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

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July, 2015

Abstract

This paper tests the commonly-used assumption that people apply a single discount rate to the utility from different sources of consumption. Using survey data from Uganda with both hypothetical and incentivized choices over different goods, we elicit time preferences from about 2,400 subjects. We reject the null of equal discount rates across goods; the average person in our sample is more impatient about sugar, meat and starchy plantains than about money and a list of other goods. We review the assumptions to recover discount rates from experimental choices for the case of good-specific discounting. Consistently with the theoretical framework, we find convergence in discount rates across goods for two groups expected to engage in or think about arbitraging the rewards: traders and individuals with large quantities of the good at home. As an application, we evaluate empirically the conditions under which good-specific discounting could predict a low-asset poverty trap.

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

Keywords: time preferences, good-specific discounting, narrow-bracketing, self-control problems, poverty traps.

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1 Introduction

Under many circumstances, individuals are 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 that discount rates are not constant, but decreasing over the time horizon (see DellaVigna, 2009 and Bryan et al., 2010 for a review). However, 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 to assess 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 econometric techniques used to elicit discount rates for monetary rewards in order to estimate discount rates over consumption goods. Few papers in the economic literature elicit time preferences over consumption goods and they do not focus on testing for differences in discount rates across goods (see section 2.1). While a number of studies in psychology find "domain-effects" or different discount rates across domains, these studies do not control for covariates, and their results are typically derived from small samples of students answering hypothetical questions in the lab in developed countries. 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 discounted at statistically significantly higher rates than money: sugar, meat 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 fifteen other goods available in the area. We find evidence of 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 of eliciting time preferences is significant since a myriad of contextual factors that can affect the results must be taken into account.[1] We review the assumptions that are needed to recover time preferences from experimental tasks. We extend the discussion in Dean and Sautmann (2014), focused on quasi-hyperbolic discounting with one type of reward, to the case of good-specific exponential discounting. First, we interpret our results under narrow bracketing, when choices offered to the individual are treated in isolation from her external environment. In this case, our findings can be directly interpreted as providing evidence for good-specific discount rates. Then, in order to understand what assumptions are required when narrow bracketing is not imposed, we allow for the possibility that respondents take into account a broader consumption-savings problem when faced with experimental choices. Recovering good-specific discount rates in this case is predicated on limited arbitrage opportunities, which implies both a lack of markets and that individuals cannot save or borrow by decreasing or increasing consumption of the good being offered.

We show that differences in discount rates persist even after controlling for several potential confounding factors 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, variations in background consumption 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: storage capacity and uncertainty about receiving future payments. We also asked respondents whether they took prices and trade opportunities into account when making their choices. Less than 20% report so, which may be interpreted as evidence for narrow bracketing or a lack of arbitrage. Furthermore, we find that discount rates for each good are strongly correlated with two self-reported variables that can be considered proxies of time-preferences: the desire to have the good in the present, and the desire to have the good in the future. This increases our confidence that the estimated discount rates are indeed capturing impatience levels.

However, in accordance with the implications of the model, we do find that differences in discounting for the high-discount goods are eliminated for two groups of people who might be more likely to either engage in or think about arbitraging the rewards: traders, who either have easier access to markets or think more about arbitrage, and individuals with higher levels of background consumption (proxied by the amount of each good available at home) who are more likely to adjust consumption of the good offered in the tasks. Since both traders and people with large amounts of each good at home represent a small share of our sample, we claim that the differences in average discount rates we estimate largely

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

reflect good-specific time preferences.[2]

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

Second, it is possible to 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 and leisure, then 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. Banerjee and Mullainathan (2010) propose a model in which a poverty trap can emerge if expenditures in goods discounted at higher rates increase less than proportionally with income. 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 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 will spend a lower share of their income on these goods and face a weaker disincentive to save than do the poor. Our data give us a unique opportunity to provide evidence for two assumptions that can predict a low-asset poverty trap generated by self-control problems in this context.[3] First, we identify the group of goods with higher discount rates. Second, we examine their Engel Curves in order to analyze whether their share of expenditures or consumption is decreasing in income. Using expenditure data, we find mixed evidence across goods. However, once we look at consumption data we find that the Engel Curve for the three goods with higher discount rates is downward-sloping. This indicates that, in our sample, individuals with fewer resources

[2]We thank a referee for suggesting these two sets of interactions. Since we did not include the study of heterogeneity in results with respect to these two groups either in our original plan for the study or in the first working paper circulated, it is important to point out that they were not the product of specification searching, but a derivation of the heuristic model introduced in the new version of the paper which was also suggested by a referee.

[3]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 credit constraints and time-inconsistent preferences generated by horizon-specific discounting.

concentrate 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 goods with higher discount rates, as we do in this paper, can be useful to obtaining a data-driven definition for "temptation" goods (as suggested in Banerjee and Mullainathan, 2010). The empirical literature has identified the category of temptation goods by asking households about the goods they would like to spend less money on (e.g. Banerjee et al., 2015) or the goods by which they are tempted. The effect of a particular program on expenditures in such a category is usually estimated. However, the procedure could be affected by reporting bias if it is differential across treatment and control groups given that, as we have found in our field work, many households do not want to recognize their own vulnerability to temptation. 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 is organized as follows. Section 2 reviews the literature eliciting time preferences over consumption goods and describes the surveys and characteristics of the sample. Section 3 presents the methodology used to estimate good-specific discount rates, discusses the assumptions that we need to recover time preferences from the experimental tasks and presents the main results. A battery of robustness checks is included. Section 4 estimates the Engel Curves of the high-discount goods, and Section 5 concludes.

2 Eliciting Good-Specific Discount Rates in the Field

2.1 Related Literature

Only a few papers- in economics literature and in psychology- have tried to test the hypothesis of a common discount rate across goods. 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) than for money or other goods for which they do not report being tempted.[4]

In economics, there are two carefully-conducted studies with incentivized choices, both

[4]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.

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 between choices across the two domains. Augenblick et al. (2015) estimate a quasi-hyperbolic utility function and find preferences to be more present-biased when choices are over effort rather than over money (lower beta parameter), while the delta parameter is not statistically significantly different between the two goods. They acknowledge that estimating aggregate discounting was not a focus of their experimental design.[5]

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 no statistically significant differences in discount rates between cash and maize, for a sample in Zambia that used hypothetical questions. Klemick and Yesuf (2008) do not observe statistically significant differences in discounting for wheat, salt and cash in Ethiopia, but they do not have enough information to estimate good-specific discount rates. In contrast, Ashraf et al. (2006) mention finding higher impatience levels for rice and ice cream than for money in their commitment savings study with bank clients in the Philippines. They do not discuss these results in the paper, however, as their focus is on horizon-specific rather than good-specific discounting.

A related question is whether there are domain-general components of time preferences. Einav et al. (2012) reject the null hypothesis of 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. Relative to time preferences, Augenblick et al. (2015) find zero correlation between effort and monetary choices; Chapman (1996) also finds low correlations between health and monetary choices. In contrast, Reuben et al. (2010) find high correlations among 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 the existence of a unique cognitive process underlying 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 beyond existing literature is the estimation of discount rates for a large variety of goods, eliciting preferences in the field from more than 2,400 individuals on the basis of both hypothetical and incentivized choices. Moreover, we discuss

[5]Both papers measure rewards in units having different value across the two types of payments. It is possible that their resulting differences in discount rates levels across reward types are due to a combination of what the literature terms a "magnitude" effect and the different value of the two goods; that is, when higher-value rewards are discounted at lower rates.

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 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.[6] In addition, we see that some factors, among them gender and the existence of a magnitude effect, affect discount rates for all goods in the same way. This provides additional evidence for domain-general components of time preferences, although 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 of eliciting discount rates for a large list of consumption goods using hypothetical choices; the second one uses incentivized choices to check for the robustness of results within a smaller set of goods, and includes additional questions to control for factors potentially affecting the elicitation procedure.

2.2.1 First Survey

The first survey was conducted for a sample of 2,442 individuals in a rural region of Uganda, whom we 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, of which 3,000 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 64% 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

[6]The correlations in discount rates across goods are between 0.6 and 0.8, using both hypothetical and incentivized rewards.

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 available goods.[7] In order to elicit good-specific discount rates, we adapted the questions for monetary rewards from Coller and Williams (1999). Similar questions have been used to elicit discount rates with monetary rewards in developing countries.[8]

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 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 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 should 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 of 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 in order 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 early 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 early choice and each possible delayed one were the same across all goods, in order to avoid possible framing effects that could affect 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 higher and lower quantities, in order to control for possible magnitude effects.

[7]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, hair salon, cellphone airtime, meat, school supplies, and shoes.

[8]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, 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 comprehend 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 in the first survey. One exception was the use of two sets of questions representing "equal value" trade-offs, one with smaller and the other with larger quantities. The early choice involved a number of units with an approximate cost of 3,000 Ush (approximately 1 nominal USD 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 truly be paid 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 early and delayed payments, respondents were told that if the early reward was chosen, an enumerator would return to their house at the end of the day with the payment. If the delayed reward was instead chosen, 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 the choice between receiving a certain quantity of a good now and a larger quantity one month from now? The question of identification of time preferences from experimental choices has been receiving substantial interest.[9] Yet the discussion has focused almost exclusively in the case of hyperbolic

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

discounting with choices over monetary rewards.[10] 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 shown 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). In section 3.2 we set-up a two-period, two-good maximization problem as in Banerjee and Mullainathan (2010) and derive 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. Under this assumption, individuals make their choice between early and delayed rewards for a given good based only on their preference parameters for that good, disregarding 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 of the good, their income and any arbitrage opportunity in financial markets. These are typical assumptions 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 outside consumption of the goods offered in the other choices, and any arbitrage opportunity in markets for those goods.

[10] An exception is Augenblick et al. (2015) who also consider choices over real effort.

Dean and Sautmann (2014) show that under narrow bracketing the ratio between the early and late 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.[11] 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 early and the late reward for a given good at the switching point approximates the discount rate for that good. Assuming that utility is separable over time and across goods, and that discount factors for the two goods are δ_x and δ_z, we can write the intertemporal utility function as:

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

We follow the typical assumption in the literature using 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 early and

[11] 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. (2015) 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 uses hypothetical rewards and implicitly assumes narrow bracketing together with linear utility functions. 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 early and late reward be the same for all goods and quantities offered. This reduces the impact of possible framing effects differing 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 meat 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.[12]

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 against all other discount rates when we assume linear utility, that is, we focus on variation in our sample within the

[12] 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 early option for all choices, the discount rate will be one interval larger, that is 2.75. Our results are robust to dropping individuals that always choose the early option, who represent approximately 14% of the sample.

range of imputed discount rates. This means that we will not be able to identify differences in discount rates across goods for those individuals having relatively low discount rates for all goods. Nevertheless, the fact that we do identify differences across goods means that these differences are indeed very large.[13]

Table 2 presents summary statistics for discount rates calculated following this basic procedure using the equal-value choices. We can see that there are three goods-sugar, matooke and meat-with statistically significantly higher average discount rates than the rest of the goods, and in particular, statistically 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. In contrast, for all the other goods the median individual switches at the first option, and has an imputed discount rate of 0.25.[14]

Other papers in the literature estimating short term discount rates also find very large values. Meier and Sprenger (2014) mention that 55% of respondents have monthly discount rates above 43% in choices between amounts of money today and in a month; they argue that these results are consistent with the literature finding substantial impatience. Tanaka et al. (2010), for rural villages in Vietnam, estimate, in some of their specifications, a 50% average monthly discount rate. Dean and Sautmann (2014), for households in Mali, find even higher discount rates, which remain high after excluding respondents always choosing the early amount. Finally, Reuben et al. (2010) find a 30% weekly discount rate for choices over chocolate bars in the lab.

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:

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

[13]We would have been able to estimate more precisely the discount rate levels 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. We therefore preferred to limit the number of choices in order to maximize response rates.

[14]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.

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.[15]

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 noise from using magnitudes with different values across goods. Only for meat, sugar and matooke are the estimated coefficients positive and highly statistically 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 are the coefficients positive and statistically significant.[16]

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 statistically significantly lower rates. This provides evidence of a magnitude effect for monetary rewards. We find that the same effect applies to each of the goods on 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 use real consumption goods and real rewards.[17]

[15]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, statistically significant differences with respect to money imply significant differences with respect to all other goods on our list, for which we find even lower discount rates.

[16]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 that 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.

[17]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 is usually found, especially when they consider median discount rates and use choices involving a time delay. While we do not include time delays, we follow a similar methodology to their paper and still find large magnitude effects in both mean and median discount rates.

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 the dependent variable. We confirm that results still hold with this data-driven procedure of choosing one point of the discount rate interval instead of arbitrarily using the midpoint. Column (3) presents differences between predicted discount rates for each good and for 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 a constant as the only explanatory variable, and we take the coefficient of the constant as 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 from 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 regarding 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 of statistically significant differences (Frederick et al., 2002, Benhabib et al., 2010, among others). On the other hand, Andersen et al. claim in a series of papers that "the evidence is overwhelming that there can be huge and systematic hypothetical biases" (Andersen et al., 2014, pp. 27).

We tested whether results obtained with hypothetical rewards differed from those found with real incentives. In the second survey, we introduced a new set of time-preference questions for six of the goods used in the first survey. One question was randomly chosen for payment. The goods for which we replicated the questions were the three 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 expected, since people mentioned wanting to save for them) and cellphone airtime (for which we expected ex-ante to see high discount rates).

Table 4 replicates Table 1, restricting observations to the 449 households interviewed again in the second survey. In comparing the two panels of Table 4, we see that there is no statistically significant difference in average discount rates for any of the six goods when we compare discount rates elicited using 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.[18]

We still find matooke, sugar and meat to be the three goods with statistically significantly higher discount rates; although the standard errors are now larger due to a smaller sample size, differences are statistically significant at the 10% level. The same conclusion is derived when we compare discount rates obtained using real rewards for these three goods and with hypothetical rewards for the others, and 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 statistically 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 one, 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 of the model will allow us to more clearly see the assumptions we need to make in order for our experimental tasks to elicit time preferences without imposing narrow bracketing.

[18] 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 data provides some evidence for time invariance as defined in Halevy (2014). We find correlations in discount rates over one year between 0.15 and 0.20 for all goods (0.20 for money), statistically significantly different from zero. Our results are in line with Meier and Sprenger (2014), who find a correlation over one year of 0.246 for the δ parameter of the quasi-hyperbolic model.

Model

Consider an individual who lives for 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.[19] We can choose units so that all prices are equal to 1, and proceed recursively to solve the optimization problem. For simplicity of exposition, we present a deterministic version of the model in Banerjee and Mullainathan. Individuals receive income y_1 in $t = 1$. They can save $w_1 = y_1 - x_1 - z_1$ and invest in an income-generating function $f(w_1)$, where f is increasing in w_1 (to allow for lending and borrowing with or without constraints at different rates), differentiable and concave in w_1. In $t = 2$, the individual receives income y_2.

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. The period 1 self is assumed to be sophisticated and to take these functions into account to maximize:

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

$$\frac{dU(x_1)}{dx_1} = \delta_x \frac{dU[x_2(c_2)]}{dx_2}\frac{df(w_1)}{dw_1} - (\delta_x - \delta_z)\frac{dU[x_2(c_2)]}{dx_2}\frac{df(w_1)}{dw_1}\frac{dz_2(c_2)}{dc_2} \tag{6}$$

Using $c_2 = x_2 + z_2$, we get:

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

If we re-arrange equation (7), we can express the marginal rate of substitution of the consumer as:

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

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 an average of the discount factors of the two goods, δ_x and δ_z, weighted by the future

[19] 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 complementarity. For a theoretical discussion on how to interpret good-specific discounting with non-separable utility functions see Gollier (2010) and Traeger (2011).

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 that the period 2 self will overconsume good z in relation to good x.[20]

Interpreting Observed Choices

In section 3.1, we showed that, under perfect narrow bracketing, experimental choices reveal approximate indifference between additions of M_{1x} units of good x to its background consumption in period 1 and additions of M_{2x} units to its background consumption in period 2, that is:

$$U(x_1 + M_{1x}) + \delta_x U(x_2) \approx U(x_1) + \delta_x U(x_2 + M_{2x}) \tag{9}$$

Then, as long as M_{1x} and M_{2x} are sufficiently small and background consumption does not change much over the two periods, we have that $\delta_x \approx \frac{M_{1x}}{M_{2x}}$. Hence, we can recover the discount factor from the experimental choices. We can see in equation (8) that, in order to get the same result without imposing narrow bracketing, we need $\frac{dx_2(c_2)}{dc_2} = 1$: consumption of good x has to increase one to one with the experimental payments for good x, so that $d_2 = \delta_x$.

For this result to hold, we need three conditions precluding the transfer of resources across goods and over time so that the extra units of the good are consumed at the time they are received: 1) No access to capital markets (no saving or borrowing in cash), 2) No access to goods markets (no trade across goods) and 3) No adjustments of background consumption (no saving or borrowing in kind by increasing or decreasing the background consumption of the good that is being offered in response to the experimental payments).

The first condition is related to standard arbitrage arguments that have been discussed in the case of monetary rewards by Pender (1996), Cubitt and Read (2007) and Dean and Sautmann (2014), among others. If individuals were able to take experimental payments to the market, then they would maximize the net present cash value for any set of choices. Hence, we would learn nothing about intertemporal preferences from the experimental choices. Similar problems arise with access to good markets. If individuals can trade at no cost the experimental rewards for other goods, then again they will maximize the net present cash value for any set of choices. In Section 3.2.3, we discuss the role of these two assumptions in our data.

[20] Dean and Sautmann (2014) discuss an analogous equation, which was derived formally by Harris and Laibson (2001). In their case, the discount factor is a weighted average of the short- and long-run discount factors derived from the quasi-hyperbolic model, weighted by the future propensity to consume out of cash-in-hand or liquidity wealth.

Finally, if individuals can reallocate their resources in response to the experimental payoffs, the level of background consumption becomes endogenous and we cannot use equation (9) to recover time preferences.[21] In section 3.2.2 we further discuss this issue by looking at data on typical monthly expenditures and quantity of each good available at home. In particular, this problem becomes more serious with better access to the markets. For example, with profitable investment opportunities, even if the individual prefers 2 kilos of sugar in a month to 1 kilo now, she can 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 had not yet bought it), and invest the money to get a return that will allow her to buy more than 2 kilos next month.

In other words, we need non-fungibility over time and across goods, so that individuals perceive the choice for good x as units of good x now vs. units of good x in one month. In practice, when arbitrage is possible and taken into account by the individual we will be less likely to detect differences in discount rates across goods. This is likely to be the case for those with better access to markets and greater 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 if we assume that the three assumptions outlined above hold, 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 a linear utility function. With binary choices it is only possible to get a range for discount rates, and if some respondents are shifted from one side of the cutoff to the other after incorporating the experimental rewards, it would be incorrect to rely on a linear approximation of 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 of the good. As in their main specification we assume expected utility theory, exponential

[21] See Sprenger (2015) for a recent short note on the importance of this assumption for time dated monetary payments.

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 as well as time preferences in order to estimate the curvature parameter.

Note that in their main specification, they choose a fixed level of background consumption over time and across individuals that is based on average monthly expenditure data. This strategy leads us back to the need to assume full narrow bracketing as explained in section 3.1. We begin by following this example, imposing a fixed level of background consumption, before relaxing this assumption in the next section.

We perform a maximum likelihood estimation of a model that follows the general latent choice process specification of 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 included in our first survey.[22] Respondents were asked to imagine that they could invest up to 1,000 Ush in a small business. Half of the time the investment succeeds and yields 2.5 times the amount invested; the other half it fails, and the entire amount invested is lost. The task presented respondents with the equivalent of six possible lotteries, one for each level of investment they could choose (see Table A3). Respondents were asked to choose one of them. The second task was similar, with larger amounts and one extra choice (see Table A4).[23] 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 of 5 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.[24] The second part

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

[23] 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, Cardenas and Carpenter, 2013 and Carvalho et al., 2014).

[24] This specification was used by Andersen et al. (2008), Coller et al. (2011) and Laury et al. (2012) in the discounting literature, but 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

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 assumed linear utility, as expected, the conclusion in terms of differences across goods still holds. We find once more that matooke, sugar and meat are the three goods to which higher discount rates are applied. 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.[25]

We next allow for individual heterogeneity by allowing the risk aversion and discount rate parameters be a linear function of observable characteristics. We include dummy variables for gender, marital status, literacy and lower-than-average ability scores (as measured by a Raven's matrix test). The predicted mean discount rates are similar to the ones estimated without controls, and 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 statistically significant. Only gender is statistically significant when the outcome is discount rates. Column (4) in Table 6 presents predicted discount rates for females allowing both discount rates and risk aversion parameters to depend on observable characteristics. We observe that women have statistically significantly lower discount rates for most goods, 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 a statistically significant impact upon discount rates as elicited from monetary rewards is gender, with an effect in the same direction as we find. This derives from the greater risk aversion of women, which means that they have a more concave utility function and a lower implied discount rate.

As a robustness check, 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 every good except money. Our findings (available upon request)

suggested by Wilcox (2011). In this case we arrive at similar conclusions. Results are available upon request.

[25]These estimations assume zero background consumption. We also estimate $r = 0.13(0.01)$, and the structural errors in the time-preference choices and risk choices: $\mu = 0.09(0.01)$ and $\varepsilon = 0.38(0.01)$. The risk parameter is low in comparison to other results from the literature, but 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, reaching a maximum of 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.

replicate the ones in the pooled estimation, with only matooke, sugar and meat showing positive and statistically significantly higher discount rates. Table 7 presents similar estimates using the incentivized choices. We derive the same conclusions from them.

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 estimated discount rates can be sensitive to the value of background consumption, mainly because the estimate of the curvature of the utility function is affected. Identification of discount rates assumes completely constrained subjects who consume the reward at the time stated and do not smooth consumption over time or across goods. In order to relax these assumptions, we allow x_t to differ from zero in the joint estimation procedure with incentivized choices. We are able to do so in this case since we included specific questions to measure background consumption in our second survey.

The first point to consider is how to measure background consumption, the amount 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 rewards. They assume a single value for all individuals, equal to the average per capita daily consumption of private non-durable goods. Similarly, Augenblick et al. (2015) set it as the required minimum work when estimating discount rates over effort.

We have data to allow this parameter to be 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 this Background 1. Our second approximation, Background 2, allows for different values of current and future background consumption; we use the answers to a question asking how much of each good respondents expect to have at home in one month.[26] We asked these questions after all time-preference choices had been made, thus not inducing subjects to think about them when making their decisions. We can see in Table 8 that the discount rates estimated using these proxies 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 changes considerably under our second measure (Background 2), although these 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

[26] 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.

their future constraints). But, in the two cases the ranking of discount rates across goods is preserved, although the differences are not statistically significant 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 $1/\lambda$ is integrated with background consumption. The parameter λ is then interpreted as the time horizon over which the subject is optimizing. The usual assumption in the literature is λ=1, implying 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 is the amount of good x consumed in one day, then 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 adopt this value as x. We also asked respondents about the period over which they would consume the rewards for matooke, meat and sugar, and we used their answers to calculate λ for each individual (the median values were 6 days for matooke, 7 for sugar and 2 for meat). Results are presented in the rows for Background 3 in Table 8; they are similar to those obtained using Background 1, and consistent with our previous estimations. Note that the discount rates for sugar and matooke increase by more than the one for meat, and those goods are the ones with larger reported average consumption periods.[27]

Finally, using the same procedure to obtain x, we defined λ as the number of days it would take to consume the reward, based on reported monthly typical consumption for each good (e.g. we divide monthly typical consumption by the amount of the reward). This method generates much larger values of potential spreading than were self-reported (with medians of 15, 10 and 15 for matooke, sugar and meat). Consistently with this result, discount rates are higher for all goods, as shown in the rows for Background 4. In this case we can also estimate potential spreading for other goods (with medians of 12, 60 and 4 days for school supplies, airtime and money), and we still find that differences between matooke, sugar and meat, on the one hand, and school supplies, money and airtime on the other, are statistically significant. The fact that discount rates increase when allowing for consumption spreading suggests that for durable goods included in the first survey (such as clothes and shoes), discount rates might be underestimated if we assume respondents to spread the relative rewards over a longer period. However, given that for airtime, with a median of 60 days calculated using the last procedure, differences with the high-discount

[27]Duquette et al. (2014) also find that discount rates increase when they allow λ to be larger than 1 for monetary rewards under quasi-optimal consumption spreading.

goods are still statistically significant; we might expect that for the goods in the first survey the estimated differences will not be strongly affected.

Thus far we have shown that if we allow for the integration of rewards with background consumption levels, our results do not change. This could mean either that 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 average differences in discount rates.

An alternative way to look at the question is by using pooled regressions in order to see whether the larger is background consumption of each good relative to the choices offered, the stronger is convergence to the cash discount factor. In equation (5) we add interaction terms between the dummies for each good and good-specific measures of background consumption. We include two sets of interactions (jointly and independently), the first with a dummy indicating possession at home of an amount of the good larger than the first choice of the reward offered and the second with typical monthly consumption for that good. Results are presented in column (3) of Table 5. The interaction terms for monthly consumption (not reported) are very small and not statistically significantly different from zero,[28] while the interaction terms with the dummies for relatively large amounts at home are negative and large in absolute value for sugar, matooke and meat; although only statistically significant for matooke.[29]

On the one hand, these results could indicate a degree of narrow bracketing. They suggest that in order to understand people's experimental choices it might be more important to consider the quantity of each good available at home at the moment of the survey than monthly consumption. We observe a convergence in discount rates for respondents with relatively large quantities of the goods available at home. For this group of people, who could be considered "non-liquidity constrained", most of the differences in the high-discount goods disappear; only for sugar is the difference with respect to money statistically significant (p-value 0.09), but also smaller.[30]

On the other hand, these results could be interpreted as evidence for arbitrage and a violation of the conditions to elicit good-specific discount rates from experimental choices.

[28]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 level of the amount available at home. Results available upon request.

[29]The coefficient on airtime is strange and we should not put much weight on it since the interaction takes a value of one for only 4 people who report having more than Ush 3,000 in airtime at the moment of the survey.

[30]It is important to note that these results are driven by the 27% of the sample who had a quantity of matooke at home larger than the reward offered, while the shares are 13% for sugar, 5% for meat, 1% for airtime and 41% for school supplies.

If individuals with large amounts available at home are less willing to increase consumption of the given good one-to-one with rewards offered, they might be more likely to search for arbitrage opportunities. Alternatively, these individuals might be thinking more about arbitrage opportunities when making their choices because these goods are more salient in their decisions. If that is the case, 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.[31] The majority of subjects have neither large quantities at home of the goods offered, nor expect to have them the following month.

Finally, we should note that identification breaks down if people adjust background consumption in response to the experimental payoff. This would imply that the background consumption measure obtained before the rewards are paid is not a good counterfactual for the one that would be observed with the rewards. In that case, neither typical consumption nor amount at home could be used as proxies for what background consumption would be after incorporating the rewards. Individuals with a larger share of their monthly consumption at home might be less likely to adjust background consumption, unless they are able to sell the rewards. If this were true, then it would be better to focus on those who have a larger share of their monthly consumption at home in order to elicit discount rates, instead of focusing on those with small amounts at home as pointed in the previous paragraph. In our sample, the share of those who have more than 50% of their monthly consumption at home is only 8, 5 and 3%, for matooke, sugar and meat, respectively. When we add interactions with these shares to equation (5), we find similar results to the ones obtained using the dummy for having large amounts at home: we tend to see convergence in discount rates for those with larger shares. This implies that we cannot discard the possibility that individuals adjust their background consumption, but it is not possible to claim that this behavior is more likely to be observed for those with a larger share of typical consumption available at home at the moment of the survey. The fact that we do not see differences in elicited average discount rates in our two surveys separated by one year, provides some evidence that changing economic situation (and background consumption) might not significantly affect estimated time preferences in our case.[32]

[31] More precisely, what matters in equation (8) is the future propensity to consume a given good out of total consumption. In our sample, the correlation between amount at home now and the amount expected at home in one month is on average 0.5; which makes the amount at home available now a good proxy for next month's amount. We tried interactions with expected amounts available at home the following month, but those measures have large standard errors and we did not find any statistically significant effect. Results available upon request.

[32] This is in line with the findings in Meier and Sprenger (2014), but also see Dean and Sautmann (2014), Carvalho et al. (2014) and Chuang and Schechter (2014) for different results.

3.2.3 Arbitrage and Good-Specific Confounders

The last section discussed the case of reallocation of consumption for a given good, which is one form of arbitrage of experimental rewards. An alternative is direct arbitrage in financial and good markets.

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 individuals more likely to have better access to the markets indeed show smaller differences in discount rates across goods.[33] 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, it is also possible that people are affected by savings constraints since there are high opening fees for savings accounts, required minimum balances and expensive monthly maintenance fees. However, there might still be better access to markets for goods.

In the first survey we asked about respondent's main source of income. Around 30% of respondents reported being farmers, 20% employees, and 50% self-employed entrepreneurs, of which 10% were traders of agricultural products (N=143). This group of traders is likely to be the one with better access to markets of the goods we offer as experimental rewards. We estimate the pooled regressions including interactions between the good dummies and a dummy for being a trader. Results are reported in Table 9. In column (1) we use the hypothetical choices from the first survey; 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 persist for traders in the hypothetical case, but when choices are incentivized we see full convergence in discount rates for traders. For all other occupations the interaction terms are small and not statistically significant (results available upon request). We therefore have evidence to claim that differences in discount rates across goods are derived from individuals with more restricted access to markets.[34]

[33] 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 explain our results (but we do not have clear evidence of this, in particular in comparison to beans, soda and salt for example). Augenblick et al. (2015) follow this direction by offering choices over effort, with low arbitrage opportunities, but they cannot exclude that people reallocate extra-lab consumption including other types of effort.

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

To provide evidence for the second point, we need to understand whether people take arbitrage opportunities into account when making 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, indicating that people think more about arbitrage opportunities once they have been reminded of them. In contrast, Coller and Williams (1999) find only 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 individual's decisions.

In the second survey, after the experimental choices we asked respondents to report the factors they took into account when making 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 obtain from selling it (Resale), what would be the price in one month compared to the price today (Price), how uncertain they were that the enumerator would come back in a month (Uncertainty), how much they would like to have the good now (Desire for good now) and how much they would like to have the good in one 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 confounders for discount rates. These variables take the value of one when respondents confirm that the factor is determinant of their choice for the particular good.[35] The questions are person- and good-specific; thus the regression uses variation both across goods and within individuals, and we control for individual fixed effects. The effects on average discount rates are positive for Uncertainty and Storage. They are negative, although not statistically significant, for Price and Resale. Nonetheless, the differences in discount rates are essentially unchanged when we include these four factors in the pooled regression.

Positive answers to the Resale and Price factors can be interpreted as people either thinking about or engaging in arbitrage when making their choices. Dohmen et al. (2010) ask whether a subject has thought about the market interest rate during an experiment with monetary choices, and they use this answer to identify individuals who engaged in arbitrage. They find that 37% of participants provide 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, 7% for meat, and 6% for school supplies, while the share mentioning the Price factor

[35]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 can also take the value of 1 in the sugar rows if it was mentioned as a relevant factor for choices about sugar.

is 19%, 26%, 13% and 21% for each good, respectively. We also find, as they do, that after 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 statistically significant correlation between being a trader and mentioning Price as a relevant factor, pointing in the direction that traders think more about or engage in arbitrage.

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, meat and sugar cannot be attributed to these four confounding factors, as coefficients on the dummies for each of these goods remain statistically significantly different from zero even after including the interactions with the potential confounders. However, some of the confounding factors did contribute to finding even larger differences across goods. In the case of matooke and sugar, an increase in discount rates can be linked to differential uncertainty about future payments (although only 6% of respondents mention the factor for these goods, while 3% do so for money). For meat, storability appears to be positively correlated with discount rates, but as expected, only for large quantities (when we restrict results to small-quantity questions the interaction is no longer statistically significant, results available upon request).

Finally, the factors related to the Desire to have the good now or in one month must be highly correlated with elicited discount rates if they are a true reflection of time-preferences. In Column (5) of Table 5 we can see that people mentioning their desire to have the good immediately as a relevant factor affecting their choices have statistically significantly higher discount rates for that good, while those mentioning their desire to have the good in one month have significantly lower discount rates. As we expected, the coefficients on the good dummies are now reduced. Note that these questions are not just measuring whether people like the good or not, but may be capturing impatience levels. Neither discounting choices nor the Desire factors are correlated with the answers from a question asking whether people like consuming the good. For example, 90% of people report they like matooke, and these are divided between the 50% mentioning they want to have it immediately, and the 50% not mentioning so.

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, meat and matooke; and another group with relatively lower discount rates: money, airtime and school supplies. 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 statistically significantly affects discount rates is 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 one month are statistically 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, meat or matooke than for money; and 22% higher rates for the three goods than for money. This provides evidence for both context specificity and for 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 both traders and individuals with large quantities of the goods at home, for whom we might not be able to 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 has a statistically significant effect on discount 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 from those of the previous maximum likelihood estimates that assumed a zero standard deviation. The estimated standard deviations for the discount rates of matooke, school supplies, money and airtime are not statistically significantly different from zero, while the ones for meat and sugar are only statistically 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 statistically 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 experience greater temptation (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 meat, 29% less sugar and 26% less matooke, with only meat being statistically 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% by school supplies and 48% by meat. These two questions are neither correlated with having discount rates larger than money, nor among themselves.[36] It is possible that time-preference choices better capture temptation levels for high-discount goods than do self-reporting questions, or that other unobserved factors also determine differences in discount rates.

As explained in Section 3.2.3, 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 one month. These questions might be capturing high impatience levels for certain goods.

Urminsky and Zauberman (2014) review other explanations given by 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, which pushes consumers to exercise more self-control. Our results for matooke, sugar and meat could be interpreted as providing evidence for the affective argument when self-control power is limited or there is no room for guilt. Even when matooke

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

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 meal without it; that is why we are not surprised to find that high discount rates are applied. Sugar and meat can also be associated with tasty food generating impatience. It is possible that given the basic quality of these goods, guilt plays no role in moderating choices. On the other hand, the low discount rates we find for airtime, meals outside and entertainment, which could be associated with temptations in other contexts, might be explained by the guilt mechanism mentioned above. If households consider these goods not as essential as matooke and sugar, then they might be more able to exercise self-control and make more patient choices.

According to Loewenstein (1996), self-control problems arise when there is a visceral need, which implies that only some immediately-available reward might generate impulsivity. His argument is that visceral factors might be enhanced by the opportunity of immediate consumption, in particular when the goods are physically close to consumers (e.g. can be smelled or seen). In our case, no environmental trigger was present. However, it is possible that by offering rewards about certain goods we make them more salient. This could have two effects: to increase impatience by making the affective component of certain goods more salient, or to decrease it if people are forced now to consider future outcomes, which can increase attention to the future.[37] This effect might interact with the quantity of each good available at home at the moment of the survey, which could explain our results if people with more units of the reward are more likely to think about future outcomes or less likely to be influenced by the affective component.

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, the three goods to which higher discount rates are applied are relatively expensive sources of calories for households in the area. Using a back of the envelope calculation, we find that meat is the most expensive source of calories, with a cost per kilo-calorie of 2.67 Ush.[38] 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 meat as a source of protein is groundnuts, with a cost per kilo-calorie of 1.28. Nevertheless, sugar, meat and matooke add up to 47% of expenditures in

[37]McClure and Bickel (2014), in a recent survey of neuroscience literature, cite evidence showing how temporal attention might foster deliberative processes and reduce impatience.

[38]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.

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 reflect 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 rather than good-specific discounting.[39]

A simple example, similar to the one presented in Banerjee and Mullainathan (2010), can help clarify the differences between horizon- and good-specific discounting models. To demonstrate time-inconsistency with a quasi-hyperbolic model, we need only 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 the time 1 self and $\beta\delta$ for the time 2 self. This generates a disagreement between the present and the future selves over the level of consumption across time.[40] 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 the time 1 self, but a weight of 1 for the time 2 self.[41] In this case, the disagreement between the present

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

[40] Dual-self 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.

[41] This is based on the assumption of additively-separable utility functions and on a discounted utility

and the future self is over 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 $\delta_x = \delta_y$ in the second case.

As we mentioned before, it is possible that people are time-inconsistent according to one model and not 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. one month and one vs. two months.[42] Out of those with present-biased preferences according to the horizon-specific model, 40% have higher discount rates for sugar than for money (43% for meat and 41% for matooke), compared to 32% for the full sample. Whereas out of the 32% with higher discount rates for sugar, 15% 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 possibility of self-control problems leading to a poverty trap rests on the 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:

$$\frac{dU(x_1)}{dx_1} = \delta_x \frac{dU[x_2(c_2)]}{dx_2}\frac{df(w_1)}{dw_1} - (\delta_x - \delta_z)\frac{dU[x_2(c_2)]}{dx_2}\frac{df(w_1)}{dw_1}\frac{dz_2(c_2)}{dc_2}$$

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:

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.

[42] 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.

$$\frac{dU(x_1)}{dx_1} = \delta_x \frac{dU[x_2(c_2)]}{dx_2}\frac{df(w_1)}{dw_1}[1 - \frac{dz_2(c_2)}{dc_2}]$$

The time 1 self does not value spending by the time 2 self 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 on 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 on 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 the last case does the model predict the possibility of a poverty trap.[43] Because 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 month, which

[43]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. Instead 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.

is available in the second survey only for the first three goods. Given that we do not have comparable data across the two surveys, we estimate the Engel curves from a cross-section of individuals.

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 that includes every possible disbursement as reported in the background survey. To avoid the influence of outliers, we follow Banks et al. (1997) and trim observations that are 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 cross-sectional kernel-weighted local linear regressions for the Engel Curves of the high-discount goods (matooke, sugar and meat) and for the low-discount good with the largest share of expenditures in our sample (school supplies). Figure 1 shows that the share of expenditures on sugar is decreasing in total expenditures, the share of meat increases initially and then decreases, and the share of matooke increases for a larger fraction of the distribution until it becomes almost flat.[44] In comparison, the share of expenditures on school supplies is constant for nearly the entire distribution. This indicates that the required assumption to predict a poverty trap might be valid for sugar, partially so for meat, but not for matooke. The matooke share exhibits an interesting pattern. The main explanation in the literature would be that households switch to higher quality food items when total consumption increases, and that they consider matooke to be a preferred food. This is a plausible explanation, since matooke is a relatively expensive source of calories.[45] 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) with the assumptions 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 decreases; with the reverse pattern holding for the low-discount group.

[44]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.

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

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 weight proportional to the individual's share of total expenditure on 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 which attempted to control for endogeneity.[46]

One key limitation of the previous figures is that that they are based on expenditure rather than consumption data, although consumption data is more relevant to evaluate the predictions of the model. The difference can be significant for matooke, which is harvested 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, meat and matooke. We asked separately for units consumed and units bought in a typical month and for estimated prices of each unit. As expected, we see that the correlation between consumption and expenditures for sugar and meat is around 0.95, with almost all consumers buying the goods, while the one for matooke is only 0.5. One limitation to using these data is that we do not have an estimate of total consumption. We use a question from a follow-up survey with the same sample conducted 2 months later (we lose 55 out of 449 observations) that asks for total expenditures in a typical month. Figure 3 is derived using the same procedures as in Figure 1, but it now 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 shares 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 statistically significantly higher discount rates, but it could be the case that there are other goods that also exhibit high discount rates. Second, it is possible that

[46]We follow a control function approach, using as instruments three dummy variables measuring expected income trends, as in Attanasio et al. (2012).

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. Third, as pointed out above, better data on consumption might lead to different results. In particular, there is an important trade-off for households in our sample between consuming the matooke they produce, or selling it at higher prices, that must be better captured. Finally, better strategies to deal with endogeneity are required. The cross-sectional estimates will be biased if richer and poorer households have different tastes, different available options, and face different prices. The bias will be relevant if total expenditures are correlated with the residuals of the demand system, and there are different taste shifters for different goods.

5 Concluding Remarks

Most of the empirical literature seeking evidence for models of self-control problems with time-inconsistent preferences has focused on the hyperbolic discounting model. However, time-inconsistent behaviors can also be derived with a model of good-specific exponential discounting. This paper provides evidence to reject the hypothesis that the same discount rate is applied to the utility of all possible sources of consumption. Hence, we provide evidence for hallmarks of dynamic inconsistency based on good-specific discounting. Future work should focus on testing for actual dynamic inconsistencies in this context (Sprenger, 2015).

We find statistically significantly higher discount rates for three goods compared to 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 used to elicit discount rates, the relative ranking across goods is stable. The differences we find in discount rates across goods are robust to controlling for the main confounding factors mentioned in the literature and for good-specific factors. Future research should relax the assumption of separability 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 (such as the ones recently proposed by Andreoni and Sprenger, 2012, Montiel Olea and Strzalecki, 2014 and Ambrus et al., 2014).

Our discussion of the assumptions required to recover good-specific time preferences from experimental choices makes clear the necessity of imposing some degree of narrow-bracketing in order to recover good-specific time preferences from experimental tasks. If subjects interpret the tasks in complete isolation from their outside world, then we do not need additional assumptions. However, when this is not the case, identification of differences in discount rates requires both lack of access to arbitrage opportunities in external markets and no adjustment in outside consumption of the goods being offered. Indeed we find that differences in estimated discount rates for the high-discount goods disappear for traders and individuals with large quantities at home of the goods offered in the experimental tasks, as the theory would predict.

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. We present evidence for good-specific discounting in at least one context, which is particularly relevant for our application.

We 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. We show that the share of expenditures on those goods that are discounted more steeply 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 on goods with high discount rates.

An implication of this finding is a demand for commitment devices as a direct consequence of self-control problems. Nevertheless, the optimal type of commitment device required to confront self-control problems generated by good-specific discounting is different from the general device restricting cash availability that has been studied in the literature.[47] An important topic for future research is to understand what specific commitment devices are best-suited to confront the disagreement over the composition of consumption between the present and the future self.

The finding that the poor spend large shares of their income on relatively expensive sources of calories is not unique to our paper, as has been mentioned as one factor 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 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, rural households in Uganda, we find that the three goods with statistically significantly higher discount rates- sugar, matooke and meat- also represent expensive sources of calories and

[47] An example could be the product explored by Gine et al. (2010) that helps people reduce expenditures on tobacco.

capture a large share (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 on 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.

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 high-discount goods might reduce their consumption, but could also increase the share of expenditures on those goods, making 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	2,442	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	3.05	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	0.88	1.00	0.33	449
Sells at least 1 crop	0.64	1.00	0.48	2,442	0.64	1.00	0.48	449
Value Crops Sold Last Harvest (dollars)	63.19	10.48	276.17	2,386	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

Dependent Variable: person-good specific discount rate	Pooled Regression+		Interval Regression++
	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	All Questions				
	(1)	(2)	(3)	(4)	(5)	(6)
Matooke	**0.157*** **	**0.172*** **	**0.169*** **	**0.170*** **	**0.136*** **	**0.142*** **
	(0.04)	**(0.04)**	**(0.06)**	**(0.04)**	**(0.04)**	**(0.04)**
Sugar	**0.224*** **	**0.262*** **	**0.222*** **	**0.266*** **	**0.239*** **	**0.256*** **
	(0.04)	**(0.04)**	**(0.05)**	**(0.04)**	**(0.04)**	**(0.04)**
Meat	**0.188*** **	**0.229*** **	**0.204*** **	**0.219*** **	**0.185*** **	**0.218*** **
	(0.04)	**(0.03)**	**(0.04)**	**(0.04)**	**(0.04)**	**(0.04)**
School Supplies	-0.026	-0.031	-0.032	-0.029	-0.047	-0.026
	(0.04)	(0.03)	(0.05)	(0.03)	(0.03)	(0.04)
Airtime	-0.072**	-0.040	-0.079**	-0.041	-0.051*	-0.036
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Question: Small Quantities		0.156***	0.160***	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						
HomeMatoke*Matoke			-0.176***			
HomeSugar*Sugar			-0.054			
HomeMeat*Meat			-0.089			
HomeSchool*School			0.002			
HomeAirtime*Airtime			-0.225			
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	0.71	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***	0.185***
	(0.02)	(0.04)
Matooke*Trader	-0.111	-0.240**
	(0.07)	(0.12)
Sugar	0.133***	0.272***
	(0.02)	(0.04)
Sugar*Trader	-0.133*	-0.172
	(0.07)	(0.12)
Meat	0.211***	0.231***
	(0.02)	(0.04)
Meat*Trader	-0.211***	-0.051
	(0.08)	(0.11)
School Supplies	-0.136***	-0.035
	(0.01)	(0.03)
School*Trader	-0.087	0.060
	(0.07)	(0.11)
Airtime	-0.156***	-0.045
	(0.01)	(0.03)
Airtime*Trader	-0.078	0.090
	(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***	0.708***
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

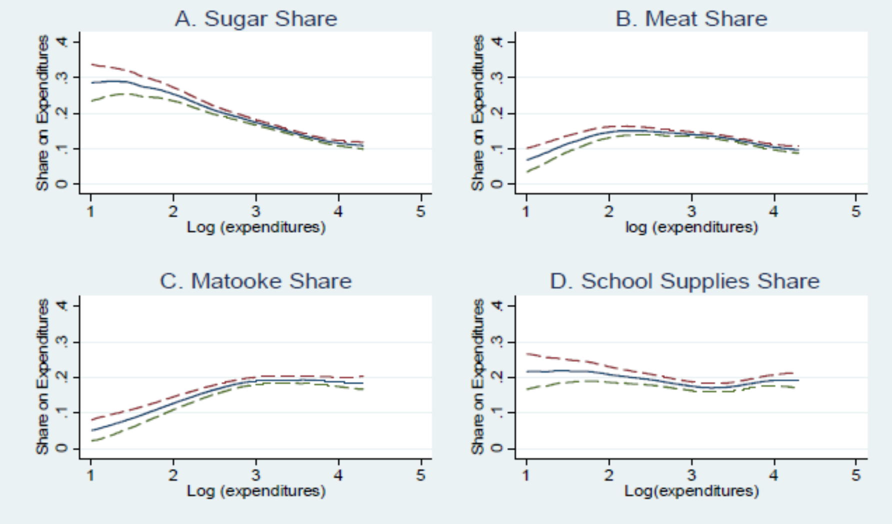
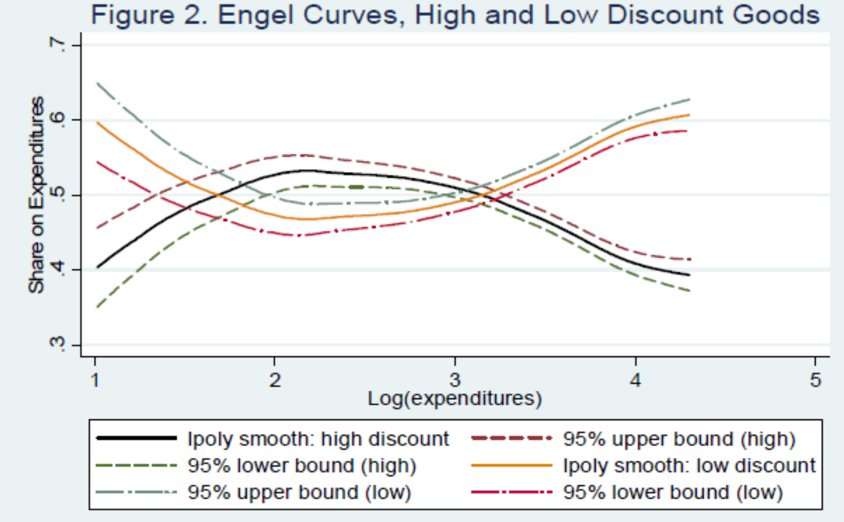


Figure 2. Engel Curves, High and Low Discount Goods



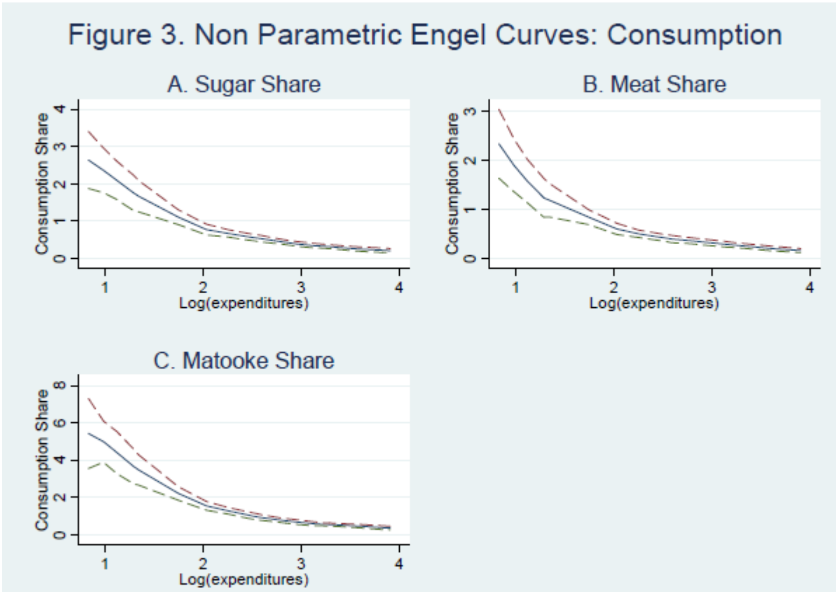


Figure 3. Non Parametric Engel Curves: Consumption
A. Sugar Share
B. Meat Share
C. Matooke Share
Consumption Share
Log(expenditures)

Appendix A. Instructions and Tasks.

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 no payment was received 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 in 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. Column (3) shows the units of the good. Column (4) presents the category for the magnitude of the goods involved in the choices: Small means 2 units of the good in the early choice, and Large, 6 units for almost all goods, Equal Value: is for an early choice with approximate value of 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 early choice for each good and each magnitude. 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.

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. 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. Column (3) shows the units of the good. Column (4) presents the category for the magnitude of the goods involved in the choices: Small and Large represent the lower and higher value of the early choice, respectively. All "Small" choices were of equal value (approximately 3,000 Ush) across goods, and the same for "Large" choices. Column (5) presents the early choice for each good and each magnitude. 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

Questions about Risk Choices from First Survey.

Table A3: Parameters for Risk Choices.

	You keep	You invest	No matter what happens, 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?"

Table A4: Parameters for Risk Choices. Second Lottery

	You keep	You invest	No matter what happens, 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	3000 Ush	0 Ush	3000 Ush	2.5 X 0 Ush = 0 Ush	0 Ush	3000 Ush all the time
2	2500 Ush	500 Ush	2500 Ush	2.5 X 500 Ush = 1250 Ush	0 Ush	3750 Ush ½ the time, 2500 Ush ½ the time
3	2000 Ush	1000 Ush	2000 Ush	2.5 X 1000 Ush = 2500 Ush	0 Ush	4500 Ush ½ the time, 2000 Ush ½ the time
4	1500 Ush	1500 Ush	1500 Ush	2.5 X 1500 Ush = 3750 Ush	0 Ush	5250 Ush ½ the time, 1500 Ush ½ the time
5	1000 Ush	2000 Ush	1000 Ush	2.5 X 2000 Ush = 5000 Ush	0 Ush	6000 Ush ½ the time, 1000 Ush ½ the time
6	500 Ush	2500 Ush	500 Ush	2.5 X 2500 Ush = 6750 Ush	0 Ush	6750 Ush ½ the time, 500 Ush ½ the time
7	0 Ush	3000 Ush	0 Ush	2.5 X 3000 Ush = 7500 Ush	0 Ush	7500 Ush ½ the time, 0 Ush ½ the time

Notes: the question asked was: "Let's say that you can invest up to 3000 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?"