

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 (Abdul Latif Jameel Poverty Action Lab, 2011; Dupas, 2011). 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 (Ahuja, Kremer, & Zwane, 2010; Ashraf, Berry, & Shapiro, 2010; Berry, Fischer, & Guiteras, 2012; Luoto et al., 2011).

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) vastly 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, present bias and the risk associated with learning to use 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 (Abdul Latif Jameel Poverty Action Lab, 2011; Dupas, 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, & Zwane, 2010; Ashraf, Berry, & Shapiro, 2010; Berry, Fischer, & Guiteras, 2012; Luoto, et al., 2011).

Many explanations for this puzzle have been proposed. This paper focuses 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, & 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 & Kremer, 2009). As a result, time payments, either micro-loans or layaways (dedicated savings), may increase adoption and improve welfare (Tarozzi & Mahajan, 2011; Dupas & Robinson, 2012). When consumers have uncertain valuation of a new product, a free trial or money-back guarantee can allow learning at low risk (Levine & 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 micro-savings 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. To maximize information from the small sample, we will measure WTP across plans for each household.

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. The impact is almost exactly the same for time payments, which poses a puzzle: households appear to discount future money heavily, but do not discount the use of the filter in the same way – almost all households 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. This result suggests that liquidity constraints are the more important factor in explaining the effect of time payments. In ongoing work, we estimate a simple structural model of time preference to investigate the mechanisms at work behind these large differences in WTP.

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 concludes.

2 Literature

There are a variety of products, ranging from modern fertilizer to efficient cookstoves, that most poor people do not purchase, but that Western experts claim would make them better off. One possibility is that the poor consumers have better information about what works in their setting than

do the experts. In other cases, barriers such as liquidity constraints, present bias, and consumers' lack of information on the effectiveness of the new product may inhibit efficient purchases.

Cotterman and Levine (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. While provocative, that study did not identify what barriers the sales offers overcame. (Tarozzi & Mahajan, 2011) (TM) and (Dupas & Robinson, 2012) (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.

Recent research, reviewed in Banerjee and Duflo [2005], estimates returns to capital in small-scale productive activities in developing countries. De Mel, McKenzie & 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 (2004) 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.

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 alternative 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 possibly 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 the table and described at greater length below. There are two basic types, loans and 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. There after 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: 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, 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.

<u>Offer type</u>	<u>Time of payment(s) (+months)</u>	<u>Filter received (month)</u>
Lump sum	0 (same day or next day upon delivery)	0
3-month loan	0, 1, 2	0

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.

<u>Offer type</u>	<u>Time of payment(s) (+months)</u>	<u>Filter received (month)</u>
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” ²	0, 1, 2	0

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. Intuitively, for risk-averse consumers one would expect the free trial to increase WTP (Levine & Cotterman, 2012), although there are counterexamples (Mobarak, Dwivedi, Bailis, Hildemann, & Miller, 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

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

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.

increases from USD 9.30 to USD 20 for a 12-month loan. Figure 2 examines differences in individual household WTP. Among households that (i) are not censored, i.e. 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. That result requires a massive market interest rate or liquidity constraints. The implied interest rates are very high relative to prior information on borrowing rates, so we favor the latter interpretation: within the context of our model, it appears that many respondents are liquidity constrained.
2. Almost all respondents had identical willingness to pay for time payments and for layaway. That result 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 willingness to pay when payments are spread out over a longer period of time. 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. That result implies implausible levels of curvature of utility or very high rates of subjective discounting.³

³ Assume incomes are USD2 / 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 curves have absurd levels of curvature.

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

5.1 Model

In order to determine which aspect of an agent, her financial constraints or time preferences, are more important for raising payments with time-plans, we use a structural model. We first state the basic model and then show how to extend it to account for more complicated time preferences and financial constraints.

For the basic model, we assume that an agent has exponential, consistent time-preferences and has no credit or savings constraints. This agent's problem is then to maximize lifetime discounted utility subject to a lifetime budget constraint. We can write the agent's indirect utility function over lifetime income as

$$U(Y) = \left[\max_{\{c_t\}} \sum_{t=0}^{T_L-1} \delta^t u(c_t) \text{ s.t. } Y - \sum_{t=0}^{T_L-1} R^t c_t = 0 \right]$$

where $Y = \sum_{t=0}^{T_L-1} R^t y_t$ is lifetime income, $R \in (0,1]$ is the interest factor, and $\delta \in (0,1]$ is the per-period discount factor. Periods in the model are month long to match the payment plan timing.

For the filter, we assume that it brings a utility benefit of b each period and it functions for T_F periods (with $T_F \ll T_L$). A payment plan for the filter specifies the number of monthly payments ($N \in \{1, 3, 7, 12\}$), the month payments begin ($\gamma \in \{0, 1\}$, $\gamma = 1$ only for the one-month delay play), and when the filter is received ($v \in \{0, 1, 3, 7\}$, $v = 0$ for the lump-sum and credit plans).

Given a payment plan indexed by l , the most this agent would pay would be the amount that makes the agent indifferent to the purchase. Without buying the filter, she has standard consumption utility

and with buying the filter she has slightly less income to spend on consumption but has the new filter benefit. We can write the condition as

$$U(Y) = U(Y - P_l) + \sum_{t=v_l}^{v_l+T_F-1} \delta^t b$$

where $P_l = \sum_{t=\gamma_l}^{\gamma_l+N_l-1} R^t p$ is the present value of the predicted monthly payments p . Given $Y \gg P_l$, the term $U(Y - P_l)$ can be written as a linear approximation around $U(Y)$. This gives a solution for predicted payment amounts given characteristics

$$(1) \quad p_l \left(R^{\gamma_l} \frac{1 - R^{N_l}}{1 - R} \right) = \left(\delta^{v_l} \frac{1 - \delta^{T_F}}{1 - \delta} \right) w_u$$

where $w_u = [U'(Y)]^{-1} b$ is the monetized value of the filter. This relation equates the net costs and benefits of the filter. For candidate values of the agents characteristics (R, δ, w) we can then use equation (1) to predict the WTP for all seven plans. For each individual we have data corresponding to their stated WTP under each plan. Estimation then finds the characteristics that minimize the distance between predicted and stated WTP amounts. To account for the fact that some bids are the maximum value allowed, we assume that the difference between the predicted WTP and non-top-code stated WTP data is normally distributed and then estimate a Tobit model using maximum likelihood estimation. Additionally, we constrain the parameters in estimation to be positive and for the factors to be within $(0,1)$.

We then look at two model extensions that highlight differences between financial constraints and time-preferences. They only differ from the above in terms of how to predict WTP given characteristics. Estimation is the same as under the base model.

Extension 1: The first extension focuses on liquidity constraints and assumes that the agent cannot borrow or save. In this case she is now constrained by a set of per-period budget constraints equating consumption to be income (y) minus possibly filter payments. The WTP then creates the following relation where, if the agent buys the filter, there are periods where their consumption is reduced by the filter payment amount.

$$\sum_{t=0}^{T_L-1} \delta^t u(y) = \left[\sum_{t=0}^{\gamma_l-1} \delta^t u(y) + \sum_{t=\gamma_l}^{\gamma_l+N_l-1} \delta^t u(y-p_l) + \sum_{t=\gamma_l+N_l}^{T_L-1} \delta^t u(y) \right] + b \sum_{t=v_l}^{v_l+T_B-1} \delta^t$$

$$\sum_{t=\gamma_l}^{\gamma_l+N-1} \delta^t u(y) = \sum_{t=\gamma_l}^{\gamma_l+N_l-1} \delta^t u(y-p_l) + b \sum_{t=v_l}^{v_l+T_B-1} \delta^t$$

In this case it seems unlikely that $y \gg p_l$ so we take a second order approximation of $u(y-p_l)$ around $u(y)$. This yields the equation of net-costs equaling net-benefits,

$$\left(p_l + \frac{1}{2} \eta p_l^2 \right) \left(\delta^{\gamma_l} \frac{1-\delta^{N_l}}{1-\delta} \right) = \left(\delta^{v_l} \frac{1-\delta^{T_F}}{1-\delta} \right) w_c$$

where $\eta = -\frac{u''(y)}{u'(y)}$ is the coefficient of absolute risk aversion, and $w_c = [u'(y)]^{-1} b$ is the monetized filter value. This is a quadratic equation that defines the predicted monthly payment amount by an individual with these characteristics for plan l .

Extension 2: The second extension we analyze is where the agent is liquidity unconstrained but has time inconsistent preferences, in this case she is present-biased. We use the Laibson beta-delta formulation which gives the form

$$\sum_{t=0}^{T_L-1} \beta^{1\{t>0\}} \delta^t u(c_t)$$

so that all future periods are additionally discounted by the factor $\beta \in (0,1]$. Agents of this form then have their predicted price equation take the form.

$$p_l \left(R^{\gamma_l} \frac{1-R^{N_l}}{1-R} \right) = \left(\sum_{t=v_l}^{v_l+T_F-1} \beta^{1\{t>0\}} \delta^t \right) w_u$$

where $w_u = [U'(Y)]^{-1} b$ is the monetized filter value.

5.2 Structural Results

We estimate the basic model and both extensions on each person individually. For convenience we look at rate terms r, d instead of their factor counterparts $R = \frac{1}{1+r}$ and $\delta = \frac{1}{1+d}$. The distribution of the model parameters across individuals is summarized in tables 1-3.

Table 1 shows the parameters for the basic model. We drop a few outliers that are poorly estimated (those that only have one bid not top-coded). The average monthly interest rate estimated is 32%. From Figure 8 we see that given the distribution most people have an estimated rate less than this, and the mode is around 10%. The estimated discount rate is quite low at 1%.

Table 2 shows the parameters for the financially constrained model. This model is less well estimated with some parameters being impossibly extreme, so we report median values. The median discount rate being 3% is quite close to that estimated in the other models. Figure 9 shows the full distribution where we can see that most people are not estimated to have high discount rates. The risk-aversion is also quite small at 0.001.

Table 3 shows the results from the extension for present-biased time preferences (we drop the same outliers as for the basic model). We see that the present-bias term $\beta \approx 1$ indicating that most people are not very present biased. The other numbers are then similar to the base model. Given that there is little evidence for present-bias and that all the models estimate low discounting, it appears there is little evidence that time-preferences are the major obstacle for increasing payments.

Finally, we compare the models based on fit. As the constrained model is not nested within the others, we compare the relative fit of the three models using the Akaike Information Criterion corrected for small samples (AIC_c). The AIC takes into account how likely the data are given the model and penalizes the model for additional parameters. There is the most empirical support for a model with the smallest AIC_c . We use the rule of thumb from Burnham and Anderson (2002) that there is “substantial support” for a model that is within 0-2 of the smallest AIC_c . By this measure, there is substantial support for the base model for 69% of the households, for the financially-constrained model for 53% of the households, and for the present-biased model for 1% (24% of the population shows strong support for the both the base model and the financially constrained model). While the present-biased model is a direct extension of the basic model with an additional parameter it does not do sufficiently better given its extra parameter.

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Table 1: Estimated parameter distribution (Base model)

Variable	Mean	Std. Dev.
d_u	0.01	0.036
w_u	68.686	39.221
r_u	0.348	0.505
N		233

Table 2: Estimated parameter distribution (Constrained model)

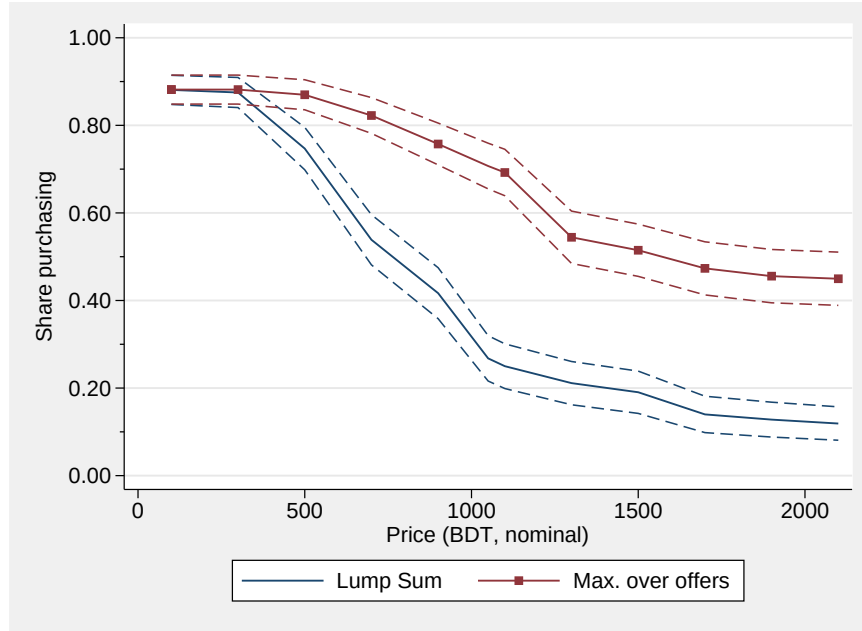
	(1)	
	Median	Std. Dev.
d_c	.0358005	3.064664
w_c	164.3014	7.01e+17
ra_c	.0013554	3.77e+13
Observations	255	

Table 3: Estimated parameter distribution (Present-Bias model)

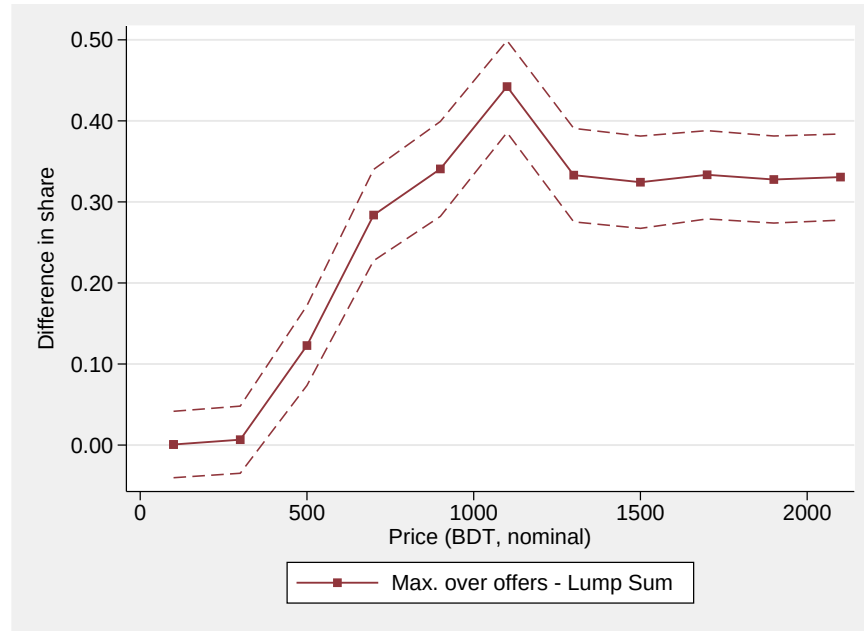
Variable	Mean	Std. Dev.
$d_{u,PB}$	0.012	0.089
$w_{u,PB}$	86.277	83.576
$r_{u,PB}$	0.319	0.365
$\beta_{u,PB}$	0.942	0.171
N		239

Figure 1: Demand: Time Payments vs. Lump Sum

(a) Levels

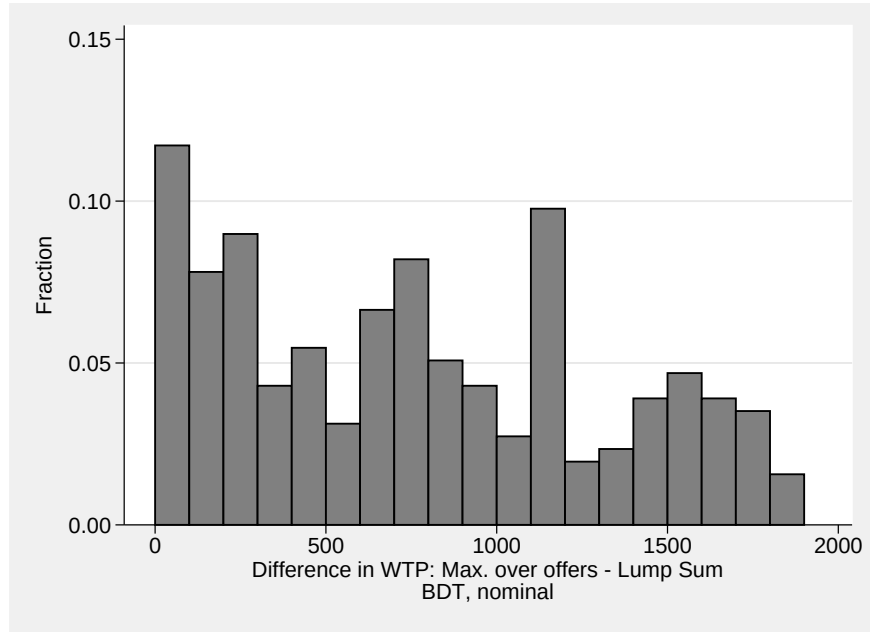


(b) Difference



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.

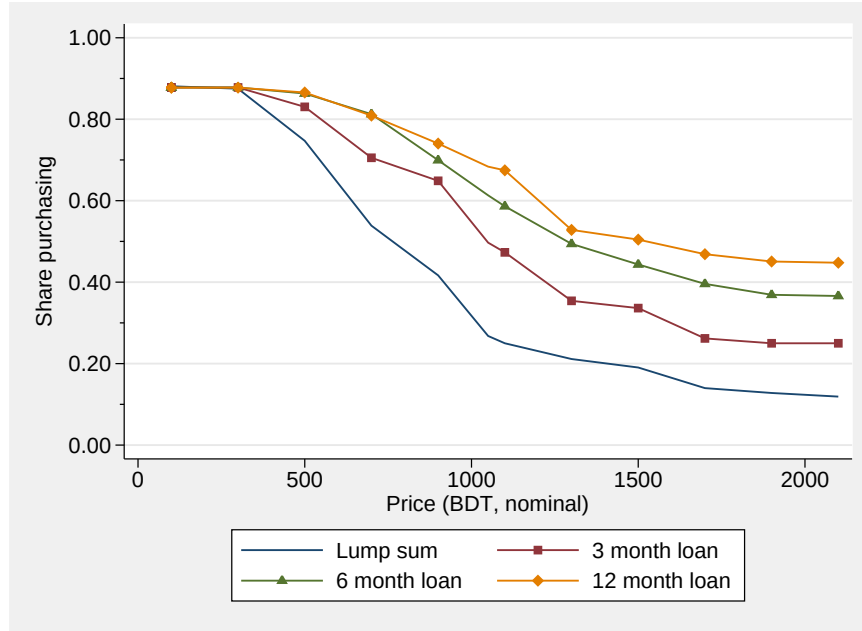
Figure 2: Distribution of household difference in WTP
Time Payments vs. Lump Sum



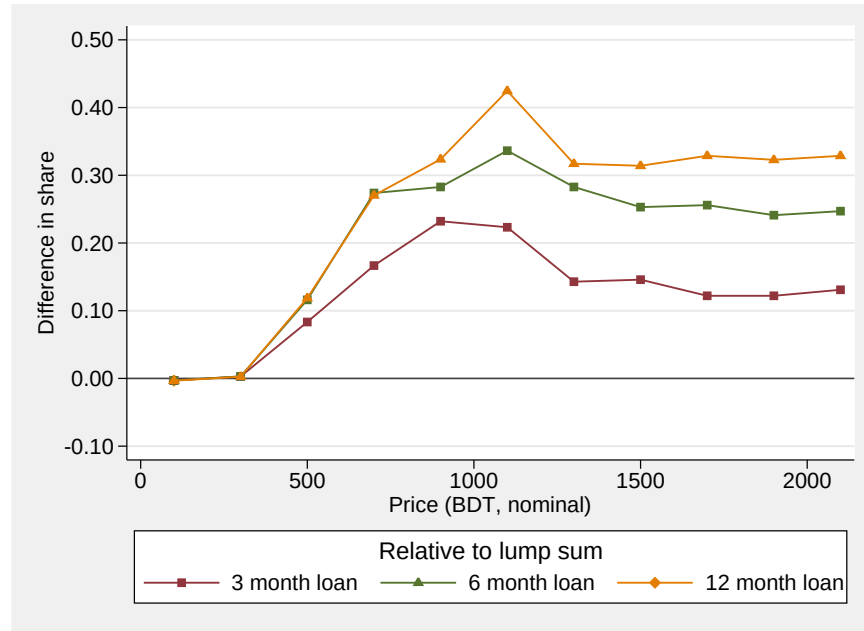
Notes: this figure plots the distribution of difference in household willingness to pay (WTP) under time payments (i.e. the maximum nominal amount across all loan and layaway offers) relative to an up-front lump-sum payment. We exclude 40 households that were top-coded, i.e. both their lump-sum and maximum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



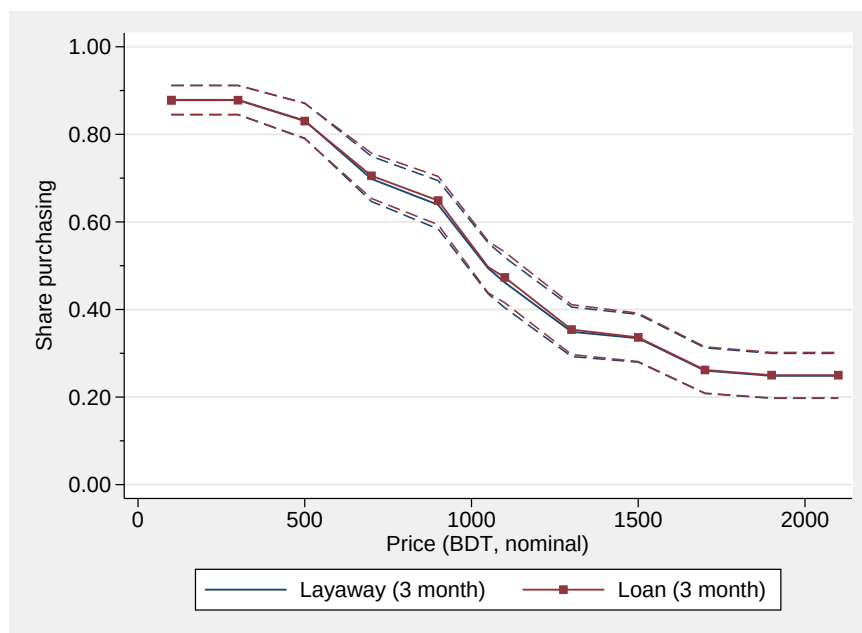
(b) Difference



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

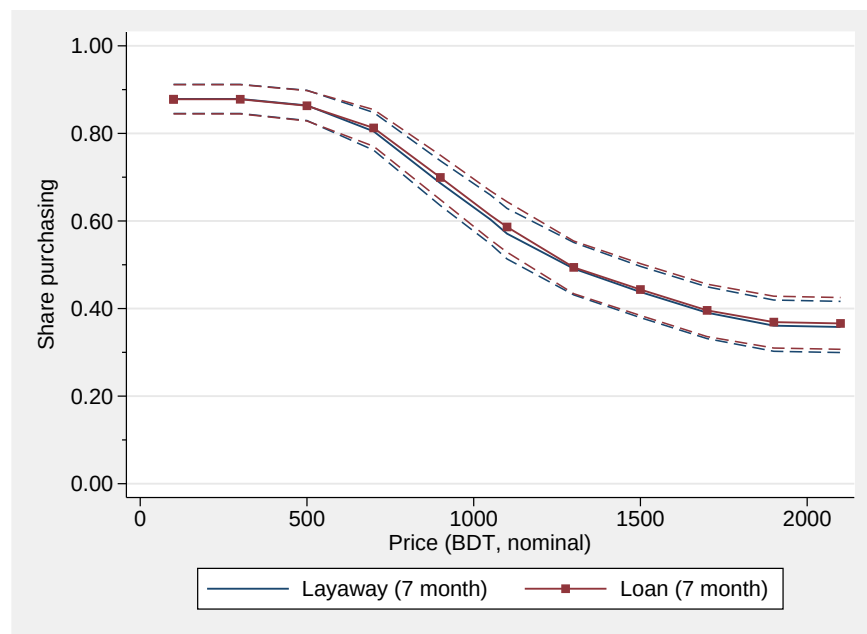
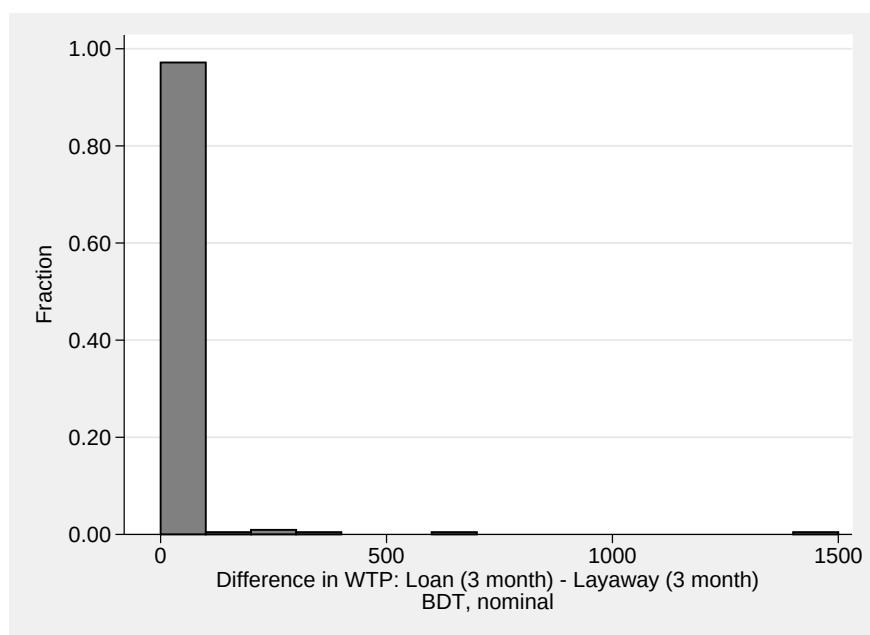


Figure 5: Difference in household WTP: Loans vs. Layaways

(a) 3 months



(b) 6 months

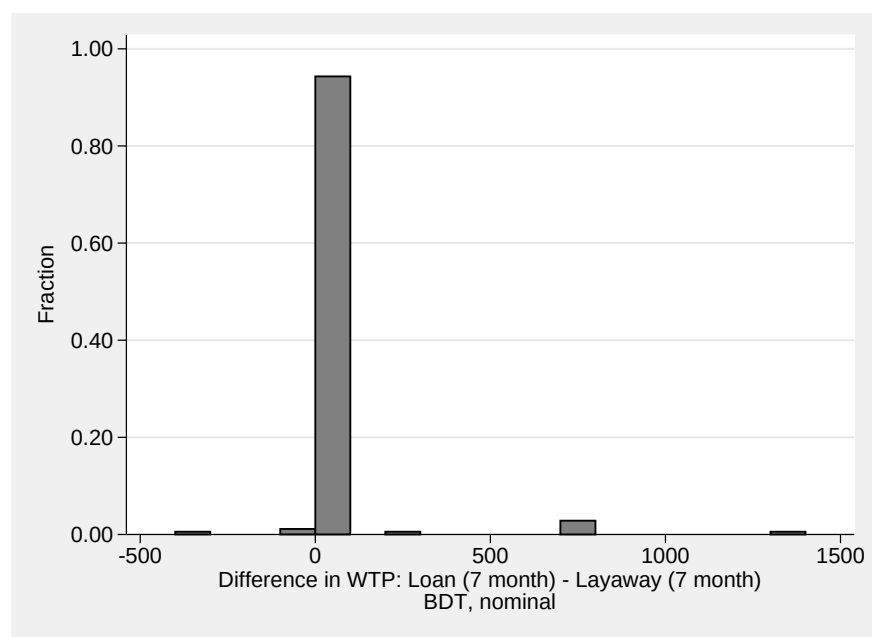
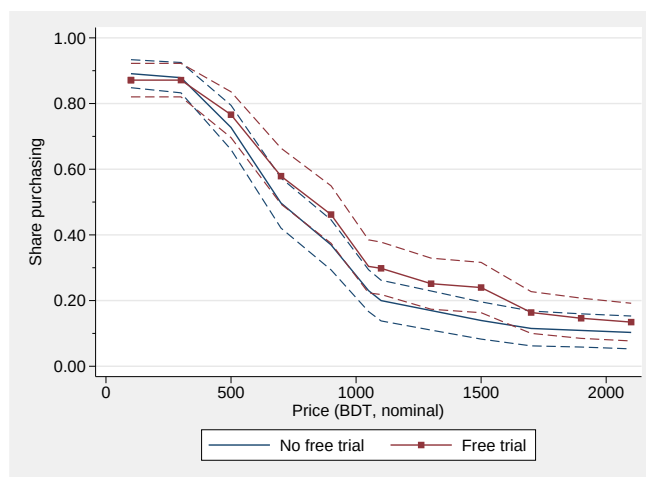
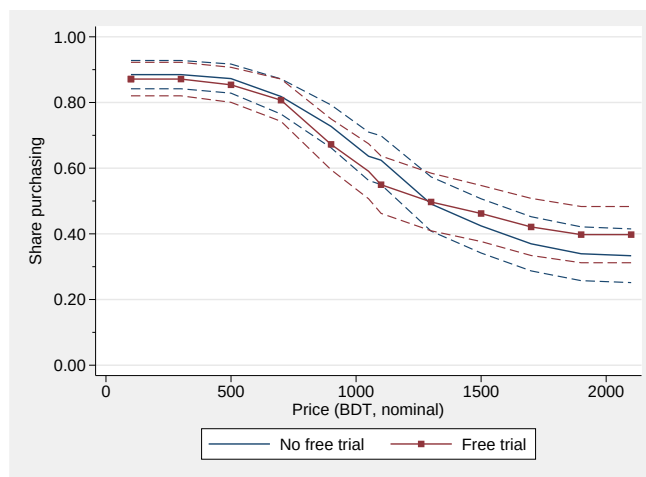


Figure 6: Effect of Free Trial Treatment on Demand

(a) Lump-sum



(b) 6-month loan



(c) Max. WTP across all offers

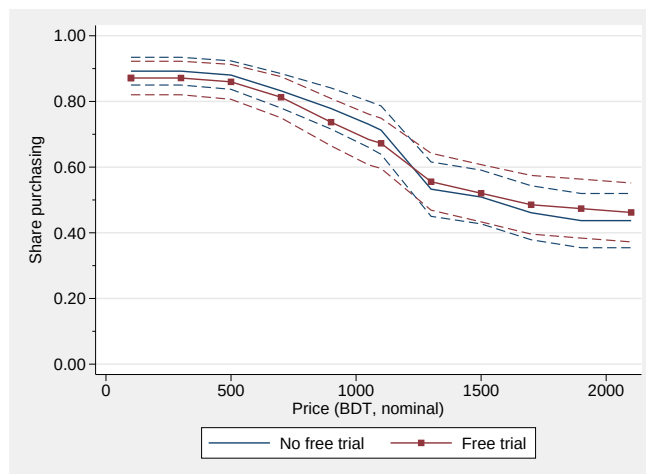
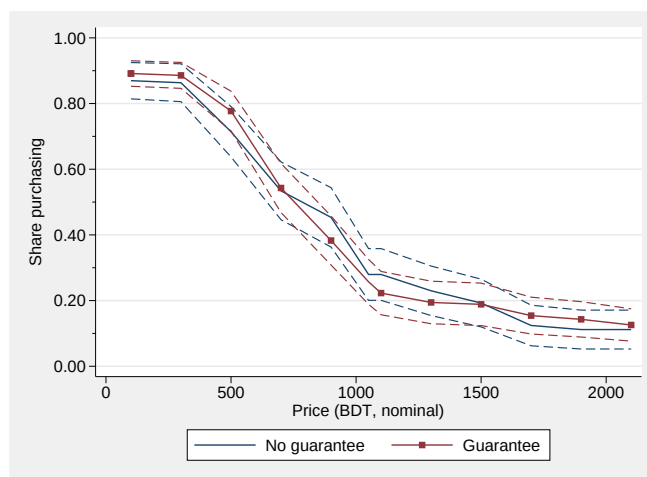
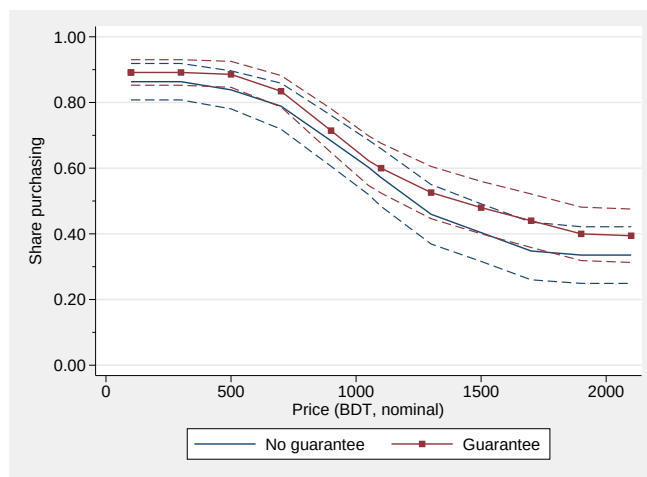


Figure 7: Effect of Money-Back Guarantee on Demand

(a) Lump-sum



(b) 6-month loan



(c) Max. WTP across all offers

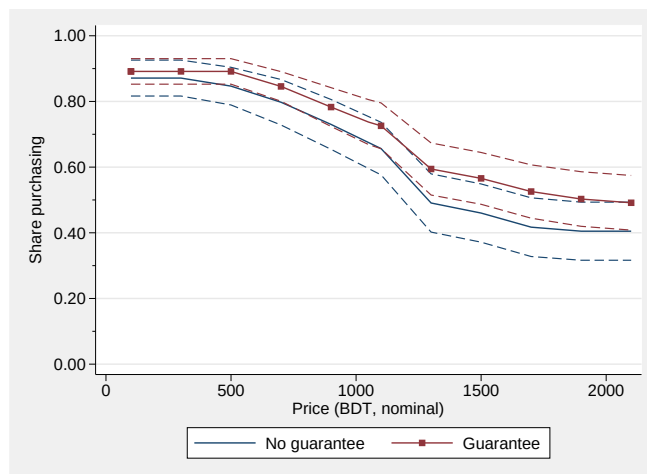


Figure 8: Distribution of estimated interest rates

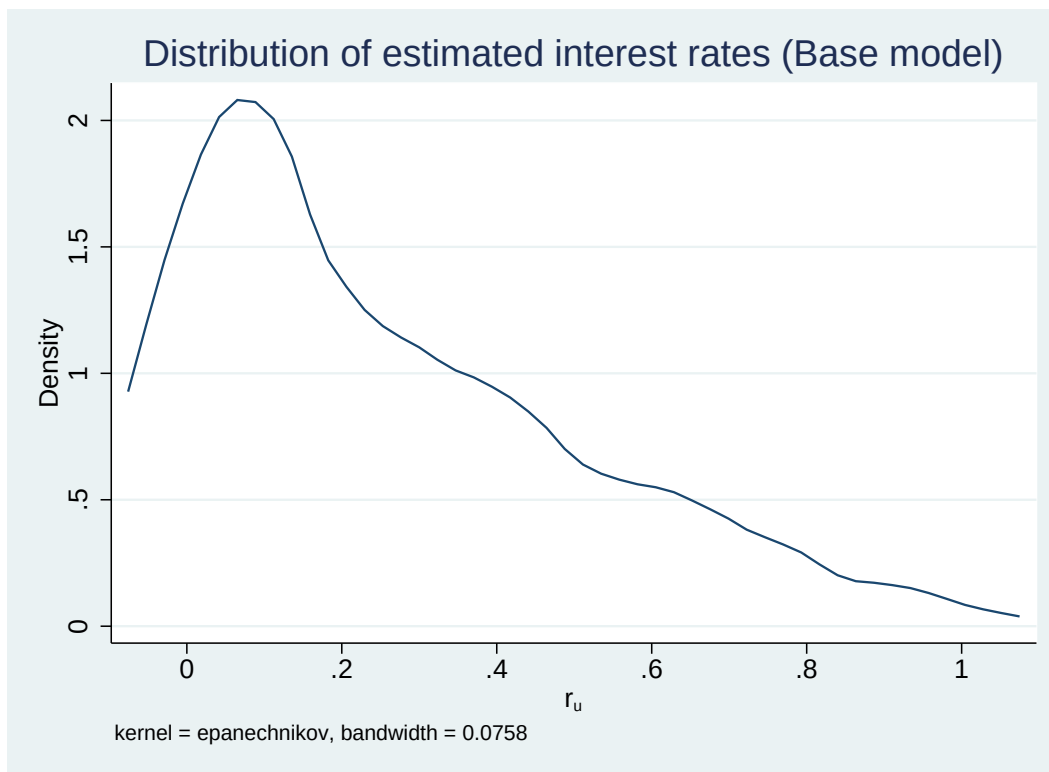


Figure 9: Distribution of estimated discount rates

