How General Are Time Preferences? Eliciting Good-Specific Discount Rates*

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Abstract

This paper tests the commonly used assumption that people apply a single discount rate to the utility from different sources of consumption. Using data from two surveys conducted in Uganda including both hypothetical and incentivized choices over different goods, it elicits time preferences from approximately 2,400 subjects. The data reject the null of equal discount rates across goods under different modeling assumptions, showing that people in Uganda are more impatient about sugar, meat and starchy plantains than about money and a list of other goods. The paper reviews the assumptions that are required to identify discount rates from time-preference choices, focusing on the case of good-specific discounting. Moreover, an application evaluates empirically the conditions under which good-specific discounting could help predict a low-asset poverty trap, based on the idea that time-inconsistent behaviors may be observed even if individuals do not exhibit horizon-specific discounting.

JEL Classification: D03, D90, O12, C90, D14

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1 Introduction

People are in many circumstances unable to be consistent with their own plans. A number of papers in economics explain self-control problems as the consequence of time-inconsistent preferences. Most theoretical and empirical research has focused on providing evidence for discount rates not being constant, but decreasing over the time horizon (see DellaVigna, 2009 and Bryan et al., 2010 for a review). The existence of horizon-specific discount rates is only one possible deviation from the broadly adopted discounted utility framework introduced by Samuelson (1937). An alternative way to model time-inconsistent behaviors is by assuming good-specific discount rates. The possibility that different discount rates are applied to the utility from different sources of consumption has been recently introduced in the models by Banerjee and Mullainathan (2010) and Futagami and Hori (2010), but there is scarce evidence that evaluates its empirical validity.

This paper attempts to fill this gap in the empirical literature by testing for differences in discount rates across a large list of goods. We adapt the procedures and the econometric techniques used to elicit discount rates for monetary rewards in order to estimate discount rates over real consumption goods. There are only a few papers in the economic literature eliciting time preferences over consumption goods and they do not focus on testing for differences in discount rates (see section 2.1 below). While there are a series of studies in the literature from psychology finding "domain-effects" or different discount rates across domains, they do not control for covariates and their results are typically derived from small samples of students answering hypothetical questions in the lab. Our study is the first to estimate discount rates for several goods using both hypothetical and actual rewards. Our results are based on time-preference choices made in the field by more than 2,400 individuals in a rural area of Uganda.

The data reject equality of discount rates across goods under several modeling assumptions. For the sample of rural households in Uganda, there are three goods with significantly higher discount rates than money: sugar, beef and matooke (a green plantain, main staple and favorite component of the diet in the region). Almost half of the sample exhibit higher discount rates for at least one of these three goods than for money and a list of other fifteen goods. We find that there is evidence for context specificity in the sense that discount rates differ across goods, but also some support for general components of time preferences since similar observable factors affect time choices for different goods and there is a high correlation in discount rates across goods. These results are qualitatively similar to those found by Einav et al. (2012) for risk preferences.

The challenge to elicit time preferences is significant since a myriad of contextual factors that can affect the results have to be taken into account.[1] We discuss the assumptions that are needed to recover time preferences from experimental tasks. We extend the discussion in Dean and Sautmann (2014) to the case of multiple rewards. We review the narrow bracketing case in which choices offered to the individual are treated in isolation from her outside world. In this case, our results can be directly interpreted as providing evidence for good-specific discount rates. We then derive the assumptions that we need to recover time preferences if individuals do take into account a broader consumption-savings problem when faced with experimental choices.

We show that differences in discount rates persist after controlling for several potential confounders that have not been taken into account in the previous literature. For example, we consider a general curvature of the utility function, the possibility that rewards are not immediately consumed, and reward magnitude effects. In addition, we control for individual characteristics by using within-individual variation in discounting choices across goods, as well as for good-specific potential confounders: expected prices, storage capacity, uncertainty about receiving future payments and trade opportunities. Furthermore, we find that discount rates for each good are strongly correlated with two self-reported variables measuring time-preferences: the desire to have the good at the present, and the desire to have the good in the future. This provides evidence that the estimated discount rates are indeed capturing individual time preferences and not other confounding factors. However, in accordance to the implications of the model, we do find that for traders, who either have easier access to markets or think more about arbitrage across goods when making their choices, all differences in discounting are eliminated. Similarly, we find that for people with higher levels of background consumption approximated by the amount of each good available at home, differences are also reduced. Since both traders and people with large amounts of the good at home represent a small proportion of our sample, we claim that the differences in average discount rates we estimate do reflect good-specific time preferences.

We can mention at least three important implications of the existence of different discount rates across goods. First, with good-specific discounting we could observe time-inconsistent behaviors even if individuals did not exhibit horizon-specific discounting (see section 4.1 for an example). Indeed, in our sample only 12% of households exhibit present-biased preferences as measured by standard preference reversal questions, while 50% present higher discount rates for either sugar, beef or matooke.

Second, we could derive new conditions for optimal taxation. For example, Futagami and Hori (2010) show that if agents apply different discount rates to the utility from consumption

[1] See Frederick et al. (2002) and Chabris et al. (2008) for a list of potential confounding factors when eliciting monetary discount rates.

and leisure, the optimal consumption tax in general equilibrium will not be zero (zero being optimal under both time-consistent and horizon-specific discounting). More generally, by allowing for different discount rates across goods, Banerjee and Mullainathan (2010) show how "sin" taxes can have undesirable effects on decision-making by the poor.

Third, good-specific discounting could provide an alternative explanation for the persistence of poverty and low savings by the poor. The model by Banerjee and Mullainathan (2010) shows that when different discount rates across goods are combined with the assumption that expenditures in goods with higher discount rates increase less than proportionally with income, a poverty trap can emerge. The intuition for their model is that there will be a disagreement between the present and the future self on the composition of consumption. If people are aware that their future self will spend a relatively large share of their income on the high-discount goods (the "temptation tax" in words of Banerjee and Mullainathan), their present self will try to limit future resources by increasing present consumption. The key testable assumption is that wealthier individuals spend a low share of their income on these goods and would therefore face a weaker disincentive to save than the poor. This is why we would observe a stronger tendency to dissave when resources are low.

Our data give us a unique opportunity to provide evidence for the two assumptions that can predict a low-asset poverty trap generated by self-control problems in this context.[2] In the first place, we identify the group of goods with higher discount rates. Secondly, we look at their Engel Curves to analyze whether their share of expenditures or consumption is decreasing in income. Using expenditures data, we find mixed evidence across goods. But, once we look at consumption data we see that the Engel Curve for the three goods with higher discount rates is downwards sloping. This indicates that people with lower resources in our sample spend a larger share of their income on high-discount goods. In this sense, the results of this paper contribute to the literature explaining the persistence of poverty and low savings among the poor.

Finally, identifying the goods with higher discount rates as we do in this paper can be useful to obtain a data-driven definition for "temptation" goods (as suggested in Banerjee and Mullainathan, 2010). The empirical literature has determined the category of temptation goods by asking households about the goods they would like to spend less money on (e.g.Banerjee et al., 2014) or the goods for which they are tempted. The effect of a particular program on expenditures in such category is usually estimated. But, this procedure could

[2]The possibility of self-control problems leading to a poverty trap is also formalized by Bernheim et al. (2013). Their focus is not on good-specific discounting, but on the combination of time-inconsistent preferences generated by horizon-specific discounting and credit constraints. In related work, Moav and Neeman (2012) show that a poverty trap can also emerge when the fraction of income spent on conspicuous consumption is decreasing with the level of human capital.

be affected by reporting bias if differential across treatment and control groups given that, as we have found in our field work, many households do not want to recognize being affected by temptations or the fact that they are spending money on goods that they consider relatively unimportant. Moreover, our techniques could also be used in other contexts, such as identifying policies to which a policy maker applies higher discount rates.

The remainder of the paper proceeds as follows. Section 2 reviews the literature eliciting time-preferences over consumption goods, describes the surveys and the characteristics of the sample. Section 3 presents the methodology used to estimate good-specific discount rates, discuss the assumptions that we need to recover time preferences from the experimental tasks and presents the main results, including a battery of robustness checks. Section 4 provides evidence for the Engel Curves of the high-discount goods in order to evaluate whether their share on total expenditures is decreasing. Finally, Section 5 includes some concluding remarks.

2 Eliciting Good-Specific Discount Rates in the Field.

2.1 Related Literature

Only a few papers have tried to test the hypothesis that the discount rate is common across goods, some in the economics literature and some in psychology. Overall, the evidence they generate is quite mixed. Psychology studies tend to find that primary rewards, those necessary for survival such as water and food, are discounted at higher rates than money (Odum and Rainaud, 2003, Estle et al., 2007 and Charlton and Fantino, 2008). Several studies also show that addicts have higher discount rates for their addiction than for money (Bickel et al., 2011). Finally, Tsukayama and Duckworth (2010) provide evidence that individuals who report being more tempted by a particular good have higher discount rates for that good (candy, chips and beer) and a higher discount rate for those goods than for money or other goods for which they do not report being tempted.[3]

In economics, there are two carefully conducted studies with incentivized choices, both use small samples of students in the U.S. Reuben et al. (2010) find higher discounting rates for chocolate bars than for money, although their main focus is to estimate the correlation among choices across the two domains. Augenblick et al. (2013) estimate a quasi-hyperbolic utility function and find more present-biased preferences with choices over effort than over

[3] They also present evidence of domain effects with candy, chips and beer showing higher discount rates than money. Results are obtained with hypothetical rewards for a sample of students in the U.S.

money (lower beta parameter), while the delta parameter is not statistically different between the two goods. They admit that estimating aggregate discounting was not a focus of their experimental design.[4]

It is not clear, however, how the findings from these papers would apply to poor households in developing countries. The few field studies conducted in developing countries tend to find no evidence that time preferences vary across goods. Holden et al. (1998) find, for a sample in Zambia and using hypothetical questions, no significant differences in discount rates between cash and maize. Klemick and Yesuf (2008) do not observe significant differences in discounting for wheat, salt and cash in Ethiopia, but they do not have enough information to estimate good-specific discount rates. On the other hand, in their commitment savings study with bank clients in the Philippines Ashraf et al. (2006) mention finding higher impatience levels for rice and ice-cream than for money. They do not discuss these results in the paper, however, since their focus is on horizon-specific discounting and not on good-specific discounting.

A related question is whether there are domain-general components of time preferences. Einav et al. (2012) reject the null hypothesis that there is no domain general component of risk preferences using actual choices over financial lotteries in different domains. They find high correlations across domains, but significantly different distributions of choices and no trivial evidence of context-specificity. For time preferences, Augenblick et al. (2013) find zero correlation between effort and monetary choices, Chapman (1996) also finds low correlations between health and monetary choices. On the other hand, Reuben et al. (2010) find high correlations for discount rates elicited with monetary rewards and with chocolate, but differences in average discount rates. These papers suggest that similar factors affect decisions in different domains and there could be a unique cognitive process behind both types of choices. In this direction, McClure et al. (2007) provide evidence for the existence of similar neurological processes for the discounting of primary rewards and money.

The contribution of our paper over the previous literature is to estimate discount rates for a large variety of goods, eliciting preferences in the field from more than 2,400 individuals and using both hypothetical and incentivized choices. Moreover, we discuss the assumptions required to elicit good-specific discount rates from experimental choices and use a series of econometric techniques to check whether differences in discount rates persist under different modeling assumptions. We find a group of goods to with significantly higher discount rates are applied, a key result for the economic application we discuss; which is a separate

[4]In both papers rewards are measured in quantities with different value across the two types of payments. It is possible that their results on the differences in levels of discount rates are due to a combination of what the literature calls a "magnitude" effect and the different value of the two goods, that is, when higher-value rewards are discounted at lower rates.

contribution of the paper.

Although it is not the focus of our study, we also find very high correlations among discount rates across goods within individuals.[5] In addition, we see that some factors affect discount rates for all goods in the same way, among them gender and the existence of a magnitude effect. This provides additional evidence for domain-general components of time preferences, even when we detect some context-specificity in the levels, which are parallel findings to the ones by Einav et al. (2012) for risk preferences.

2.2 Surveys Design and Sample Characteristics

We designed and conducted two surveys with modules to elicit time preferences. The first one has the goal to elicit discount rates for a large list of consumption goods using hypothetical choices; while the second one uses incentivized choices to check for the robustness of results with a smaller set of goods and it includes additional questions to control for factors potentially affecting the elicitation procedure.

2.2.1 First Survey

The first survey was conducted with a sample of 2,442 individuals in a rural region of Uganda, who where visited at home between October and November, 2010. Time-preference questions for nineteen goods were asked at the beginning of a long background survey. A census performed in June, 2010 found 9,287 households in the area and 3,000 of them were randomly selected for the baseline survey; for 2,442 households one of the heads or the single head was successfully interviewed. The fact that we interviewed the head of the household present at home led to a majority of female respondents in our sample.

The area under study is mainly rural and poor, Table 1 describes the sample. Most of the households are small-scale farmers, 85% farm at least one crop and 65% sell at least one crop. The median plot size is 1 acre, the median value of crops sold for the last harvest is around 10 dollars (or 25 in PPP), and investments in agricultural inputs are low, with only 10% using fertilizer. The majority of the respondents are female, with less than 6 years of education on average (the minimum to complete elementary school is 7 years); almost a quarter of the sample cannot read or write in Luganda, the local language, and correct responses both in a digit recall memory test and a Raven's matrix cognitive test are around 50%.

From a series of interviews with local households, we constructed a list of nineteen locally

[5]The correlations in discount rates across goods are between 0.6 and 0.8 both with hypothetical and incentivized rewards.

available goods.[6] In order to elicit good-specific discount rates, we adapted the questions for monetary rewards by Coller and Williams (1999). Similar questions have been used to elicit discount rates with monetary rewards in developing countries.[7]

Subjects are faced with five paired choices between smaller rewards that would be received the same day and larger rewards that would be received one month later. Questions are designed to maximize respondent's understanding and to detect large differences in discount rates across goods. For example (see Appendix A for the complete list), respondents have the option to choose between 1 kilo of sugar now and 1.5 kilos of sugar in a month. If they choose the first option, they are asked for their preference between 1 kilo now and 2 kilos in a month, and the delayed quantity is increased until they switch to the delayed option.

We assume monotonicity in responses: if respondents prefer 2 kilos of sugar in a month to 1 kilo now, they would also prefer 3 kilos in a month to 1 kilo now. This eliminates multiple switching by design, which can be undesirable since it is usually used as an indicator for miscomprehension. Our design choice was based on time constraints due to the large number of questions already included in the survey. We conducted example tasks before the elicitation tasks to improve understanding among our respondents. Moreover, all our results are robust to controlling for education, cognitive ability measures and total time spent answering the questions.

These questions were based on hypothetical choices; while respondents were encouraged to reveal their preferences as if their choices were real, no additional incentives were provided. We used "equal-value" trade-offs across goods, with the sooner choice given by a number of units with an approximate cost of 2,500 Ugandan Shillings (approximately 1 USD at nominal exchange rate or 2.5 in PPP). The ratios between the sooner and each possible delayed choice were the same across goods, in order to avoid possible framing effects affecting the estimation of discount rates. Units were chosen during a field pilot with the condition of not being too large to generate satiation or too small to make choices irrelevant in relation to typical consumption patterns. We also asked two additional sets of questions for each good including lower and higher quantities in order to control for possible magnitude effects that will prove to be significant.

[6] Besides money (the standard good used in the literature to elicit time preferences), the list includes: beans, matooke (green plantain and main staple), salt, sugar, soda, meals at restaurants, snacks, alcohol, bar games, clothes, lotion, perfume, entertainment, hairdresser salon, cellphone airtime, meat, school supplies, and shoes.

[7] See, among others, Shapiro (2010), Bauer et al. (2012), Dupas and Robinson (2013) and Schaner (2014).

2.2.2 Second Survey

The second survey was conducted between August and September, 2011. The sample was constructed as a random subsample of 500 individuals taken from the 2,442 individuals in the first survey, out of which 449 respondents were located and interviewed. Summary statistics for this sample are presented in the right panel of Table 1. There is no evidence of statistically significant differences in any of the variables with respect to the full sample.

The survey consisted of time-preference questions to elicit discount rates for six goods and a series of questions to better understand the factors behind those choices. The quantity of each good was adapted to reflect changes in relative prices over time, but questions followed the same format as the one in the first survey. The exception is that we used two sets of questions representing "equal value" trade-offs, one with smaller and one with larger quantities. The sooner choice involved a number of units with an approximate cost of 3,000 Ush (approximately 1 USD in nominal exchange rate or 2.6 in PPP, see Appendix A for full list of the choices).

In this case, respondents were told that one of their choices would be paid for real and that, for each good, every answer would have the same probability of being chosen. At the end of the survey, each respondent drew a piece of paper from a bag containing the names of the six goods, and then another piece of paper from a second bag to determine the question to be paid among the ones they answered. To minimize differential uncertainty and transaction costs between the sooner and the delayed payment, respondents were told that if the sooner reward was picked, an enumerator would come back to their house at the end of the day with the payment. Whereas, if the delayed reward was picked, an enumerator would come back with the payment in a month. In both cases, respondents were given a certificate with the logo and signature of the NGO we worked with. They had already participated in the initial census and background survey, and had signed an informed consent in which they were told that new interviews would be conducted in the following year. Therefore, they were familiar with the NGO and trust issues about payments did not represent a significant problem as confirmed by self-reported trust measurements included in the survey.

3 Econometric Methods, Assumptions and Results

Can we recover good-specific discount rates by observing choices between receiving a certain quantity of a good now and a larger quantity a month from now? The question of identification of time preferences from experimental choices has been receiving a lot of interest.[8]

[8]See, among others, Andersen et al. (2008), Andreoni et al. (2012), Ambrus et al. (2014), Montiel Olea and Strzalecki (2014) and Dean and Sautmann (2014).

But, the discussion has focused almost exclusively in the case of hyperbolic discounting with choices over monetary rewards.[9] In this section we use our two surveys including hypothetical and incentivized time-preference questions over multiple goods to elicit good-specific time preferences.

We extend the discussion in Dean and Sautmann (2014) to the case of multiple rewards, in order to understand how to interpret our results. First, section 3.1 reviews the narrow bracketing case in which choices offered to the individual are treated in isolation from her outside world. In this case, our results can be directly interpreted as providing evidence for good-specific discount rates. Most of the literature eliciting time preferences has assumed a certain degree of narrow bracketing. Moreover, narrow bracketing has been proved to be a common behavior in risk choices (Rabin and Weizsacker, 2009), and there is some evidence that time-preference choices are uncorrelated with shocks and liquidity constraints (Meier and Sprenger, 2014, Chuang and Schechter, 2014, Carvalho et al., 2014). However, the assumption of extreme narrow bracketing in discounting choices has been contested in recent papers (Cubitt and Read, 2007, Dean and Sautmann, 2014, Ambrus et al., 2014). Section 3.2, sets-up a two-period two-good maximization problem as in Banerjee and Mullainathan (2010) and derives its Euler equation. We re-interpret our results considering that individuals can take into account the broader consumption-savings problem when faced with experimental choices. We then describe the additional constraints that must be satisfied for choices to reveal time preferences and perform several robustness checks to evaluate whether our results still hold when we control for some of the potential confounding factors. Finally, section 3.3 gives a tentative interpretation of the results trying to explain why we find goods with higher discount rates.

3.1 Good-Specific Discounting Under Narrow Bracketing

This section presents our results under perfect Narrow Bracketing. That is, when individuals make their choices between sooner and delayed rewards for a given good based only on their preference parameters for that good, without regard to the circumstances and other decisions they face. This implies, as we will see, that when making choices for a given good, individuals do not take into account their outside current and future consumption for that good, their income and any arbitrage opportunity in financial markets; as it is usually assumed in experiments with monetary rewards. In the case of multiple goods, we need to add other elements to the list of factors assumed to be ignored, such as the outside consumption of the goods offered in the other choices, and any arbitrage opportunity in markets for those

[9] An exception is Augenblick et al. (2013) who also consider choices over real effort.

goods.

Dean and Sautmann (2014) show that under narrow bracketing the ratio between the earlier and the later reward at the switching point approximates $\beta\delta$, the product of the time-preference parameters from a quasi-hyperbolic utility function. We abstract from the possibility of horizon-specific discount rates and focus on testing for short-term good-specific discount rates.[10] It is easy to show that in the case of two periods ($t = 1, 2$) and two goods (x and z), the ratio between the earlier and the later reward for a given good at the switching point approximates the discount rate for that good. Assume utility is separable overt time and across goods, and discount factors for the two goods are δ_x and δ_z :

$$U(x_1) + V(z_1) + \delta_x U(x_2) + \delta_z V(z_2)$$

We follow the typical assumption in the literature and for monetary rewards. We assume that, under narrow bracketing, the individual does not consider her actual consumption of each good at each point in time, but a constant level of "background consumption" for each good, constant over time and independent from the other goods. This could make sense, as Ambrus et al. (2014) point out, if small rewards are viewed as windfalls under different mental accounts and enjoyed separately from background consumption. Let $\bar{x}$ be a measure of constant background consumption for good x, the quantity integrated with the reward into the utility of good x. A subject evaluating consumption using an expected discounted utility model who is offered choices between M_{0x} units of good x in $t = 0$ and M_{1x} units in $t = 1$ will be indifferent between the two payment options if and only if the present value of the two options is the same:

$$U(\bar{x} + M_{0x}) + \delta_x U(\bar{x}) + V(\bar{z}) + \delta_z V(\bar{z}) = U(\bar{x}) + \delta_x U(\bar{x} + M_{1x}) + V(\bar{z}) + \delta_z V(\bar{z}) \tag{1}$$

$$U(\bar{x} + M_{0x}) - U(\bar{x}) = \delta_x U(\bar{x} + M_{1x}) - \delta_x U(\bar{x}) \tag{2}$$

$$\delta_x = \frac{U(\bar{x} + M_{0x}) - U(\bar{x})}{[U(\bar{x} + M_{1x}) - U(\bar{x})]} \tag{3}$$

If the experimental payments are assumed to be small relative to background consumption, we can approximate the discount factor for good x by the ratio between the sooner and

[10] We do estimate that 12% of our sample exhibit present-biased choices, but we only have data for monetary hypothetical rewards. See Augenblick et al. (2013) for differences in present-bias over effort and money.

delayed reward at the switching point:

$$\delta_x \approx \frac{U'(\bar{x})M_{0x}}{U'(\bar{x})M_{1x}} = \frac{M_{0x}}{M_{1x}} \tag{4}$$

3.1.1 Basic Procedure

Most of the literature reviewed in section 2.1 implicitly assumes narrow bracketing together with linear utility functions and use hypothetical rewards. We begin by replicating this literature using data from our first survey with hypothetical rewards for nineteen goods. We calculate the discount rate ρ_g for good g using equation (4), as the inverse of the discount factor minus one.

We compute discount rate bounds for each individual, each good and each choice. As an initial step, we take the midpoint of the interval of discount rates derived from the question at which the respondent switches to the delayed option. The following table gives an example of the implied bounds for each choice and the imputed discount rate:

Choice	M_{og}	M_{1g}	Implied Bounds if Respondent Chooses M_{1g}	Discount Rate
1	1	1.5	[0, 0.5)	0.25
2	1	2	[0.5, 1)	0.75
3	1	2.5	[1, 1.5)	1.25
4	1	3	[1.5, 2)	1.75
5	1	3.5	[2, 2.5)	2.25

We designed the choices with the condition that for each row, the ratio between the earlier and the later reward be the same for all goods and levels of the principal. This reduces possible framing effects, and facilitates comparison across goods. For example, the second choice for sugar is between 1 kilo today and 2 kilos in a month (or 3 kilos and 6 kilos in the case of large quantities), while the one for meat is between 0.5 kilos today and 1 kilo in a month (note that both 1 kilo of sugar and half a kilo of beef are worth approximately 2,500 Ush). If the respondent switches at the second choice for a given good, we assign a discount rate of 0.75 for that good.[11]

Another important point is that the imputed rate for those switching at the first option is already very large, a 25% monthly discount rate. This will be our baseline value to compare all other discount rates when we assume linear utility. Moreover, this means that we will not

[11] We assume non-negative discount rates, which gives us a lower bound of 0. In order to get an upper bound we assume that if the respondent chooses the sooner option for all choices, the discount rate will be one interval larger, that is 2.75. Our results are robust to dropping individuals always choosing the sooner option who represent approximately 14% of our sample.

be able to identify differences in discount rates across goods for those individuals having low discount rates for all goods. Nevertheless, the fact that we do identify significant differences across goods means that these differences are very large.[12]

Table 2 presents summary statistics for discount rates calculated following this basic procedure. We can see that there are three goods: sugar, matooke and meat with significantly higher average discount rates than the rest of the goods, and in particular, significantly higher than the one for money. Furthermore, we can see that the median individual has a discount rate of 0.75 for these three goods, implying a switch at the second option. Whereas, for all the other goods the median individual switches at the first option, and has an imputed discount rate of 0.25.[13]

3.1.2 Basic Procedure, Pooled Estimation

In order to test whether differences in average discount rates are statistically significant and to take into account that the same individuals are providing answers across goods, we estimate a pooled regression, clustering standard errors at the individual level. We use good-specific dummies (using money as the omitted category) to test for differences in discount rates across goods. We estimate:

$$\rho_{img} = \beta_0 + \sum_{g=1}^{n} \beta_g \mu_g + \varepsilon_{img} \tag{5}$$

where ρ_{img} is the discount rate (calculated following the basic procedure described in 3.1.1) of individual i, for the question of amount m and good g. The goal is to estimate the coefficients β_g on the good effects μ_g. The estimates for the coefficients β_g can be interpreted as the average difference between the individual discount rate applied to good g and the one applied to money.[14]

Results from estimating equation (5) can be seen in Table 3. Column (1) presents results for discount rates calculated using the "equal-value" questions in order to avoid the noise from

[12] We would have been able to estimate more precisely the level of discount rates if we had offered additional choices for each good. But, in order to reduce the size of the intervals, we would have needed to include choices with further decimal units for some goods. Decimal units of certain goods proved to be difficult to understand for our respondents, thus we preferred to limit the number of choices in order to maximize their understanding and response rates.

[13] We do not present results for beer and bar games since more than 50% of respondents refused to answer the questions on the basis of religious reasons. The discount rates calculated for those who did answer the questions are in the range of the ones for the low-discount goods.

[14] While choosing money as the baseline category is arbitrary, we do so taking into account that the results in the time-preference literature are based on monetary rewards. Moreover, significant differences with respect to money imply significant differences with respect to all other goods in our list, for which we find even lower discount rates.

using magnitudes with different value across goods. Only for meat, sugar and matooke the estimated coefficients are positive and highly significant, indicating higher average discount rates for these goods than for money. In Column (2) we use discount rates calculated using all questions, including those with different magnitudes. In this case we include two indicators for questions with equal-value trade-offs (Equal Value) and small-value trade-offs (Small) to control for magnitude effects. The omitted category is large-value trade-offs, which implies trade-offs between larger quantities than in the previous two cases. Differences across goods are reduced, but only for the same three goods the coefficients are positive and statistically significant.[15]

The coefficients on the Small Quantities and Equal Value question dummies at the bottom of Column (2) imply that larger rewards, the omitted category, are discounted at significantly lower rates. This provides evidence for a magnitude effect for monetary rewards. We find that the same effect applies to each of the goods in our list, and it is robust to different modeling assumptions (results available upon request). This is a unique finding of our paper; while evidence for lower magnitudes being discounted at higher rates has been provided by a large number of articles, none of them uses real consumption goods and real rewards.[16]

Finally, we run interval regressions to account for the fact that dependent variables are measured in intervals, and can be considered as right- and left-censored. An interval regression is equivalent to an ordered probit model with fixed cut-points in which the two bounds of discount rates intervals are used as dependent variable. We confirm that results still hold with this data-driven procedure to choose one point of the discount rates interval instead of arbitrarily using the midpoint. Column (3) presents differences in predicted discount rates for each good and money obtained by estimating interval regressions for each good. We estimate by maximum likelihood one equation for each good using the equal-value questions, with only a constant as explanatory variable and we take the coefficient of the constant as

[15]It is important to clarify that, given that we use three set of questions for each good, we can control for possible framing effects linked to different quantities (with two tasks keeping quantities constant across goods, e.g. 2 and 6 units at time zero) and different monetary values across goods (with one task equalizing the monetary value of the goods at time zero). Nevertheless, it is still possible that choices are affected by differences in the value each individual attributes to the consumption of the given units of each good, which could depend on storability, duration and other unobservable good-specific factors. To the extent that we do find a magnitude effect when using questions including different nominal quantities, results using the equal-monetary value questions are our preferred choice. Moreover, our findings are robust to controlling for self-reported storability and duration for different goods.

[16]See Frederick et al. (2002) for a list of papers. Andersen et al. (2013) claim that the evidence for the magnitude effect in the literature is at least questionable. After controlling for different modeling assumptions, they show that the effect is still present, but with a smaller magnitude than usually found, specially when they look at the median discount rates and use choices involving a time delay. While we do not include time delays, we follow similar methodologies as in their paper and we still find large magnitude effects in both mean and median discount rates.

the corresponding predicted value, standard errors are based on the linear combination of estimates obtained from seemingly unrelated regressions. For the interval regressions we still use bottom coding at 0 (non-negative discount rates), but we do not impose any top coding. Differences in predicted discount rates obtained with this method are statistically indistinguishable to those presented in Column (1), and thus the ranking across goods does not change.

3.1.3 Discount Rates Elicited with Real Incentives

There is a significant discussion in the literature on whether the use of hypothetical payments instead of incentivized responses can generate a bias in discount rates. In order for this potential bias to be relevant to our study, it has to be the case that respondents fail to reveal their true preferences with hypothetical rewards and that this behavior differs by good.

The evidence on whether the use of real or hypothetical monetary rewards makes a difference is mixed. On the one hand, a series of papers argue that similar results are found in the two cases or that there is at least no evidence for significant differences (Frederick et al., 2002, Benhabib et al., 2010, among others). On the other hand, in a series of papers Andersen et al. claim that "(...) the evidence is overwhelming that there can be huge and systematic hypothetical biases" (Andersen et al., 2014, pp. 27).

We test whether results obtained with hypothetical rewards differ from those found with real incentives. In our second survey we performed a new set of time-preference questions for six of the goods used in the first survey and one question was randomly chosen for payment. The goods for which we replicated the questions were the three ones for which we had found high discount rates with hypothetical rewards: matooke, sugar and meat, the standard good used in the literature: money; and two goods for which we had found low discount rates: school supplies (as we expected since people mention wanting to save for them) and cellphone airtime (for which we expected ex-ante to see high discount rates).

Table 4 replicates Table 1, but it now restricts the observations to the 449 households interviewed again in the second survey. By comparing the two panels of Table 4, we can appreciate that there is no statistically significant difference in average discount rates for any of the six goods when we compare discount rates elicited with hypothetical and real incentives, confidence intervals overlap in all cases. We are actually testing the joint hypothesis that there are no differences between real and hypothetical rewards and that average discount rates remain constant over the period of one year; we do not find evidence to reject it.[17]

[17]For a recent discussion on the stability of time preferences see Krupka and Stephens (2013), Chuang and Schechter (2014) and Meier and Sprenger (2014). Our correlations over one year are between 0.15 and 0.20 for all goods (0.20 for money), and statistically different from zero. Our results are in line with Meier

We still see that matooke, sugar and meat are the three goods with significantly higher discount rates; although the standard errors are now larger due to a smaller sample size, differences are still significant at the 10% level. The same conclusion is derived when we compare discount rates obtained with real rewards for these three goods and with hypothetical rewards for the others, or the other way around.

In Table 5, we present results for a pooled estimation with the new data. We can see in Column (1) that the same results hold, and when we cluster the standard errors at the individual level all differences become largely significant. In Column (2) we present results using both "small quantity" and "large quantity" questions. In this survey, the two sets of questions represent the same monetary values across goods, so it is not problematic to combine them. The differences are larger, but conclusions remain the same. Moreover, the "small quantity" question dummy is positive and statistically significant confirming the magnitude effect mentioned above.

3.2 Good-Specific Discounting Without Narrow-Bracketing

The assumption that individuals completely disregard their circumstances and other decisions when making time-preference choices is an empirical question, but it is admittedly too strong. In this section we set-up a two-period two-good maximization problem following Banerjee and Mullainathan (2010), which we also use in our application below. The Euler equation from this model will allow us to see more clearly the assumptions we need to make in order for our experimental tasks to elicit time-preferences without imposing narrow bracketing.

Consider an individual who lives two periods $t = 1, 2$ and can spend her income on two different components of consumption x_t and z_t (or indexes of spending on two groups of goods). The utility function is as described in 3.1 above.[18] We can choose units so that all prices are equal to 1, and proceed recursively to solve the optimization problem. For simplicity of exposition, following Banerjee and Mullainathan, assume that individuals receive deterministic income y_1 in $t = 1$. They can save $w_1 = y_1 - x_1 - z_1$ and invest in an income generating function $f(w_1, \theta)$ with random shock θ, where f is increasing in w_1(to

and Sprenger (2014) who find a correlation over one year of 0.246 for the δ parameter of the quasi-hyperbolic model.

[18]The utility used by Banerjee and Mullainathan (2010) is separable over time and across goods. The separability over time is an assumption typically adopted in the discounting literature (see Andersen et al., 2011 for a discussion on how to relax it; imposing additive separability over time is equivalent to assuming correlation neutral individuals in their model). It rules out, for example, models of addiction and habit formation. The separability across goods rules out complementarities. For a theoretical discussion on how to interpret good-specific discounting with non-separable utility functions see Gollier (2010) and Traeger (2011).

allow for lending and borrowing with or without constraints at different rates), differentiable and concave in w_1. In $t = 2$, the individual receives an uncertain income $y_2(\theta')$.

Period 2 self maximizes $U(x_2) + V(z_2)$ subject to the budget constraint $x_2 + z_2 = c_2$; from this problem the standard demand functions $x_2(c_2)$, $z_2(c_2)$ are derived. Period 1 self is assumed to be sophisticated and to take these functions into account to maximize:

$U(x_1) + V(z_1) + \delta_x E_{\theta,\theta'}\{U(x_2[c_2(\theta, \theta')]\} + \delta_z E_{\theta,\theta'}\{V(z_2[c_2(\theta, \theta')]\}$, subject to $w_1 = y_1 - x_1 - z_1$, $c_2 = f(w_1, \theta) + y_2(\theta')$, and non-negativity constraints. Assuming an interior solution exists, the Euler Equation for the problem is:

$$\frac{dU(x_1)}{dx_1} = \delta_x E_{\theta,\theta'}\{\frac{dU(x_2(c_2))}{dx_2}\frac{df(w_1, \theta)}{dw_1}\} - (\delta_x - \delta_z)E_{\theta,\theta'}\{\frac{dU(x_2(c_2))}{dx_2}\frac{df(w_1, \theta)}{dw_1}\frac{dz_2(c_2)}{dc_2}\} \quad (6)$$

In order to compare this equation with the one found by Dean and Sautmann (2014) in the case of one good under $\beta - \delta$ discounting, take f to be deterministic and re-arrange equation (6) , using $c_2 = x_2 + z_2$, to get:

$$\frac{dU(x_1)}{dx_1} = \frac{df(w_1)}{dw_1} E_1\{\frac{dU(x_2(c_2))}{dx_2}(\delta_x \frac{dx_2(c_2)}{dc_2} + \delta_z \frac{dz_2(c_2)}{dc_2})\} \quad (7)$$

$$MRS_1 \equiv \frac{U'(x_1)}{E_1\{U'(x_2)d_2\}} = f'(w_1),\ d_2 = \delta_x \frac{dx_2(c_2)}{dc_2} + \delta_z \frac{dz_2(c_2)}{dc_2} \quad (8)$$

This differs from the standard Euler equation because the marginal utility of income in period 2 from the perspective of period 1 is modified by a factor d_2. This discount factor is a weighted average of the discount factors of the two goods δ_x and δ_z, weighted by the future propensity to consume each good out of changes in total consumption. If z is the good with lower discount factor, when the propensity to consume good z increases, the future is discounted more heavily (d_2 decreases) as the decision maker anticipates period 2 self will overconsume good z in relation to good x.

Dean and Sautmann (2014) find an equation analogous to (8), with $d_2 = \beta\delta\frac{dc_2(y_2)}{dy_2} + \delta(1 - \frac{dc_2(y_2)}{dy_2})$. That is, the discount factor is a weighted average of the short-run and long-run discount factors, weighted by the future propensity to consume.[19] Therefore, the following arguments are closely related to the ones presented in their paper.

In the case of perfect capital markets, f does not depend on savings, and the MRS should be constant, equal to 1 plus the market interest rate. On the other hand, in the case of no access to the markets (capital and good markets), the individual is not able to reallocate consumption across goods and over time, and we get $d_2 = \delta_x$. Then:

[19] We adapt their notation to ours. In particular, their function $R(S)$ is similar to $f(w)$, and instead of the direct dependence of the instantaneous utility on a preference shock we have the shock affecting future income.

$$MRS_1 \equiv \frac{U'(x_1)}{\delta_x E_1\{U'(x_2)\}} \tag{9}$$

What can our time-preference choices recover from equation (8)? Assume that, when experimental choices are offered, the individual has derived the optimal stream of consumption for each good and savings given income. Then, the choice between M_{0x} now and M_{1x} in a month will not only depend on the actual possibility of bringing good x to the market, but also on whether the individual adapts the consumption plan to the interest rate and takes this into account when choosing between the two possible rewards.

As has been noted, among others, by Pender (1996), Cubitt and Read (2007) and Dean and Sautmann (2014), if the subject can take monetary experimental payments to the market, standard arbitrage arguments apply. If the payments are relatively small, the subject will compare the derivative of f at the optimal savings (or just the interest rate in the case of perfect markets) with the ratio between the later and the sooner reward. The point at which the respondent switches from the present to the future reward should then be approximately: $f'(w^*) \approx \frac{M_{1x}}{M_{0x}}$. In this case, we cannot learn about intertemporal preferences, the subject will maximize the net present cash value for any set of choices. For example, with profitable investment opportunities, even if the individual prefers 2 kilos of sugar in a month to 1 kilo now, she could choose the 1 kilo now, sell it in the market (or avoid buying it if she was planning to consume 1 kilo in any case and has not bought it yet), and invest the money to get a return that will allow her to buy more than 2 kilos next month. As we can see, this arbitrage argument would require access to technologies allowing to transfer resources across goods and over time.

On the other hand, assume the individual does not have access to such technologies, and consumes the reward in the period received. Then, we get that the switching point approximates $\frac{M_{1x}}{M_{0x}} \approx \frac{U'(x_1^*)}{\delta_x E_1\{U'((x_2^*)\}}$, which is equal to the MRS at the optimum.

Note that the key condition to derive this result is that $\frac{dx_2(c_2)}{dc_2} = 1$, consumption of good x increases one to one with the experimental payments for good x, so that $d_2 = \delta_x$ in (8). To get this it is not enough to assume the lack of markets, we also need to assume that individuals cannot save and borrow by running up or down the good that is offered. In other words, we need non-fungibility over time and across goods so that individuals perceive the choices for good x as units of good x now vs. units of that good in a month. In practice, when arbitrage is possible and contemplated by the individual, we might see differences in the estimated MRS for people with differential access to markets across domains, liquidity constraints and different availability of the goods. We provide evidence for this below.

3.2.1 Controlling for the Curvature of the Utility Function: Joint Elicitation Procedure

Even when we assume full constraints, implying that rewards are consumed in the period received, we still need additional assumptions to recover discount rates from observed choices. One possibility is to impose constant marginal utility over time, another is a linear approximation of the curvature of the utility function.

Most of the papers reviewed in Section 2.1 assume linear utility function. With binary choices it is only possible to get a range for the MRS, and if some respondents are shifted from one to the other side of the cut-offs after incorporating the experimental rewards, it would be incorrect to rely on a linear approximation to the curvature of the utility function. Andersen et al. (2008) highlight the importance of performing a joint estimation of the shape of the utility function and the discount rate. By Jensen's inequality, the implied discount rate will be lower if utility is concave in rewards than if it is assumed to be linear, and differences in discount rates across goods may also be affected even if we apply the same curvature to the utility of different goods.

We follow Andersen et al. (2008) and use a utility function of the form $(x_t + M_{tx})^{1-r}$. Where M_{tx} is the reward offered in period t for good x, and x_t is the background consumption for that good. As in their main specification we assume expected utility theory, exponential discounting, and that utility is stable and perceived to be stable over one month. Identification is achieved by varying the size of the payoffs, and by measuring risk preferences in addition to time preferences in order to estimate the curvature parameter.

Notice that in their main specification they choose a fixed level of background consumption over time and across individuals based on data on average monthly expenditures, this will bring us back to the need to assume full narrow bracketing as explained in section 3.1. We begin following this case, imposing a fixed level of background consumption, and relax this assumption in the next section.

We perform a maximum likelihood estimation of a model that follows the general latent choice process specification in Andersen et al. (2008). The difference is that we jointly estimate a single risk aversion parameter and good-specific discount rates. To recover the curvature parameter we use a constant relative risk aversion utility function and we elicit the single risk aversion parameter from two sets of hypothetical questions on preferences over lotteries that were available in our first survey (see table A3).[20] Respondents were asked to

[20]While it would have been desirable to design tasks providing separate identification of the curvature for different goods, this was not feasible for the current study given the difficulty involved in the required tasks, the low educational levels of our respondents, and the time restrictions of field interviews. That is why we use the basic measure of risk preferences available in our baseline survey. Recent papers introduce new procedures to estimate curvature-controlled discount rates that do not require a separate curvature

imagine that they could invest up to 1,000 Ush in a small business, which would yield 2.5 times the amount invested half of the time, and 0 the other half of the time. They were given the analogous to six possible lotteries, and asked to choose one of them. The second task was similar, but amounts were multiplied by 3.[21] We use these choices assuming the preferred lottery would also be preferred in all binary comparisons with the other five lotteries, giving us the equivalent to 11 choices for each individual and task.

The estimation is based on a two-part likelihood function. The first part makes use of the risk-preference questions to estimate a single risk aversion parameter r, which we use for all goods. To estimate the probability of choosing a given lottery, we incorporate a structural noise parameter that reflects possible errors in the expected utility model.[22] The second part of the likelihood function uses the time-preference choices.

Table 6 presents the maximum-likelihood estimates for the good-specific discount rates We can see in Column (1) that while the level of the estimated discount rates is lower than when we assume linear utility, as expected, the conclusion in terms of differences across goods still holds. We see again that matooke, sugar and meat are the three goods to which higher discount rates are applied. By looking at the 95% confidence interval bounds for these estimates presented in Columns (2) and (3), which were calculated using standard errors clustered at the individual level, we can see that the differences in discount rates between these three goods and all the other goods are statistically significant.[23]

We next allow for individual heterogeneity by letting the risk aversion and discount rate parameters be a linear function of observable characteristics. We include dummy variables for gender, being married, being literate and having an ability score (measured by a Raven's matrix test) lower than the average. The predicted mean discount rates are similar to the ones

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estimation (Andreoni and Sprenger, 2012, Montiel Olea and Strzalecki, 2014, Ambrus et al., 2014). The application of these new methods to good-specific discounting can be a promising topic for future research.

[21] The questions are similar to those designed by Binswanger (1981) and have been used by several studies in poor countries (e.g. Dupas and Robinson, 2013, Carvalho et al., 2014 and Cardenas and Carpenter, 2013).

[22] This specification was used by Andersen et al. (2008), Coller et al. (2011) and Laury et al. (2012) in the discounting literature, but it is only one possible specification of errors. Andersen et al. (2014) use an alternative specification of errors in which the probability of choosing a given lottery is defined as the difference in expected utilities, and linked to choices by a cumulative distribution function. When we follow this alternative specification, our results converge only when we introduce the contextual error correction suggested by Wilcox (2011), in this case we get similar conclusions. Results are available upon request.

[23] These estimations assume zero background consumption. We also estimate $r = 0.13(0.01)$, and the structural errors as $\mu = 0.09(0.01)$ and $\varepsilon = 0.38(0.01)$. The risk parameter is low in comparison to other results from the literature, but it still indicates risk aversion. The fact that the errors for the discount choices are higher than the ones for the risk choices might be due to the larger number of choices for each good in the former case. The different number of observations in Column (5) of Table 6 is due to missing values for some households not giving responses for some of the choices. The number of missing choices is low for the goods presented in the table, being the maximum 0.9% for perfume. We do not present results for beer, bar games and entertainment since large percentages of the sample refused to reveal their choices for these goods.

estimated without controls and the differences across goods are still statistically significant. We find that having a low ability score and being a woman significantly increase risk aversion, while the other covariates are not significant. Only gender significantly affects discount rates. Column (4) in Table 6 presents predicted discount rates for females based on the coefficient obtained when we allow both discount rates and risk aversion parameters to depend on observable characteristics. We can see that women have significantly lower discount rates for each of the goods (except for hairdresser salon visits for which the difference is positive, but not significant), but the ranking of discount rates across goods is the same for women as for the full sample. Andersen et al. (2014) also find that the only covariate with statistically significant impact on discount rates elicited with monetary rewards is gender, with an effect in the same direction as in our case. This derives from women being more risk averse, which means that they have a more concave utility function and a lower implied discount rate.

As robustness checks we also include controls for small-quantity and equal-value questions, and we find that the magnitude effect is present for all goods, but we derive the same conclusions in terms of differences across goods. Finally, we pool choices over all goods and include dummy variables for each good, except for money. Our findings (available upon request) replicate the ones in the pooled estimation, with only matooke, sugar and meat showing positive and significantly higher discount rates. Table 7 presents similar estimations using the incentivized choices and from them we derive the same conclusions.

3.2.2 Allowing for Integration with Background Consumption

The assumption of fixed background consumption is standard in the literature. Both Andersen et al. (2008) and Andreoni and Sprenger (2012) show that the estimates can be sensitive to the value of background consumption, but mainly the estimates of the curvature of the utility function are affected and not so much the discounting parameters. Nevertheless, identification requires assuming completely constrained subjects who consume the sooner or delayed reward at the time stated and do not smooth consumption over time or across goods. In order to relax these assumptions, we allow for x_t being different than zero in the joint estimation procedure with incentivized choices, since we included specific questions to measure background consumption in the second survey.

The first point to consider is how to measure background consumption, the amount that is integrated with the reward and evaluated in the utility function. Andersen et al. (2008) define it as the optimized consumption stream that is perfectly anticipated before allowing for the rewards, and they assume a single value for all individuals in their sample equal to the average per capita daily consumption of private non-durable goods. Similarly, Augenblick et al. (2013) set it as the required minimum work when estimating discount rates over effort.

In our case, we have data to make this parameter person-specific.

Our first approximation identifies background consumption with the amount of each good that individuals have at home at the time of the survey, we call it Background 1. Our second approximation, Background 2, allows for different values for current background consumption and the one in a month; we use the answers to a question asking how much of each good respondents expect to have at home in a month.[24] We asked these questions after all time-preference choices have been made, thus we did not induce subjects to think about them when making their decisions. We can see in Table 8 that the discount rates estimated using these assumptions for background consumption are similar to the ones in Table 7 obtained under zero background consumption for our first measure (Background 1). The level of the estimated discount rates change considerably under our second measure (Background 2), where they are less precisely estimated due to the noise in reported expected background consumption. It is possible that individuals overestimate the availability of the good in the future (underestimating their future constraints). But, in the two cases the ranking of discount rates across goods is preserved, although the differences become insignificant in the second case.

The second estimation issue is the period over which rewards are integrated with background consumption. We assume that rewards can be divided evenly over λ periods of time for the discounting choices, and a fraction $1/\lambda$ integrated with background consumption. This parameter λ is then interpreted as the time horizon over which the subject is optimizing. The usual assumption in the literature is λ=1, which implies that subjects consume the monetary amounts at the time stated in the instrument. Andersen et al. (2008) allow for different values of λ and find that the fit of the model is maximized when it is equal to 1. They assume a unique value of λ for all individuals; we use proxy variables based on our data. In particular, if x_j is the amount of the good consumed for a given day, λ is the number of days over which the subject expects to consume the quantity of the good received as reward. We first calculate daily consumption for each individual from data on consumption of each good in a typical month and we use this value as x_j. We also asked respondents about the period over which they would consume the rewards for matooke, beef and sugar, and we use their answers to calculate λ for each individual (the averages were 6 days for matooke, 7 for sugar and 2 for beef). Results are presented in the rows for Background 3 in Table 8; they are similar to those using Background 1 and consistent with our previous estimations. Finally, using the same procedure to get x_j, we defined λ as the ratio between reported typical

[24] Andreoni and Sprenger (2012) also allow for the two parameters to differ, but they estimate them as endogenous variables in their model. See Noor (2009) for the possible implications of time-varying background consumption.

monthly consumption for each good and the amount of each good potentially received as reward. Results are presented in the rows for Background 4. Discount rates are higher for all goods in this case, but differences between matooke, sugar and beef on the one side, and school supplies, money and airtime on the other, become again statistically significant.

So far we showed that if we allow for the integration of rewards with backward consumption levels our results do not change. But, this could mean that either people do not adjust their consumption when offered rewards (narrow bracketing) or that on average this behavior is not relevant enough in our sample to change the estimated differences in discount rates. Indeed, since the level of the estimated discount rate changes when we incorporate background consumption, we can argue that there is some evidence for the later.

An alternative tentative way to look at the question is by using the pooled regressions. In equation (5), we add interactions terms between each good and a dummy variable for having at home an amount of the good that is larger than the first choice of the reward offered, and we control for the interactions with typical monthly amount consumed of each good. When we estimate the pooled regression, the interaction terms for monthly consumption are very small and not significantly different from zero, while the interaction terms with the dummy for amounts at home are large in absolute value for sugar, matooke and meat; but only statistically significant for matooke.[25]

Results from this estimation are presented in column (3) of table 5.[26] It is interesting to see that for those having a quantity larger than the reward at home, most of the differences in the high discount goods disappear, only for sugar the difference with respect to money is significant (p-value 0.06). It is important to note that these results are coming from 27% of the sample having more than the offered reward at home for matooke, 13% for sugar, 5% for meat, 1% for airtime and 41% for school supplies. The larger the amount of each good available at home, the more convergence we see between the high-discount goods and money. If the amount available at home is a good proxy for background consumption, this implies that people do take into account their background consumption when making their choices. Thus, in order to get a cleaner estimate of differences in discount rates we should focus on subjects who are "liquidity constrained" in the sense that they do not have too much of the good at home. Fortunately for us, this is the majority of our sample. An alternative explanation is that there is a physical need for some goods which make people very impatient for them, or that people are tempted for a splurge and they consume their rewards when

[25]The coefficient on airtime is weird and we should not put much weight on it since it is coming from only 4 people who report having more than Ush 3,000 in airtime at the moment of the survey.

[26]The interaction coefficients are almost identical when we include the two set of interactions independently. We also find similar conclusions if we include interactions with the share of monthly consumption that is available now at home or we just use the level of amount at home. Results available upon request.

received if they do not have any unit of that good at home.

3.2.3 Arbitrage and Good-Specific Confounders

The previous section was related to the case of re-allocation of consumption over time for a given good, which is one form of arbitrage for experimental rewards. An alternative option we need to consider is direct arbitrage in financial and good markets.

We have seen that under smoothly functioning markets we should see no differences in discount rates across goods, since the marginal rate of substitution should be equal to the interest rate. Given this, there are two possible reasons why we can see differences in discount rates across goods: 1) people do not have access to complete markets or 2) people do not consider the possibility of using the markets when offered the experimental rewards (narrow bracketing).

To provide evidence for the first point, we study whether people that are more likely to have better access to the markets indeed show smaller differences in discount rates across goods.[27] Access to capital markets are underdeveloped in the area and credit is very scarce with only 12% of the sample reporting ever having received a loan from a bank or microfinance institution. Moreover, there could also be savings constraints with high opening fees for savings accounts, required minimum balances and expensive monthly fees. But, there could still be large access to good markets.

In the first survey we asked about the main source of income of respondents, around 30% are farmers, 20% employees, and 50% self-employed entrepreneurs out of which around 10% are traders of agricultural products (N=143). This group of traders could be the one with better access to the markets of the goods we offer as experimental rewards. We estimate the pooled regressions including interactions of the good dummies with a dummy for being a trader. Results are reported in Table 9. In column (1) we use the hypothetical choices from the first survey and in column (2) the incentivized ones from the second survey. We can verify that for traders almost all differences in discount rates between the high-discount goods and money disappear, as expected. The difference between these goods and the low-discount goods are even larger for traders in the hypothetical case, but not when choices are incentivized. For all the other occupations the interaction terms are low and not significant (results available upon request). Thus, we have evidence to say the differences in discount

[27] An alternative would be to use variation in trading constraints across goods. If there are better markets for matooke, sugar and meat than for the other goods in our study, this could be explaining our results (but we do not have clear evidence for it, in particular in comparison to beans, soda and salt for example). Augenblick et al. (2013) follow this direction by offering choices over effort, with low arbitrage opportunities, but they cannot exclude that people re-allocate extra-lab consumption including other types of effort.

rates across goods we estimate are coming from people with less access to the markets.[28]

To provide evidence for the second point, we need to understand whether people take arbitrage opportunities into account when making the experimental choices. Chapman (2002) shows that when people are told that hypothetical rewards are tradeable, the correlation between the discount rates of money and health increases significantly, which indicates that people think more about arbitrage opportunities once they are reminded about them. On the other hand, Coller and Williams (1999) find small effects from explaining arbitrage arguments to respondents when choices are incentivized. It is possible that with real choices, arbitrage opportunities were already a salient feature in people's decisions.

In the second survey, after the experimental choices, we asked respondents to report the factors they considered in their decisions. We structured the answers by reading one by one the following options for each good if applicable: how to store the good (Storage), how much they would get from selling it (Resale), what would be the price in a month compared to the price today (Price), how uncertain they were that the enumerator would come back in a month (Uncertainty), how much they want to have the good now (Desire for good now) and how much they want to have the good in a month (Desire for good in a month).

Column (4) of Table 5 presents the results for the pooled regression when we include dummy variables for the first four factors that may act as potential confounds for the discount rates. These variables take the value of one when respondents answer positively about the factor determining their choice for the particular good.[29] The questions are person and good-specific, thus the regression uses both variation across goods and within individual, and we control for individual fixed effects. The effects on average discount rates are positive for Uncertainty and Storage. They are negative, although not significant, for Price and Resale. Nevertheless, the differences in discount rates are practically unaffected when we include these four factors in the pooled regression.

Positive answers to The Resale and Price factors can be interpreted as people considering arbitrage opportunities when making their choices. Dohmen et al. (2010) asked whether a subject had thought about the market interest rate during an experiment with monetary choices, and they use the answers to identify individuals who engaged in arbitrage. They find that 37% of their participants give a positive answer and they conclude that most subjects do not engage in arbitrage at all. In our case, the fraction of the sample giving a positive answer to the Resale question is even lower: 17% for matooke, 10% for sugar,

[28]We also find that people who sell matooke have similar discount rates for money and matooke (but not those just producing or harvesting it).

[29]For example, the variable Storage takes the value of 1 in the rows of data corresponding to matooke if the respondent mentions that storage was a relevant factor when making choices about matooke, and it can also take the value of 1 for the rows of sugar if it was mentioned as a relevant factor for choices about sugar.

7% for beef, and 6% for school supplies, while the share mentioning the Price factor is 19%, 26%, 13% and 21% for each good, respectively. We also find, as they do, that for those mentioning these factors, discount rates are lower, but we cannot reject that average differences in discount rates between money and each good are statistically the same as for those not reporting these factors. Interestingly, we find a positive and significant correlation between being a trader and mentioning Price as a relevant factor.

In Column (6) we see that differences in discount rates across goods persist even when we allow for interactions with dummies for mentioning Price, Resale, Storage and Uncertainty. The differences in discount rates for matooke, beef and sugar cannot be attributed to these four confounding factors since the coefficients on the dummies for each of these goods remain significantly different from zero even after including the interactions with the potential confounders. However, some of the confounding factors did contribute to find even larger differences across goods. In the case of matooke and sugar, an increase in discount rates was linked to differential uncertainty about future payments (although only 6% of respondents mention this factor for these goods, 3% did so for money). For beef, storability appears to be a factor correlated to higher discount rates, but as expected, only for large quantities (when we restrict results to small-quantity questions the interaction is no longer significant, results available upon request).

Finally, we expected that the factors related to the Desire to have the good now or in a month would be highly correlated with elicited discount rates if they are truly reflecting time-preference. In Column (5) of Table 5 we can see that people mentioning their desire to have the good the same day of the survey as a relevant factor affecting their choices have significantly higher discount rates for that good and those mentioning their desire to have the good in a month significantly lower discount rates. As we expected, the coefficients on the good dummies are now reduced. Notice that these questions are not measuring just whether people like the good or not, but the differential desire to have the good now vs. in a month. Indeed we asked a question on whether people enjoys consuming the good and it is not correlated neither with discounting choices nor with the Desire factors.

Table 7 replicates the jointly elicited coefficients in Table 5 with incentivized choices. By looking at the maximum likelihood estimates and the corresponding 95% confidence intervals from Column (1) to (3), we can see that our conclusions in terms of differences across goods still hold. We have a group of goods with high discount rates: sugar, beef and matooke; and another group with relatively lower discount rates: money, airtime and school supplies (the difference between matooke and beef is almost significant at the 10% level). This time we also included the good-specific factors discussed above. As we can see from Column (6) to (11), where we use data for both small-quantity and large-quantity questions of equal value across goods, the only confounding factor that significantly affects discount rates is the uncertainty about future payments, with a positive sign as expected. However, even after controlling for these potential confounders in Column (5), the rank across goods is preserved. Finally, Columns (10) and (11) show that the variables capturing the desire to have the good the same day or in a month are significantly correlated with discount rates for all goods and with the expected signs. This suggests that we are actually measuring time preferences, and not the effect of confounding factors.

3.2.4 Effect of Demographic Characteristics

We find that approximately 50% of our sample exhibit higher discount rates for sugar, beef or matooke than for money; and 22% higher rates for the three goods than for money. This provides evidence for both context specificity and some general components of time preferences since discount rates are not statistically different across goods for the other 50% of the sample. We also need to take into account that among the 50% who exhibit no difference in discounting across goods we have traders, and people with large quantities of the goods at home for which we cannot detect differences in discounting with our procedures.

Considering that the results presented in the pooled estimations control for individual fixed effects, we can claim that the differences we observe in discount rates across goods are not driven by individual characteristics if they affect similarly all goods. On the other hand, the joint elicitation procedure estimates an average discount rate for each good, which can depend on demographic characteristics.

As we have mentioned before, we find that gender significantly affects the estimated discounts rates in the joint elicitation, with women having higher risk aversion and lower discount rates. However, as we have seen in Table 4 (see also Column (4) of Table 7), we find that the ranking across goods is preserved even for women. In order to also allow for heterogeneity of responses not captured by observable characteristics, we estimate random coefficients by Simulated Maximum Likelihood. The risk aversion parameter and the discount rate for each good are considered random coefficients, and a bivariate Normal distribution is assumed for the two of them. We simulate the likelihood functions for random draws using Halton sequences of uniform deviates from this distribution and we average over these simulated likelihoods (see Andersen et al., 2014 for alternative strategies) .

The estimated means for the discount rates are all very similar and statistically indistinguishable to those of the previous maximum likelihood estimates that assumed zero standard deviation. The estimated standard deviations for the discount rates of matooke, school supplies, money and airtime are not significantly different from 0, while the ones for beef and sugar are only significant at the 10% level. Furthermore, we cannot reject the hypothesis that the standard deviation of discount rates is the same for all goods, and we still find the same significant differences in means.

3.3 Why Differences in Discount Rates Across Goods? Qualitative Discussion.

As some of the early twentieth century economists argued, time preferences can be the result of diverse psychological motives (Frederick et al., 2002). One explanation that motivated our study is that individuals apply higher discount rates to goods for which they are more tempted (Banerjee and Mullainathan, 2010, Tsukayama and Duckworth, 2010). In our second survey we included two self-reported measures previously used to distinguish temptation goods: 1) prefers to spend or consume less of the good assuming the same income, and 2) sometimes is "tempted" or has the impulse to consume or to buy the good even when would rather not do it. For the first question, 35% report wanting to consume less beef, 29% less sugar and 26% less matooke, with only beef being significantly larger than the 23% for school supplies, or the 30% for phone airtime. For the second question, 64% report having been tempted by sugar, 57% by matooke and airtime, 51% for school supplies and 48% by beef. These two questions are neither correlated with having discount rates larger than money, nor among themselves.[30] It is possible that time-preference choices capture better temptation levels for high-discount goods than self-reported questions, or that there are also other factors determining differences in discount rates.

As explained in Section 3.3.3, it is not that discount rates are uninformative. We see a strong correlation between discount rates for each good and the self-reported questions about the desire for that good the same day or in a month. These questions might reflect an approximation to "pure" time-preferences.

Urminsky and Zauberman (2014) present other possible explanations given by the psychology literature. The most prevalent one is the possibility that people have higher discount rates for goods higher in affective dimensions, for which the "hot" system is more influential (Loewenstein, 1996, Metcalfe and Mischel, 1999). They claim that this mechanism could be moderated by guilt pushing consumers to exercise more self-control for these goods. Our results could be interpreted as providing evidence for the affective argument when self-control power is limited.

It is important to clarify that even when matooke is the main staple in the area, it is also the favorite component of the diet, and households mention that they cannot have a decent

[30] Brown et al. (2009) also find no correlation between impulsivity measures and discounting parameters estimated using beverage sips with thirsty subjects who exhibit overspending.

meal without it; that is why we are not surprised to find high discount rates in that case. Sugar and meat can also be associated with tasty food generating impatience. There are also some biological explanations on why people might be more impatient for high-sugar and high-starch food (such as matooke), and that these impatience levels might be correlated with self-control problems (Agras, 2010). It could be the case that people has to satisfy minimum consumption levels and they become very impatient when they do not have the goods at home, as our evidence showed.

Moreover, these three goods are relatively expensive sources of calories for households in the area. With a back of the envelope calculation, we find that beef is the most expensive source of calories, with a cost per kilo-calorie of 2.67 Ush.[31] For matooke and sugar the cost is 0.97 and 0.64 Ush respectively, more expensive than beans or rice (0.58) and maize flour (0.24), which are also available in the area. In addition, an alternative to beef as a source of proteins is groundnuts, with cost per kilo-calorie of 1.28. Nevertheless, these three goods add up to 47% of expenditures in our list of goods, which in turn represent 57% of total non-durable expenditures reported in the background survey. At least part of these expenditures might be reflecting the existence of self-control problems.

In the next section, we apply these results to a model that explain how self-control problems generated by good-specific discounting can interact with poverty. We abstract from the causes of the differences and focus on the consequences of observing good-specific discount rates.

4 Application: Good-Specific Discounting and Poverty Traps

4.1 Self-Control Models: Good-Specific vs. Horizon-Specific Discounting

The lack of self control can be understood as the inability of a person to follow through on a desired plan or action (Bernheim et al., 2013). As mentioned in the introduction, most of the attention in the literature modeling self-control problems has been focused on horizon-specific discounting models instead of good-specific discounting.[32]

[31] We follow the procedures and data on calories and retention for Uganda from Appleton (2009) and we update prices with information from INFOTRADE (2010) for the relevant market in August 2010.

[32] An alternative literature models self-control problems without assuming time-inconsistent behaviors. See Lipman and Pesendorfer (2011) for a recent survey of models where preferences are defined over menus instead of over consumption.

A simple example, similar to the one presented in Banerjee and Mullainathan (2010), might help understand the differences between horizon- and good-specific discounting models. To show time-inconsistency with a quasi-hyperbolic model, we only need one good and three periods. The first period self maximizes $U(x_1) + \beta\delta U(x_2) + \beta\delta^2 U(x_3)$, while the second period self maximizes $U(x_2) + \beta\delta U(x_3)$, where δ is the discount factor (the inverse of the discount rate). The intertemporal marginal rate of substitution between period 3 and period 2 consumption has a weight of δ for period 1 self, but one of $\beta\delta$ for period 2 self. This generates a disagreement between the present and the future selves on the level of consumption over time.[33] In the case of good-specific discount rates we can show time inconsistency with two goods and two periods. The first period self maximizes $U(x_1) + \delta_x U(x_2) + V(y_1) + \delta_y V(y_2)$, while the second period self maximizes $U(x_2) + V(y_2)$. Therefore, the marginal rate of substitution between goods x and y in period 2 has a weight of δ_x/δ_y for period 1 self, but a weight of 1 for period 2 self.[34] In this case, the disagreement between the present and the future self is on the composition of consumption. The time-consistent case of no disagreement between the two selves is obtained when β is one in the first case, and when $\delta_x = \delta_y$ in the second case.

As we mention before, it is possible that people are time-inconsistent according to one model and not to the other. For example, in our sample we estimate that 12% are present-biased according to the horizon-specific model, estimated by using hypothetical questions with monetary rewards for now vs. 1 month and 1 vs. 2 months.[35] Out of those with present-biased preferences, 40% have higher discount rates for sugar than for money (43% for meat and 41% for matooke). On the other hand, 32% have higher discount rates for sugar than for money, and out of those with this type of good-specific discounting 15% also have present-biased preferences using monetary rewards, with very similar values for meat and matooke.

4.2 Good-Specific Discounting and Poverty Traps: Testable Conditions

Banerjee and Mullainathan (2010) present the first general model of self-control problems based on time inconsistency on the composition and not on the level of consumption. The

[33]Dual-selves economic models (for example: Thaler and Shefrin, 1981 and Fudenberg and Levine, 2006) capture the idea that people are governed by multiple agents with different preferences.

[34]This is based on the assumption of additively-separable utility functions and on a discounted utility model that leads us to interpret the weight placed upon atemporal utilities as discount factors. We also need to assume that the utility function is perceived to be stable over time.

[35]Since this was not the goal of our paper we do not conduct robustness checks for the estimation of horizon-specific preferences and take the values in this paragraph just as preliminary evidence.

possibility of self-control problems leading to a poverty trap rests on their assumption that expenditures in goods with higher discount rates increase less than proportionally with income.

In order to understand the assumptions required to predict a poverty trap, we can look at the Euler Equation we derived above in equation (6), from a general version of Banerjee and Mullainathan (2010), in the spirit of the extension presented in their appendix. We reproduce it here for convenience:

$$\frac{dU(x_1)}{dx_1} = \delta_x E_{\theta,\theta'}\{\frac{dU(x_2(c_2))}{dx_2}\frac{df(w_1,\theta)}{dw_1}\} - (\delta_x - \delta_z)E_{\theta,\theta'}\{\frac{dU(x_2(c_2))}{dx_2}\frac{df(w_1,\theta)}{dw_1}\frac{dz_2(c_2)}{dc_2}\}$$

We can distinguish three relevant cases: 1) If $\delta_x = \delta_z$, the second term vanishes and we get the traditional Euler Equation for time-consistent consumer maximization problems; 2) if $\delta_z = 0$, we get the case described in Banerjee and Mullainathan, the Euler equation becomes:

$$\frac{dU(x_1)}{dx_1} = \delta_x E_{\theta,\theta'}\{\frac{dU(x_2(c_2(\theta,\theta'))}{dx_2}\frac{df(w_1,\theta)}{dw_1}(1 - \frac{dz_2(c_2(\theta,\theta'))}{dc_2})\}$$

Period 1 self does not value tomorrow's self spending on good z, which is seen as a good with no anticipatory utility, while x is seen as a good that provides at least some anticipatory utility. The last term represents the part of the marginal unit moved to the future spent in goods that yield no utility for the present self (what Banerjee and Mullainathan call the "temptation tax"). Only the fraction $1 - \frac{dz_2(c_2)}{dc_2} = \frac{dx_2(c_2)}{dc_2}$ is spent in what the forward-looking self wants; sophistication about future expenditures pushes the decision maker to spend more today than she would under perfect commitment. Finally, 3) if $\delta_x > \delta_z > 0$, the intuition is similar to the second case. We can see that there is a disincentive to save when the discount factors applied to the two goods are different. Lacking other commitment mechanisms, the individual will increase present consumption in order to limit the resources available for her future self.

When discount rates are different across goods, the shape of the last term plays an important role for the possibility of a poverty trap. It is precisely this term that allows self-control problems to be related to economic circumstances. In particular, if $\frac{dz_2(c_2)}{dc_2}$ is constant, rich and poor are affected similarly by self-control problems: both groups face a disincentive to save. On the other hand, if $\frac{dz_2(c_2)}{dc_2}$ is decreasing in c_2, richer individuals are less affected by self-control problems because they spend a smaller share of their income on high-discount goods and, therefore, they face a weaker disincentive to save. Only in this last case, the model predicts the possibility of a poverty trap.[36] Since we find higher discount rates for a group of goods, we can test the assumption required to predict a poverty trap by looking at the Engel Curves for the share of expenditures on these goods.

4.3 Engel Curves

The assumption that $\frac{dz_2(c_2)}{dc_2}$ is decreasing in c_2 can be evaluated in our case by checking whether the fraction spent or consumed on matooke, sugar and meat (the three goods with higher discount rates identified as z goods) decreases with income (proxied by total expenditures). In order to do this, we first use a module specially developed to capture expenditures in a typical month for the same goods for which we estimated discount rates in the first survey. Then, we replicate the analysis using data on consumption in a typical months, which is available in the second survey only for the first three goods.

4.3.1 Estimation

Our measure of total expenditures is the sum of reported expenditures for the 18 goods used in the time-preference questions (excluding money). It exhibits a high correlation (0.63) with a measure of expenditures including every possible disbursement as reported in the background survey. To avoid the influence of outliers, we follow Banks et al. (1997) and trim observations with more than three standard deviations from the mean, for log expenditures and the expenditure share of each good.

As a first piece of evidence, we present nonparametric kernel-weighted local linear regressions for the Engel Curves of the high-discount goods (matooke, sugar and meat) and for the low-discount rate good with largest share of expenditures in our sample (school supplies). Figure 1 shows that the share of expenditures in sugar is decreasing in total expenditures, the share of meat increases initially and then decreases with total expenditures, and the share of matooke increases with total expenditures for a larger fraction of the distribution until it becomes almost flat.[37] In comparison, the share of expenditures on school supplies is constant for almost all the distribution. This indicates that the required assumption to predict a poverty trap might be valid for sugar, partially for meat, but not for matooke. The one for matooke is an interesting pattern. The main explanation in the literature would

[36]Technically, Banerjee and Mullainathan prove that if the derivative is constant, the maximization problem is strictly convex and the corresponding demand functions for x_t and z_t vary continuously with income. Whereas in the decreasing case the second order conditions of the problem would be violated for valid demand functions and a local minimum can be found at a certain level of consumption, which implies that c_2 jumps discontinuously at a certain threshold of income.

[37]The turning point for the meat share Engel Curve is around 7.4 dollars or the 15^{th} percentile in the distribution of total expenditures, while for matooke it is only at around 20 dollars or the 45^{th} percentile.

be that households switch to higher quality food items when total consumption increases, and that they consider matooke as a preferred food. This is a plausible explanation, since matooke is a relatively expensive source of calories.[38] When we divide goods into a high-discount (including sugar, meat and matooke) and a low-discount group (including the other 15 goods), we can see in Figure 2 that the Engel Curve for the share of the high-discount group presents a pattern more in accordance (except for the initial increase) to the assumption of the model. As Banerjee and Mullainathan (2010) remark, the assumption does not necessarily hold for people who are at the margin of starvation, for whom the first units of nutritious goods might be more valuable than any other good. This can explain the initial increase in the Engel Curve for the high-discounting group in Figure 2. It initially increases until around 9 dollars or the 20^{th} percentile in total expenditures, and then it decreases; with the inverse pattern for the low-discount group.

As additional checks (available upon request) we computed elasticities which confirmed the intuition from the graphs. We estimated quadratic OLS equations for the share of each good on log expenditures, controlling for observable characteristics (size of the household, share of children, age, dummies for gender, literacy, ability scores, and location) and using the estimated coefficients for each individual. A weighted average was then constructed with weights being equal to the individual's share of total expenditures for the good. The results for sugar and meat are elasticities statistically significantly lower than one, while for matooke the elasticity is larger than one. When we divide goods into two groups, we see that the average weighted elasticity for the high-discount group, which represents 47% of expenditures, is 0.91 and statistically significantly smaller than 1. Similar results were obtained in preliminary analysis with an attempt to control for endogeneity.[39]

One key limitation of the previous figures is that that they are based on data on expenditures instead of consumption, being consumption data the most relevant to evaluate the predictions of the model. The difference can be significant for matooke which is produced by a large share of households in our sample. In our second survey, one year later, we included questions both on consumption and on expenditures, but only for sugar, beef and matooke. We asked separately for units consumed and units bought in a typical month and for estimated prices for each unit. As expected, we see that the correlation between consumption and expenditures for sugar and beef is around 0.95, with almost all consumers buying the goods, while the one for matooke is only 0.5. One limitation to use these data is that we do

[38] See also Jensen and Miller (2010) for a related explanation in terms of Engel Curves for calories shares.

[39] Endogeneity will be relevant if total expenditures are correlated with the residuals of the demand system and different taste shifters for different goods generate bias in opposite directions. We follow a control function approach, using as instruments three dummy variables measuring expected income trends as in Attanasio et al. (2012).

not have an estimate of total expenditures including consumption data. We use a question from a follow up survey with the same sample conducted 2 months later (we loose 55 out of 449 observations) that asks for total expenditures in a typical month. Figure 3 follows the same procedures as in Figure 1, but now it shows the share of self-reported consumed units times the median price reported for each good divided by total self-reported expenditures. The patterns presented in Figure 3 are now in complete accordance with the assumptions of the model, with decreasing share for the three goods. Note the significant increase in the share of matooke when we include consumption data. Of course these results should be taken with caution given our measure of total expenditures instead of total consumption.

4.3.2 Caveats

The results in this section are subject to some caveats. First, we have detected only three goods with significantly higher discount rates, but it could be the case that there are other goods that also exhibit high discount rates. Secondly, it is possible that for a population with a greater variation in income, consumption of goods like matooke would reach satiation at even lower percentiles of the distribution, and the assumption of decreasing expenditures might become more feasible. Thirdly, as pointed above, better data on consumption might lead to different results. In particular, there is an important trade-off for households in our sample about consuming the matooke they produce or selling it at higher prices that has to be better captured.

5 Concluding Remarks

Most of the literature providing empirical evidence to model self-control problems has focused on showing that discount rates might decrease with the time horizon. However, we can also obtain time-inconsistent behaviors if we allow for discount rates being different across goods. This paper provides evidence to reject the hypothesis that the same discount rate is applied to the utility of all possible sources of consumption, implying that self-control problems could be modeled using good-specific discount rates.

We find significantly higher discount rates for three goods than for money and a list of other goods available in the area under study. Furthermore, we show that although the estimated levels of discount rates vary when we relax the main modeling assumptions needed to identify discount rates, the relative ranking across goods is stable. The differences we find in discount rates across goods are not only robust to controlling for the main confounding factors mentioned in the literature (such as the use of incentivized choices instead of just hypothetical choices, the assumption of zero background consumption and a general curvature of the utility function), but also for good-specific factors (including resale opportunities, expected prices and storage capacity). Further research should relax the separability assumptions for the intertemporal utility function and either incorporate good-specific estimation of the curvature of the atemporal utility function or use curvature-controlled elicitation methods (Andreoni and Sprenger, 2012, Montiel Olea and Strzalecki, 2014, Ambrus et al., 2014).

Our discussion on the assumptions that are required to recover good-specific time preferences from experimental choices makes clear that our results are straightforward if we can assume that people do not take into account factors outside the world presented in the frame of the experimental choices. However, when we relax this assumption, we show that identification of differences in discount rates requires both lack of access to arbitrage opportunities in external markets and no adjustments in outside consumption of the goods offered, or at least that people do not think about these options when making their choices. Indeed we find that differences in estimated discount rates for the high-discount goods disappear for traders and people with large quantities of the goods offered in the experimental tasks, as the theory would predict. But, this represents only a small fraction of our sample.

We estimate discount rates for a sample of poor rural households with characteristics that are also observed in other countries of Eastern Africa. While our list of goods is specific to the area under study in Uganda, our procedures can be replicated in other contexts. Our goal is to present evidence for good-specific discounting in at least one context.

In addition, this context is particularly relevant for our application. This paper is the first to provide empirical evidence for the assumptions required to predict a low-asset poverty trap generated by self-control problems in the form of good-specific discounting. By estimating Engel Curves, we show that the share of expenditures on goods with higher discount rates is decreasing with income, with stronger evidence when we use consumption rather than expenditures data. Although several extensions should be considered in the estimation of the Engel Curves, such as better data on consumption and improved methods to control for endogeneity, our results imply that the poor might face a stronger disincentive to save. They might be pushed to increase present consumption in order to prevent their future selves from spending resources in goods with high discount rates.

An implication of this finding is a general demand for commitment devices as a direct consequence of self-control problems. Nevertheless, the optimal type of commitment device that would be required to face self-control problems generated by good-specific discounting might be different from the general device restricting cash availability that has been studied in the literature.[40] An important topic for future research is to understand what

[40] An example could be the product explored by Gine et al. (2010) that reduces expenditures in tobacco, although the goal of that product was to help people quit smoking.

specific commitment devices are best fitted to face the disagreement in the composition of consumption between the present and the future self.

The existence of a poverty trap would indicate that one-time interventions helping the poor start saving can have high impact. In ongoing work, we are conducting a field experiment in which we encourage a random sample of the unbanked individuals studied in this paper to open a savings account by covering account opening fees. This design will enable us to test whether a simple bank account can offer enough of a commitment mechanism to reduce future consumption on high-discount goods and encourage savings.

The finding that the poor spend large shares of their income on relatively expensive sources of calories is not unique to our paper and it has been mentioned as one of the factors behind their low savings. Banerjee and Duflo (2007) show that the poor around the world spend up to 7% of their income on "expensive calories", such as in sugar, while neglecting cheaper alternatives. Subramanian and Deaton (1996) note that the poorest decile of rural households in Maharashtra spends 12% of their expenditures on sugar, oils and fats. In our case, for rural households in Uganda, we find that the three goods with significantly higher discount rates: sugar, matooke and beef, also represent expensive sources of calories and capture a large share of total expenditures (a 13% of total expenditures).

In this paper, we present indirect evidence for the conditions that generate a higher disincentive to save for the poor due to self-control problems in the form of good-specific discount rates. A topic for future research is to design direct tests to estimate the relationship between differences in discount rates across goods, expenditures in expensive sources of calories and low savings. Furthermore, there could be an interesting link between good-specific discount rates and the choice of the composition of the diet, with potential implications for studies on nutrition and obesity. Whether we can explain high discount rates exclusively by temptation is still an open question. In our paper we do not find strong correlations between good-specific discount rates and self-reported impulsivity measures, it could be because the latter do not measure temptation appropriately or due to the existence of other factors affecting discount rates.

Finally, another topic for future research is the effect of taxes on goods with high discount rates. In a two-good model (consumption and leisure) and infinite periods, Futagami and Hori (2010) show that the optimal consumption tax is not zero. However, with n goods and a finite number of periods, as in Banerjee and Mullainathan (2010), a tax on the high-discount goods might reduce their consumption, but it could also increase the share of expenditures on those goods, making the self-control problem worse. The result will depend on the price elasticities of demand. Studies relating these elasticities to good-specific discount rates can help us understand the impact of taxation and food subsidies.

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Table 1. Basic Socio-Economics Characteristcs. Samples for Survey 1 and 2

Variable	Full Sample				Survey 2 Subsample			
	Mean	Median	Sd.	Obs.	Mean	Median	Sd.	Obs.
Female	0.71	1.00	0.45	2,442	0.70	1.00	0.46	449
Age	36.15	34.00	11.83	2,442	37.04	35.00	12.06	449
Married	0.73	1.00	0.44	2,441	0.76	1.00	0.43	449
Household Size	5.18	5.00	2.42	2,442	5.27	5.00	2.34	449
Education (years)	5.72	6.00	3.03	2,440	5.54	6.00	3.01	449
Literate (in Luganda)	0.77	1.00	0.42	2,437	0.75	1.00	0.43	449
Land (acres)	1.56	1.00	2.18	2,390	1.53	1.00	1.90	441
Farms at least 1 crop	0.85	1.00	0.36	2,442	0.90	1.00	0.31	440
Sells at least 1 crop	0.65	1.00	0.48	2,442	0.64	1.00	0.48	449
Value Crops Sold Last Harvest (dollars)	51.26	10.37	104.19	2,372	58.61	8.73	132.51	440
Used Fertilizer Last Harvest	0.10	0.00	0.30	2,178	0.09	0.00	0.29	411
Digits memory test (% correct)	44.88	43.75	14.39	2,441	45.16	43.75	14.94	449
Raven's matrix cognitive test (% correct)	48.74	50.00	23.79	2,431	46.94	41.67	23.48	447

Notes: Summary statistics for the 2,442 individuals included in the first survey are presented in the left panel, while those resticting the sample to the 449 individuals interviewed again in the second survey are presented in the right panel.

Table 2. Discount Rates Basic Procedure

Discount Rate	Mean	95% Lower Bound	95% Upper Bound	Median	Obs.
Meat	1.100	1.060	1.140	**0.750**	2,434
Sugar	1.020	0.990	1.060	**0.750**	2,441
Matooke	1.000	0.970	1.040	**0.750**	2,438
Average Over All Goods+	0.810	0.780	0.840	**0.530**	2,442
Money	0.900	0.860	0.940	0.250	2,440
Beans	0.880	0.850	0.920	0.250	2,438
Meals Outside	0.810	0.780	0.850	0.250	2,436
Lotion	0.810	0.780	0.850	0.250	2,419
Perfume	0.770	0.740	0.810	0.250	2,411
School Supplies	0.760	0.720	0.790	0.250	2,438
Snacks	0.740	0.710	0.780	0.250	2,440
Airtime	0.740	0.700	0.770	0.250	2,434
Clothes	0.740	0.710	0.770	0.250	2,433
Shoes	0.740	0.710	0.770	0.250	2,440
Entertainment	0.730	0.700	0.770	0.250	2,332
Soda	0.720	0.690	0.750	0.250	2,440
Saloon	0.700	0.670	0.730	0.250	2,430
Salt	0.660	0.630	0.690	0.250	2,436

Notes: + Average over the discount rates for all goods in the list. See Appendix A for a description of the choices for each good.

Table 3. Pooled Regression

	Pooled Regression+		Interval Regression++
Dependent Variable: person-good specific discount rate	Equal Value	All Questions	Equal Value
	(1)	(2)	(3)
Matooke	**0.104*** **	**0.047*** **	**0.101*** **
	(0.02)	**(0.01)**	**(0.02)**
Sugar	**0.125*** **	**0.049*** **	**0.130*** **
	(0.02)	**(0.01)**	**(0.02)**
Meat	**0.199*** **	**0.066*** **	**0.216*** **
	(0.02)	**(0.01)**	**(0.02)**
Beans	-0.014	-0.040***	-0.017
Soda	-0.178***	-0.079***	-0.188***
Salt	-0.239***	-0.124***	-0.252***
Meals Outside	-0.087***	-0.011	-0.106***
Snacks	-0.154***	-0.003	-0.173***
Clothes	-0.159***	-0.141***	-0.163***
Lotion	-0.081***	-0.094***	-0.095***
Shoes	-0.162***	-0.139***	-0.166****
Perfume	-0.119***	-0.121***	-0.134***
Entertainment	-0.165***	-0.116***	-0.182***
Saloon	-0.200***	-0.135***	-0.212***
School Supplies	-0.141***	-0.115***	-0.15***
Airtime	-0.161***	-0.105***	-0.17***
Question: Small Quantities		0.055***	
Question: Equal Value		0.091***	
Constant	0.896	0.765	0.889
Households	2,442	2,442	2,442
Observations	43,170	124,646	

Notes: ***, **, *: significant at 1, 5 and 10% level, respectively. + Money is the omitted good. Columns 1-2 show the results from the regression of the discount rate, estimated at the question level, on goods and magnitudes dummies, the constant captures the average discount rate for money. Column 1 is restricted to equal-value choices. ++ Column 3 shows the results of interval regressions for each good, the differences in predicted discount rates between each good and money are presented; the constant captures the predicted discount rate for money. For columns 1-2 standard errors clustered at the individual level are presented in parenthesis, available upon request where omitted. For Column (3) standard errors of the differences between each good and money are calculated using a linear combination of the estimators from the interval regressions.

Table 4. Basic Procedure. Real vs. Hypothetical Rewards (equal-value questions)

	Survey 1: Hypothetical Rewards				Survey 2: Real Rewards				
Good	**Mean**	**95% Lower Bound**	**95% Upper Bound**	**Median**	**Mean**	**95% Lower Bound**	**95% Upper Bound**	**Median**	**Obs.**
Sugar	1.08	0.99	1.18	**0.75**	1.11	1.00	1.21	**0.75**	449
Beef	1.10	1.00	1.19	**0.75**	1.07	0.97	1.18	**0.75**	449
Matooke	1.01	0.92	1.10	**0.75**	1.04	0.94	1.15	**0.75**	449
Cash	0.84	0.76	0.92	0.25	0.88	0.79	0.98	0.25	449
Airtime	0.74	0.66	0.82	0.25	0.81	0.72	0.91	0.25	449
School Supplies	0.70	0.66	0.78	0.25	0.86	0.72	0.95	0.25	449

Notes: Summary statistics for the discount rates calculated using hypothetical rewards are presented in the left panel (only for those who were also surveyed in the second survey), while those calculated with real rewards are presented in the right panel.

Table 5. Fixed Effects Regression. Real Rewards

Dependent Variable: person-good specific discount rate	Small Quantities (1)	All Questions (2)	(3)	(4)	(5)	(6)
Matooke	**0.157*****	**0.172*****	**0.186*****	**0.170*****	**0.136*****	**0.142*****
	(0.04)	**(0.04)**	**(0.05)**	**(0.04)**	**(0.04)**	**(0.04)**
Sugar	**0.224*****	**0.262*****	**0.236*****	**0.266*****	**0.239*****	**0.256*****
	(0.04)	**(0.04)**	**(0.05)**	**(0.04)**	**(0.04)**	**(0.04)**
Meat	**0.188*****	**0.229*****	**0.220*****	**0.219*****	**0.185*****	**0.218*****
	(0.04)	**(0.03)**	**(0.04)**	**(0.04)**	**(0.04)**	**(0.04)**
School Supplies	-0.026	-0.031	-0.012	-0.029	-0.047	-0.026
	(0.04)	(0.03)	(0.05)	(0.03)	(0.03)	(0.04)
Airtime	-0.072**	-0.040	-0.062*	-0.041	-0.051*	-0.036
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Question: Small Quantities		0.156***	0.187***	0.156***	0.156***	0.156***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Interactions with dummies for having more than reward at home						
ExMatoke*Matooke			-0.176***			
ExSugar*Sugar			-0.053			
ExMeat*Meat			-0.086			
ExSchool*School			-0.002			
ExAirtime*Airtime			-0.229			
Interactions with typical monthly consumption			Yes			
Interactions with Factors Considered in Choices						
Factor: Storage				0.097*	0.066	
Storage*Matooke						0.074
Storage*Sugar						-0.102
Storage*Beef						0.133*
Factor: Resale				-0.050	-0.009	
Resale*Matooke						-0.038
Resale*Sugar						0.001
Resale*Beef						-0.043
Resale*School						-0.149
Factor: Future Price				-0.022	-0.004	
Price*Matooke						0.023
Price*Sugar						-0.027
Price*Beef						-0.104
Price*School						-0.002
Factor: Uncertainty about payment				0.148*	0.163*	
Uncert*Matooke						0.353**
Uncert*Sugar						0.262*
Uncert*Beef						0.202
Uncert*School						0.054
Uncert*Airtime						-0.099
Factor: Desire for good today					0.232***	
Factor: Desire for good in a month					-0.159***	
Constant	0.88	0.71	0.69	0.70	0.70	0.71
Households	449	449	428	449	449	449
Observations	2,694	5,388	5,136	5,388	5,388	5,388

Notes: ***, **, *: significant at 1, 5 and 10% level, respectively. Money is the omitted good. Columns 2-6 show the results from the regression of the discount rates on goods and question magnitudes dummies, the constant captures the average discount rate for money. Column 1 restricts the data to small-quantities choices. Column 3 also include interactions between each good and typical monthly consumption for that good. Standard errors clustered at the individual level in parenthesis, available upon request where omitted.

Table 6. Joint Estimation. Equal-Value Questions

Individual Estimation for each good	Coefficient	95% Lower Bound	95% Upper Bound	Predicted Value for Females*	Obs.
	(1)	(2)	(3)	(4)	(5)
Meat	0.589	0.55	0.63	0.50	41,456
Matooke	0.560	0.52	0.60	0.48	41,480
Sugar	0.544	0.50	0.58	0.46	41,498
Beans	0.416	0.38	0.45	0.33	41,480
Money	0.362	0.32	0.40	0.29	41,492
Lotion	0.349	0.31	0.38	0.28	41,366
Perfume	0.295	0.26	0.33	0.25	41,318
ALL GOODS**	0.257	0.23	0.29		739,958
Clothes	0.217	0.18	0.26	0.18	41,450
Shoes	0.212	0.17	0.25	0.18	41,492
School Supplies	0.192	0.15	0.23	0.15	41,480
Meals Outside	0.171	0.13	0.22	0.12	41,468
Soda	0.153	0.11	0.20	0.11	41,492
Airtime	0.152	0.11	0.19	0.09	41,456
Saloon	0.099	0.06	0.14	0.09	41,432
Entertainment	0.058	0.01	0.11	0.06	40,844
Snacks	0.049	0.00	0.10	0.07	41,492
Households					2,442

Notes: Column 1-3 present MLE estimates for each good, the upper and lower bounds were calculated with standard errors clustered at the individual level. The risk aversion parameter and structural errors terms for risk and time preferences were also re-estimated in each case. *Column 4 presents the predicted discount rate for females based on the coefficient obtained when we allow both the discount rate and risk aversion parameter to depend on observable characteristics, dummies for being female, married, low ability scores and literate were also included. ** Presents results from a similar regression pooling choices for all goods.

Table 7. Joint Estimation and Real Rewards

Individual Estimation for each good	Coefficient	95% Lower Bound	95% Upper Bound	Predicted Value for Females+	Average Predicted Value with controls++	Factors Determining Choice					
						Storage	Resale	Future Price	Uncertainty about payment	Desire to have Today	Desire to have in a month
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Sugar	0.616	0.53	0.71	0.55	0.70	(o)	(o)	(o)	*** (+)	*** (+)	*** (-)
Beef	0.591	0.50	0.68	0.52	0.66	(o)	(o)	(o)	*** (+)	*** (+)	*** (-)
Matooke	0.537	0.45	0.62	0.49	0.60	(o)	* (-)	(o)	*** (+)	*** (+)	*** (-)
Money	0.417	0.35	0.48	0.36	0.49	(o)	(o)	(o)	(o)	*** (+)	*** (-)
School Supplies	0.393	0.33	0.45	0.35	0.45	(o)	(o)	(o)	(o)	*** (+)	*** (-)
Airtime	0.392	0.33	0.45	0.33	0.45	(o)	(o)	(o)	*** (+)	*** (+)	*** (-)
Observations	11,220										
Households	449										

Notes: Column 1-3 present MLE estimates for each good, the upper and lower bounds were calculated on the basis of standard errors clustered at the individual level. The risk aversion parameter and structural errors terms for risk and time preferences were also re-estimated in each case. +Column 4 presents the predicted discount rate for females based on the coefficient obtained when we allow both the discount rate and risk aversion parameter to depend on observable characteristics, dummies for being female, married, low ability scores and literate were also included, we included as well a small-quantities dummy. ++ Column 5 presents predicted discounted rates including also the factors in columns 6-11 in the regression. (+) and (-) means positive or negative coefficient on the regression, (o) means non-significant effect. ***, **, * mean significant at 1, 5 and 10% level, respectively.

Table 8. Joint Estimation and Real Rewards. Effect of Background Consumption

Individual Estimation for each good	Sugar (1)	Beef (2)	Matooke (3)	Money (4)	School Supplies (5)	Airtime (6)
Background 1+						
Coefficient	0.605	0.596	0.537		0.377	0.390
95% Lower Bound	0.51	0.51	0.45		0.31	0.33
95% Upper Bound	0.70	0.69	0.63		0.44	0.45
Background 2++						
Coefficient	0.765	0.613	0.511		0.346	0.364
95% Lower Bound	0.40	0.42	0.35		0.18	0.28
95% Upper Bound	1.13	0.81	0.67		0.51	0.45
Background 3+++						
Coefficient	0.668	0.593	0.550			
95% Lower Bound	0.56	0.50	0.46			
95% Upper Bound	0.78	0.69	0.64			
Background 4++++						
Coefficient	0.725	0.710	0.615	0.446	0.431	0.455
95% Lower Bound	0.62	0.60	0.52	0.37	0.36	0.38
95% Upper Bound	0.83	0.82	0.71	0.52	0.50	0.53

Notes: MLE estimates for each good, upper and lower bounds calculated on the basis of standard errors clustered at the individual level. Estimation includes: + quantity of the good available at home at the moment of survey, ++ also expected quantity available at home in a month, +++ daily typical consumption and reported days to consume reward, ++++ daily typical consumption and estimated days to consume reward.

Table 9. Fixed Effects Regression: Traders vs Non Traders.

Dependent Variable: person-good specific discount rate	Hypothetical Rewards (Equal Value)	Real Rewards (Small and Large Equal Value)
	(1)	(2)
Matooke	0.111***	0.203***
	(0.02)	(0.04)
Matooke*Trader	-0.111	-0.238**
	(0.07)	(0.12)
Sugar	0.133***	0.286***
	(0.02)	(0.04)
Sugar*Trader	-0.133*	-0.171
	(0.07)	(0.12)
Meat	0.211***	0.247***
	(0.02)	(0.04)
Meat*Trader	-0.211***	-0.057
	(0.08)	(0.11)
School Supplies	-0.136***	-0.017
	(0.01)	(0.03)
School*Trader	-0.087	0.067
	(0.07)	(0.11)
Airtime	-0.156***	-0.027
	(0.01)	(0.03)
Airtime*Trader	-0.078	0.092
	(0.06)	(0.09)
Beans	-0.009	
Beans*Trader	-0.095	
Soda	-0.172***	
Soda*Trader	-0.105	
Salt	-0.232***	
Salt*Trader	-0.121	
Meals Outside	-0.082***	
Meals*Trader	-0.078	
Snacks	-0.148***	
Snacks*Trader	-0.107	
Clothes	-0.158***	
Clothes*Trader	-0.022	
Lotion	-0.070***	
Lotion*Trader	-0.192***	
Shoes	-0.158***	
Shoes*Trader	-0.073	
Perfume	-0.109***	
Perfume*Trader	-0.172**	
Entertainment	-0.155***	
Entertainment*Trader	-0.163**	
Saloon	-0.197***	
Saloon*Trader	-0.054	
Constant	0.694***	0.896***
Households	2,442	449
Observations	43,170	5,388

Notes: Money is the omitted good. Results from the regression of the discount rates on good dummies. Standard errors clustered at the individual level in parenthesis, available upon request where omitted. ***, **, *: significant at 1, 5 and 10% level, respectively.

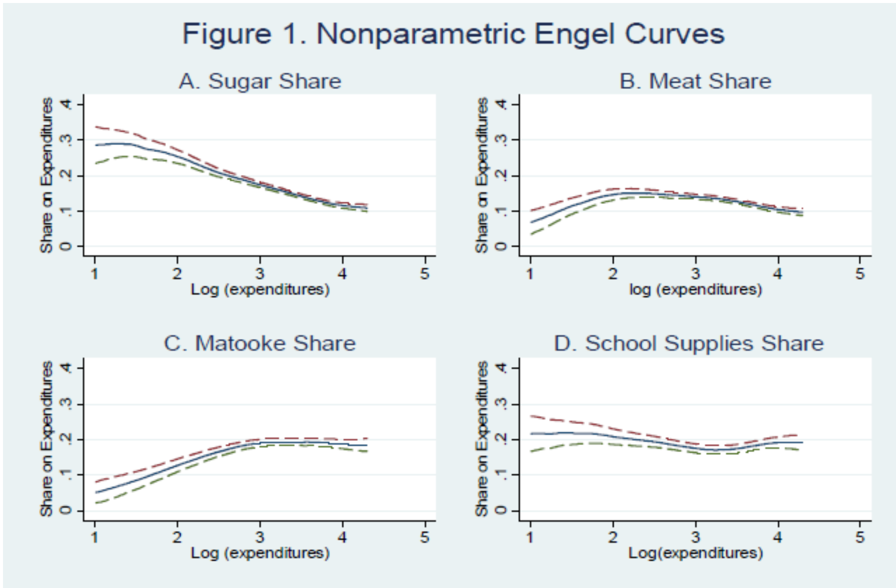
Figure 1. Nonparametric Engel Curves
A. Sugar Share
B. Meat Share
C. Matooke Share
D. School Supplies Share
Share on Expenditures
0
.1
.2
.3
.4
1
2
3
4
5
Log (expenditures)
log (expenditures)
Log(expenditures)

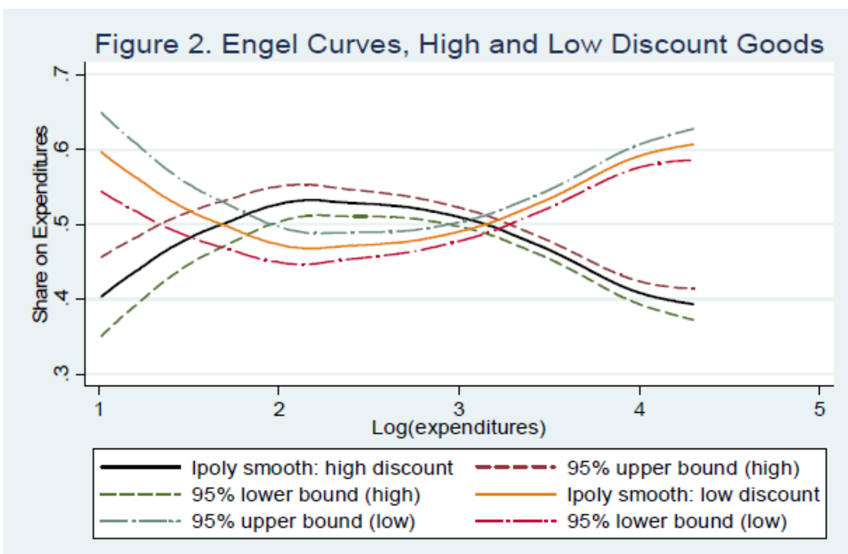
Figure 2. Engel Curves, High and Low Discount Goods
Share on Expenditures
.3
.4
.5
.6
.7
1
2
3
4
5
Log(expenditures)
lpoly smooth: high discount
95% upper bound (high)
95% lower bound (high)
lpoly smooth: low discount
95% upper bound (low)
95% lower bound (low)

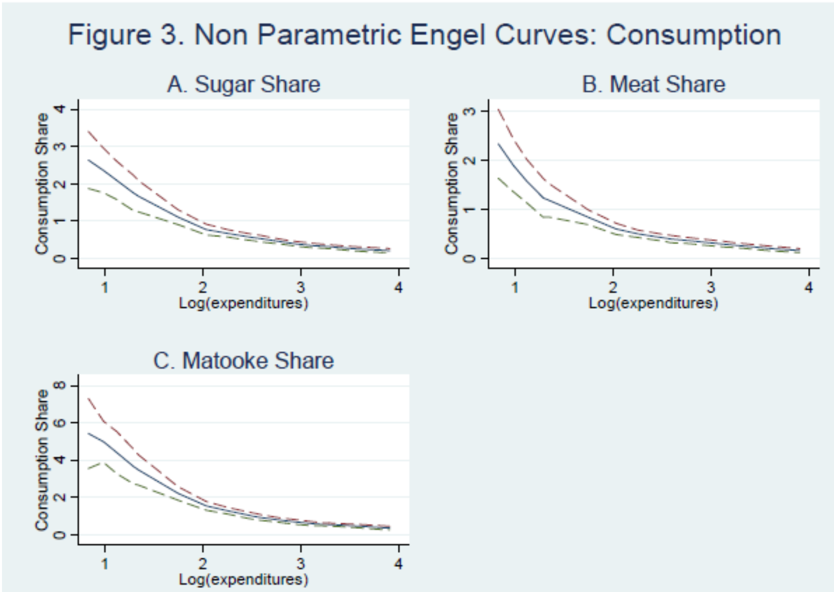
Figure 3. Non Parametric Engel Curves: Consumption
A. Sugar Share
B. Meat Share
C. Matooke Share
Consumption Share
Log(expenditures)
0
1
2
3
4
6
8

Appendix A. Instructions and Tasks (NOT FOR PUBLICATION).

In this appendix we present the instructions given to enumerators and read to respondents in the field (at their home), together with the tables of parameters in the time-preference choices. The originals were in English and translated into Luganda (available upon request).

The first survey was carried out between October and November 2010, 2,442 respondents were interviewed at home. The time-preference questions were asked at the beginning of a long background survey, all questions were hypothetical and there was no payment per answer, just a gift (a piece of soap or a packet of sugar) as a compensation for participating in the survey. The second survey was shorter and focused on the time-preference tasks. It was carried out between August and September 2011. In this case, 449 respondents were interviewed at home, and all respondents received a payment in kind or cash according to the procedure described below, no participation gifts were given.

Instructions to enumerators. First Survey.

"For each item read the choice between column A and each cell of column B, and wait for an answer. If the respondent chooses the units for today, repeat the question using the value in the next cell of column B. [Column A is equivalent to Column (5) in Table A1 below, and Column B contained the values from Columns (6) to (10) in different rows] If he/she chooses to wait, stop, circle the amount he/she has chosen to wait for in a month and move to next line. Only circle the number for which he/she chooses to wait. Example Question: "Would you choose to receive 2 kilos of beans today or 3 kilos in a month?" If respondent says 3 kilos, circle 3 kilos and move to next line. If respondent says 2 kilos, don't circle anything and ask: "Would you choose to receive 2 kilos of beans today or 4 kilos in a month?" Continue this pattern (e.g.: 2 units today vs. X units in a month) until he/she chooses an option for which he/she is willing to wait (circle that choice).

TIPS: 1. When quantities are expressed in decimal units ask respondents to think in terms of fractional quantities: e.g. do they prefer 1 tin of lotion or 1 tin and a half. Read: 0.5=half, 1.25=one and a quarter, 1.75=one and three quarters, etc. 2. Skip questions about beer/alcohol for Muslim or Born Again/Savedee households and about bar games for women. 3. Mention that vouchers can help cover cost if they are not enough to cover the full cost of the item (e.g. 2,500 Ush voucher for school supplies). If more than 1 voucher is offered, they do not have to be used all at once."

Parameter Values. First Survey.

Table A1 shows the parameters of the time-preference tasks. Column (1) presents the good referred to for the choices (all respondents made choices about all goods and all quantities). Column (2) presents the tasks in alphabetical order (read in random order to respondents). Column (3) shows the units of the good. Column (4) presents the category for the magnitude of the principal: Small represents a principal of 2 units and Large a principal of 6 units for almost all goods, Equal Value: represents the choices with a principal of a value of approximately 2,500 Ush. These were the categories used in the econometric estimations (see for example Column 1 of Table 3), when data were pooled all choices were used (e.g. Column 2 of Table 3). Column (5) presents the principal for each good and each choice. Finally, Columns (6) to (10) list the delayed payments (which were read separately beginning by the value in Column (6) and only moving to the next columns if the respondent chose the value in Column (5)).

Table A1: Parameters for Discounting Choices. First Survey

Good	Task	Units	Quantity Categories	Sooner Hypothetical Payment (now)	Delayed Payments (One Month)				
					Choice 1	Choice 2	Choice 3	Choice 4	Choice 5
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Bar games (e.g. pool billiard)	A1	Paid Games	Small	2	3	4	5	6	7
	A2	Paid Games	Equal Value	5	8	10	13	15	18
	A3	Paid Games	Large	6	9	12	15	18	21
Beans	B1	Kilos	Equal Value/Small	2	3	4	5	6	7
	B2	Kilos	Not Used	5	7.5	10	12.5	15	17.5
	B3	Kilos	Large	6	9	12	15	18	21
Bear/Alcohol	C1	Worth in Ush	Equal Value	2500	3750	5000	6250	7500	8750
	C2	Bottles	Small	2	3	4	5	6	7
	C3	Bottles	Large	6	9	12	15	18	21
Cash	D1	Ush	Equal Value/Small	2500	3750	5000	6250	7500	8750
	D2	Ush	Large	7500	11250	15000	18750	22500	26250
Chapatti/Mandazi (Snacks)	E1	Number	Small	2	3	4	5	6	7
	E2	Number	Not Used	5	8	10	13	15	18
	E3	Number	Equal Value/Large	6	9	12	15	18	21
Clothes	F1	Ush worth in clothes	Equal Value	2500	3750	5000	6250	7500	8750
	F2	Sets	Small	2	3	4	5	6	7
	F3	Sets	Large	6	9	12	15	18	21
Entertainment	G1	Movie Tickets	Equal Value/Small	2	3	4	5	6	7
	G2	Movie Tickets	Not Used	5	7.5	10	12.5	15	17.5
	G3	Movie Tickets	Large	6	9	12	15	18	21
Lotion	H1	Small Tins	Equal Value	1	1.5	2	2.5	3	3.5
	H2	Small Tins	Small	2	3	4	5	6	7
	H3	Small Tins	Large	6	9	12	15	18	21
Matooke	I1	Small Bunches	Equal Value	1	1.5	2	2.5	3	3.5
	I2	Small Bunches	Small	2	3	4	5	6	7
	I3	Smal Bunches	Large	6	9	12	15	18	21
Meals Outside	J1	Voucher (Ush)	Equal Value	2500	3750	5000	6250	7500	8750
	J2	Number of free meals	Small	2	3	4	5	6	7
	J3	Number of free meals	Large	6	9	12	15	18	21
Meat	K1	Kilos	Equal Value	0.5	0.75	1	1.25	1.5	1.75
	K2	Kilos	Small	2	3	4	5	6	7
	K3	Kilos	Large	6	9	12	15	18	21
Perfume	L1	Small Bottles	Equal Value	1	1.5	2	2.5	3	3.5
	L2	Small Bottles	Small	2	3	4	5	6	7
	L3	Small Bottles	Large	6	9	12	15	18	21
Phone Airtime	M1	Ush in Airtime	Equal Value	2500	3750	5000	6250	7500	8750
	M2	1000 Ush Cards	Not Used	2	3	4	5	6	7
	M3	1000 Ush Cards	Large	6	9	12	15	18	21
Salt	N1	Kilos	Small	2	3	4	5	6	7
	N2	Kilos	Equal Value/Large	6	9	12	15	18	21
	N3	Kilos	Not Used	10	15	20	25	30	35
Saloon/Barber	O1	Voucher (Ush)	Equal Value	2500	3750	5000	6250	7500	8750
	O2	5000 Ush vouchers	Small	2	3	4	5	6	7
	O3	5000 Ush vouchers	Large	6	9	12	15	18	21
School Supplies	P1	Voucher (Ush)	Equal Value/Small	2500	3750	5000	6250	7500	8750
	P2	Voucher (Ush)	Large	7500	11250	15000	18750	22500	26250
Shoes	Q1	Worth in Ush	Equal Value	2500	3750	5000	6250	7500	8750
	Q2	Pairs	Small	2	3	4	5	6	7
	Q3	Pairs	Large	6	9	12	15	18	21
Soda	R1	Bottles	Small	2	3	4	5	6	7
	R2	Bottles	Equal Value	4	6	8	10	12	14
	R3	Bottles	Large	6	9	12	15	18	21
Sugar	S1	Kilos	Equal Value	1	1.5	2	2.5	3	3.5
	S2	Kilos	Small	2	3	4	5	6	7
	S3	Kilos	Large	6	9	12	15	18	21

Instructions read to respondents. Second Survey.

"Today I will ask you to make a number of choices between two options, A and B. DO EXAMPLE [The example consisted of choices between 1 kilo of beans now and larger quantities in a month]. We will present you with similar choices for six different goods (beef, cash, matooke, phone airtime, school supplies and sugar), and twice for each good (first set of questions and second set of questions for each good), but for different amounts. You will be paid for one of all the decisions you make. We will do a draw after you have answered all the questions that will determine which question you will be paid for:

1. From bag 1, you will draw ONE piece of paper with the name of the good you will be paid for. Since we ask you the same questions twice for each good (but for different quantities) in the bag the papers will appear as: beef1, beef2, cash1, cash2, etc. Some goods will have higher chances of being chosen than others.

2. From bag 2, you will draw ONE piece of paper with the number of one of the questions you chose for the corresponding good and set of questions. Here all questions will have an equal chance of being selected. DO MOCK DRAW AND EXPLAIN WHAT RESPONDENT WOULD HAVE GOT FROM THE EXAMPLE. Since for each good, every question that you answered has an equal chance of being selected, be sure you answer what you really prefer for all the questions!

Your answer will determine how much you get and when. If the question is picked in which you chose to receive the good today, one enumerator will come back later today to bring you the good. In the case that the payment is next month, one enumerator will come back in one month to bring you the good. In both cases, we will give you a Certificate with the signature from IPA, certifying that we will come back either later today or in one month to leave the good, and a phone number you can call if there is any problem. For us, it is very important that you trust that we will pay you the choice that is drawn, either today or in a month. As we told you, we are planning to keep on interviewing people in the area and your trust for us is essential. SHOW EMPTY CERTIFICATE TO RESPONDENT."

Parameter Values. Second Survey.

Table A2 presents the parameters of the time-preference tasks for the second survey. Column (1) presents the good referred to for the choices (all respondents made choices about all goods and all quantities). Column 2 presents the tasks in alphabetical order (read in random order to respondents). Column (3) shows the units of the good. Column (4) presents the category for the magnitude of the principal: Small and Large represent the lower and higher value of the principal, respectively, for each good. All "Small" choices were of equal value (approximately 3,000 Ush) across goods, and the same for "Large" choices. Column (5) presents the principal for each good and each choice. Finally, Columns (6) to (12) list the delayed payments (which were read separately beginning by the value in Column (6) and only moving to the next columns if the respondent chose the value in Column (5)).

Table A2: Parameters for Discounting Choices. Second Survey

Good	Tasks	Units	Quantity Categories (Equal Value)	Sooner Payment (now)	Delayed Payments (One Month)						
					Choice 1	Choice 2	Choice 3	Choice 4	Choice 5	Choice 6	Choice 7
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Beef	A1	Kilos	Small	0.5	0.5	0.75	1	1.25	1.5	1.75	2
	A2		Large	1	1	1.5	2	2.5	3	3.5	4
Cash	B1	Ush	Small	3000	3000	4500	6000	7500	9000	10500	12000
	B2		Large	6000	6000	9000	12000	15000	18000	21000	24000
Matooke	C1	Small Bunches	Small	1	1	1.5	2	2.5	3	3.5	4
	C2		Large	2	2	3	4	5	6	7	8
Phone Airtime	D1	Ush in Airtime	Small	3000	3000	4500	6000	7500	9000	10500	12000
	D2		Large	6000	6000	9000	12000	15000	18000	21000	24000
School Supplies	E1	Voucher (Ush)	Small	3000	3000	4500	6000	7500	9000	10500	12000
	E2		Large	6000	6000	9000	12000	15000	18000	21000	24000
Sugar	F1	Kilos	Small	1	1	1.5	2	2.5	3	3.5	4
	F2		Large	2	2	3	4	5	6	7	8

Parameter Values. Risk Choices from First Survey.

Table A3: Parameters for Risk Choices.

	You keep	You invest	No matter what happens, for sure, you get what you kept:	Half of the time the investment works out and you get from the investment:	Half of the time the investment doesn't work out and you get from the investment:	So in the end. you get:
1	1000 Ush	0 Ush	1000 Ush	2.5 X 0 Ush = 0 Ush	0 Ush	1000 Ush all the time
2	800 Ush	200 Ush	800 Ush	2.5 X 200 Ush = 500 Ush	0 Ush	1300 Ush ½ the time, 800 Ush ½ the time
3	600 Ush	400 Ush	600 Ush	2.5 X 400 Ush = 1000 Ush	0 Ush	1600 Ush ½ the time, 600 Ush ½ the time
4	400 Ush	600 Ush	400 Ush	2.5 X 600 Ush = 1500 Ush	0 Ush	1900 Ush ½ the time, 400 Ush ½ the time
5	200 Ush	800 Ush	200 Ush	2.5 X 800 Ush = 2000 Ush	0 Ush	2200 Ush ½ the time, 200 Ush ½ the time
6	0 Ush	1000 Ush	0 Ush	2.5 X 1000 Ush = 2500 Ush	0 Ush	2500 Ush ½ the time, 0 Ush ½ the time

Notes: the question asked was: "Let's say that you can invest up to 1000 Ush in a small business. In this scenario, half the time you will get back 2.5 times what you invest, but half the time you will lose the whole investment. How much would you like to invest?"