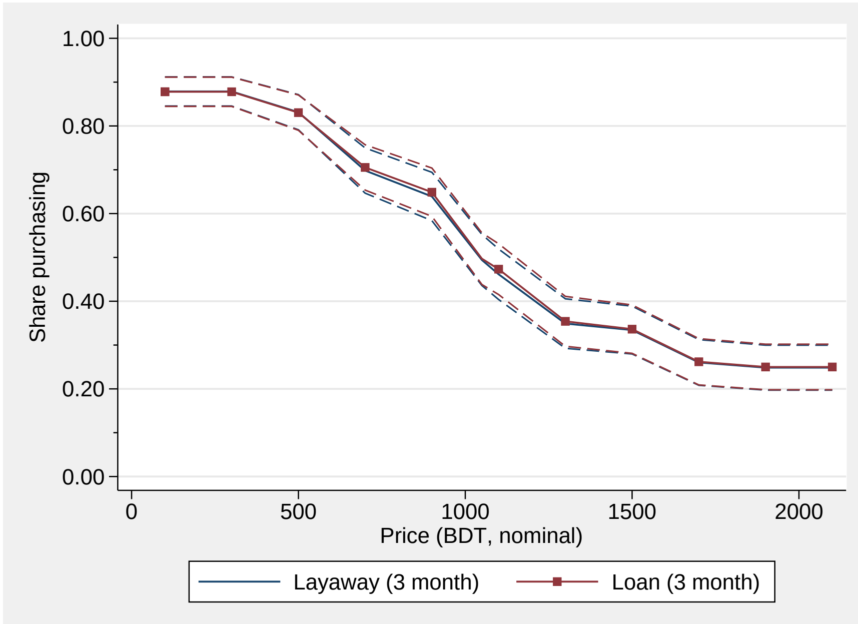
(b) Difference



Notes: the top figure compares BDM demand curves across loan offers: lump-sum (no markers), 3-month (square markers), 6-month (triangles) and 12-month (diamonds). The bottom figure plots the estimated differences for the three loan plans relative to lump-sum. Pointwise inference from logit regressions (at prices BDT 100, 300, 500, . . . , 2100). Standard errors clustered at the compound level. 336 observations.

Figure 4: Demand: Loans vs.Layaways

(a) 3 months



(b) 7 months

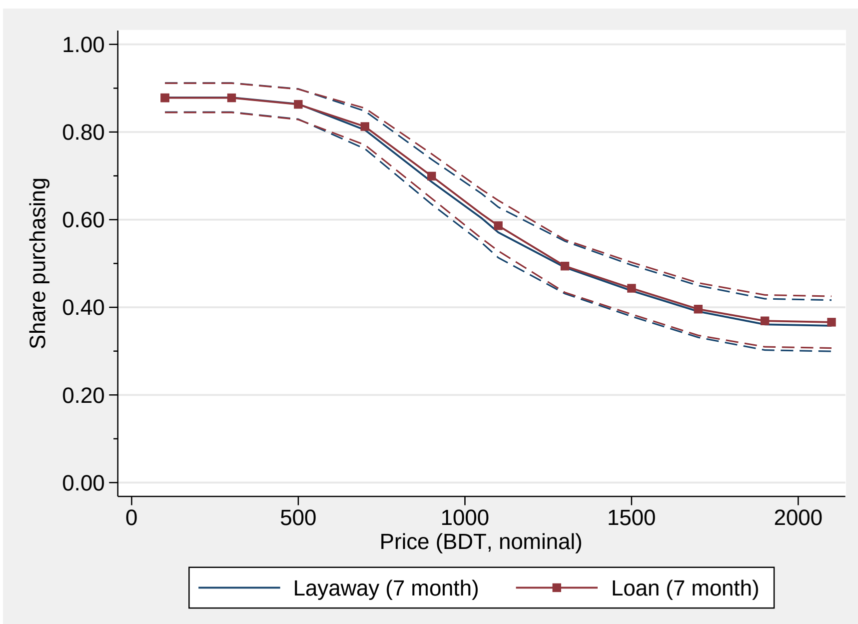
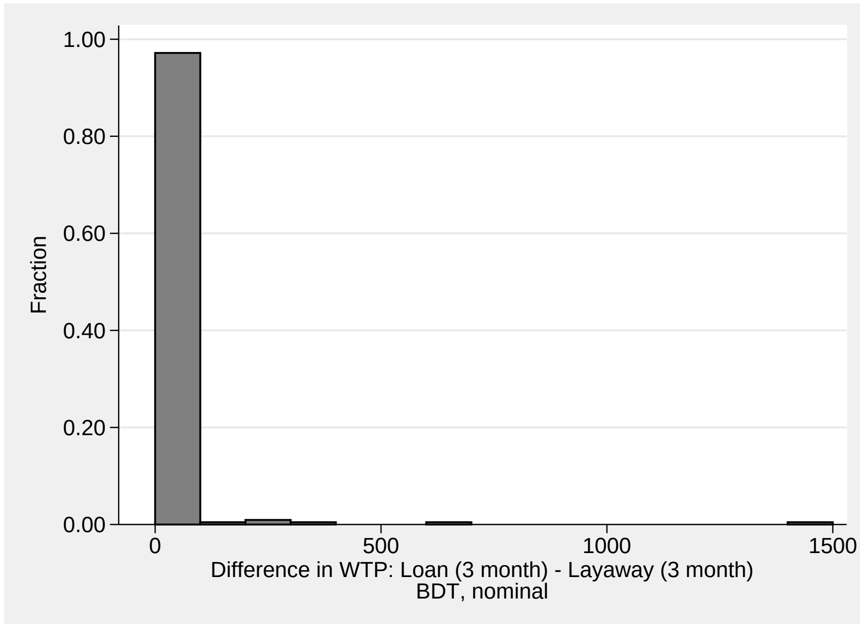


Figure 5: Difference in household WTP: Loans vs.Layaways

(a) 3 months



(b) 6 months

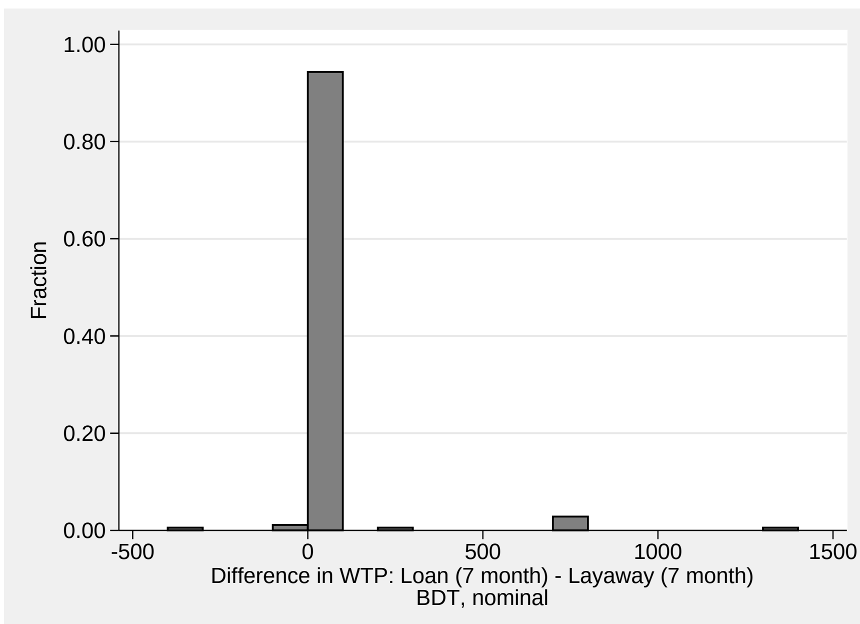
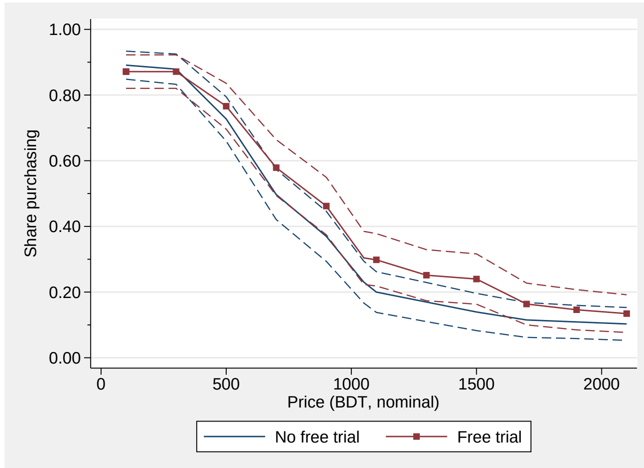
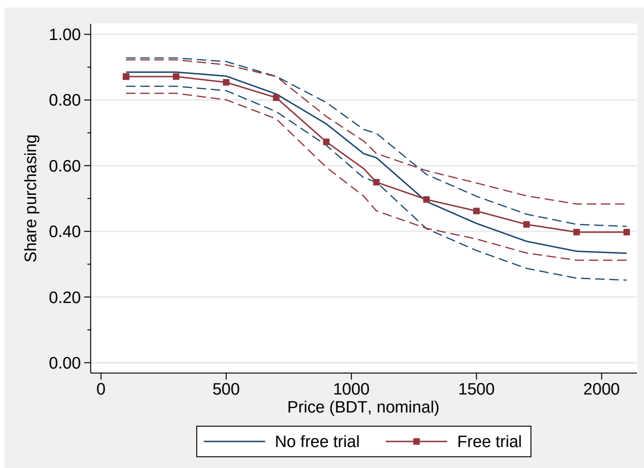


Figure 6: Effect of Free Trial Treatment on Demand

(a) Lump-sum



(b) 6-month loan



(c) Max. WTP across all offers

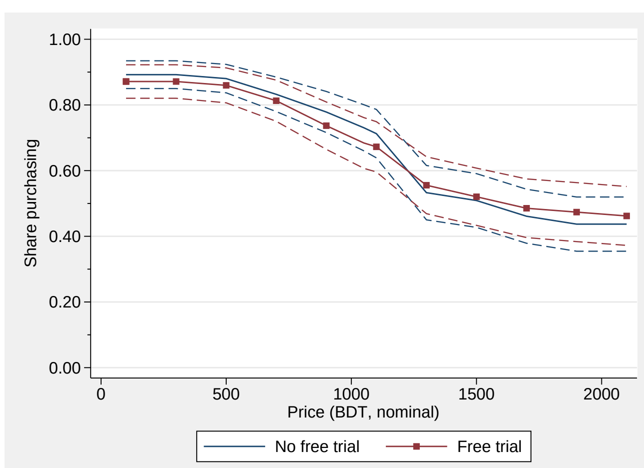
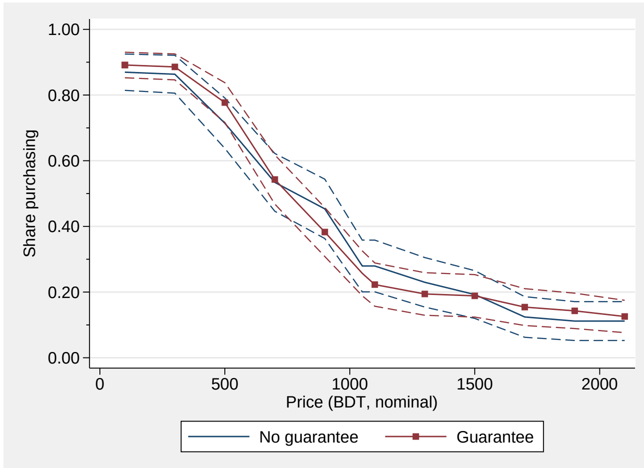
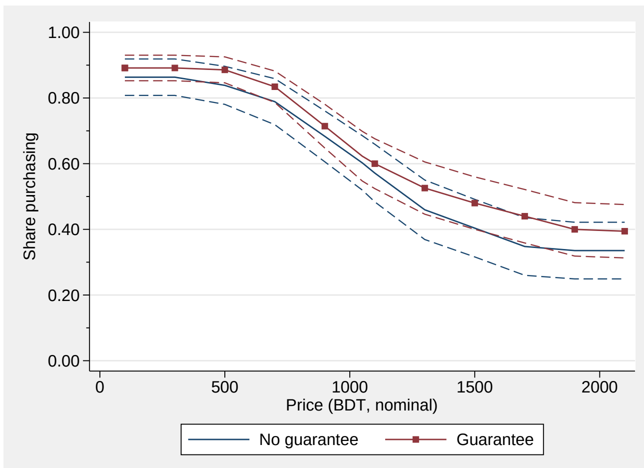


Figure 7: Effect of Money-Back Guarantee on Demand

(a) Lump-sum



(b) 6-month loan



(c) Max. WTP across all offers

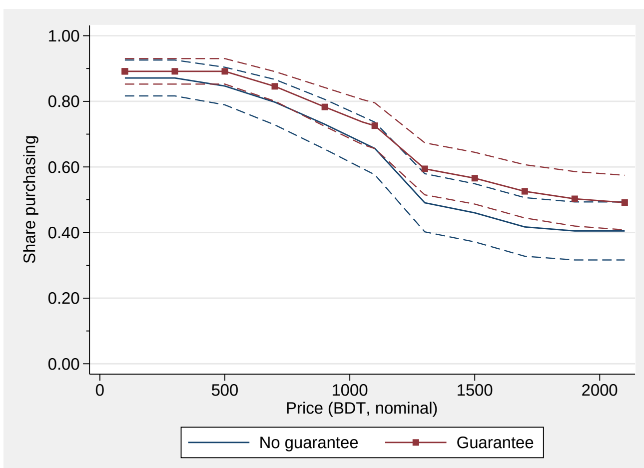


Figure 8: Density of estimated individual monthly discount rate

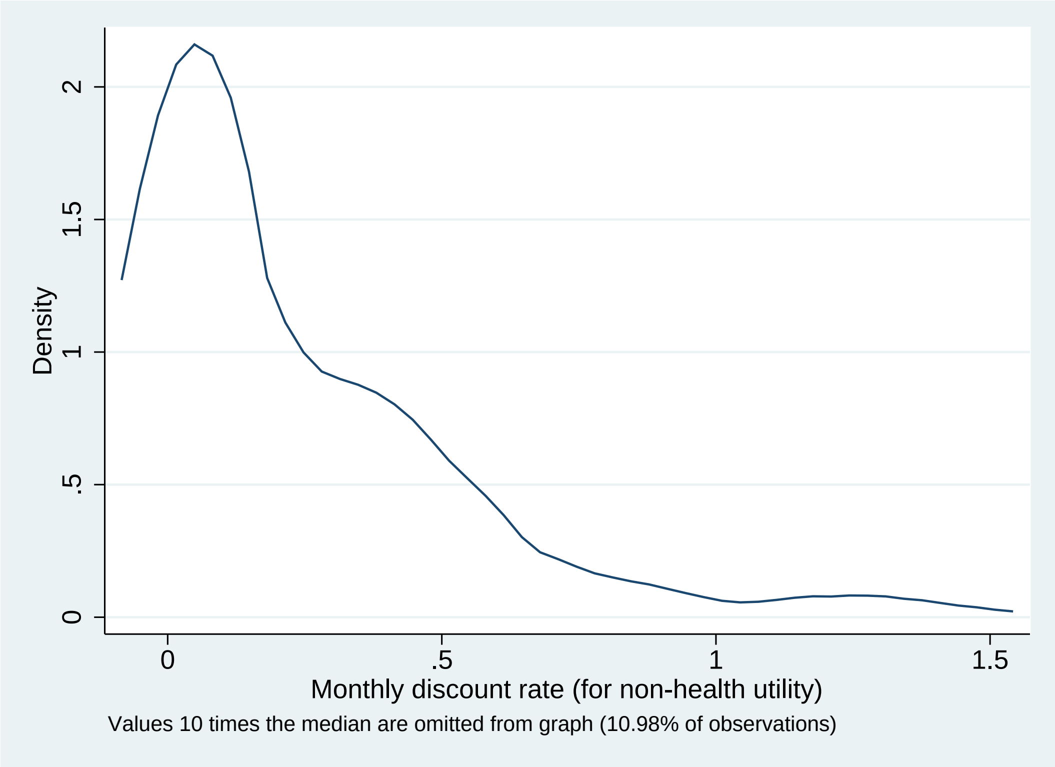


Figure 9: Density of estimated individual filter values

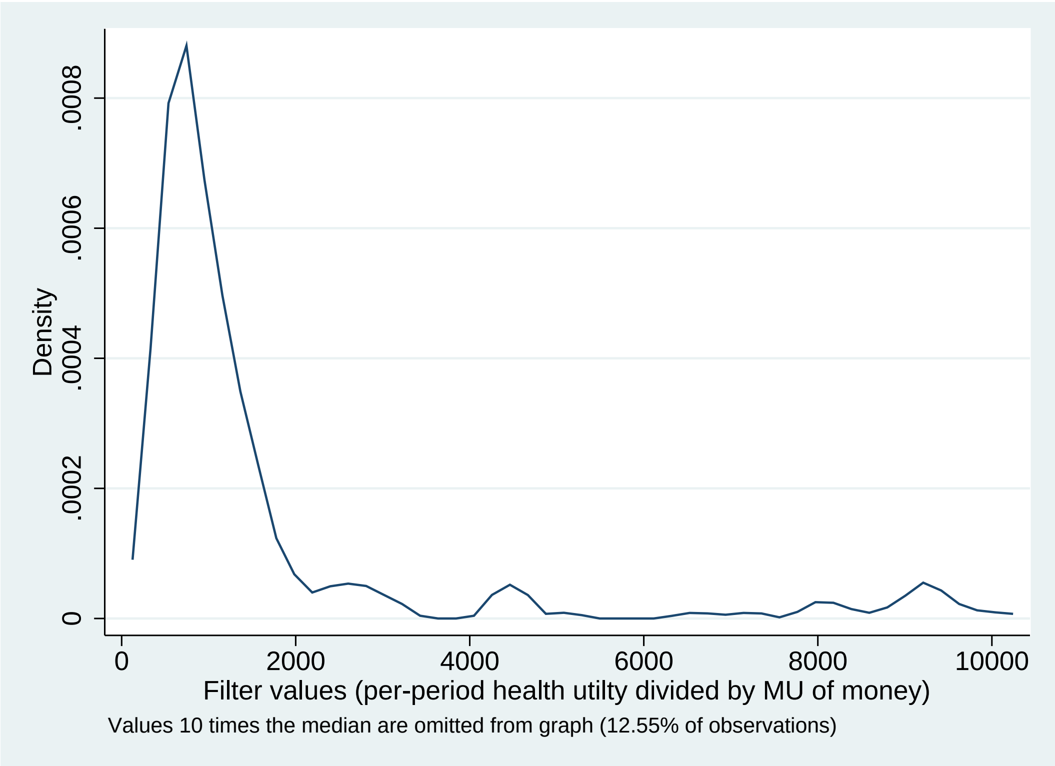


Figure 10: Density of estimated individual absolute risk aversion

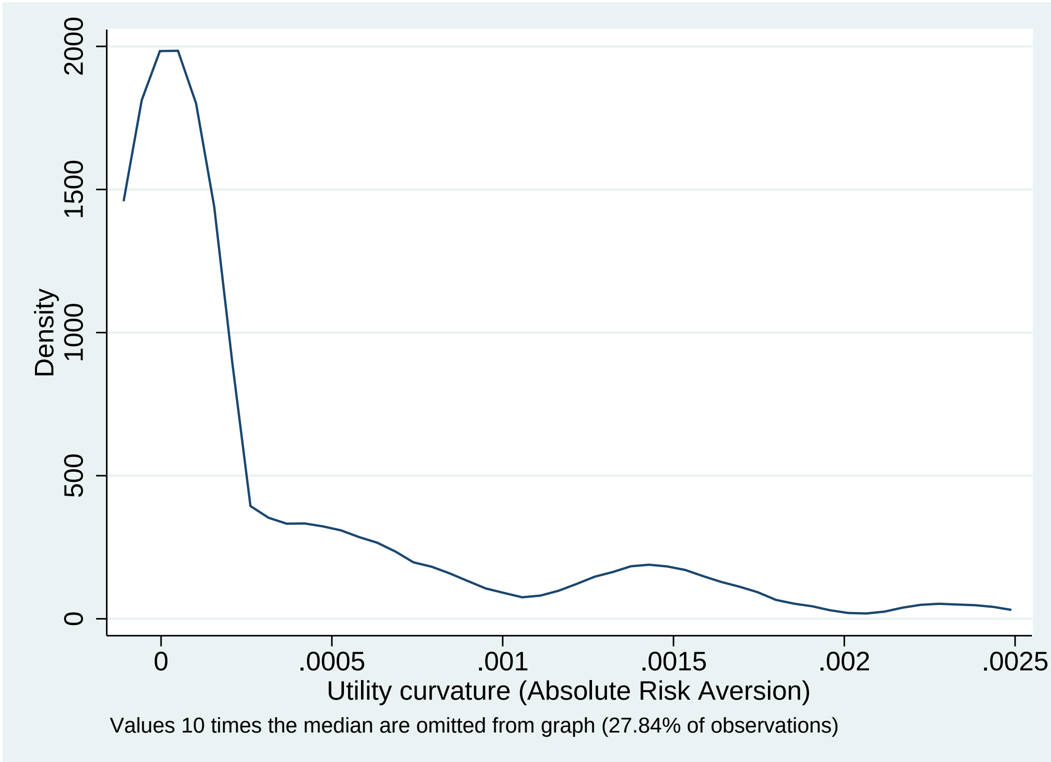


Figure 11: Credit constraints as curvature of repayment function (population estimates)