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Time Discounting and Credit Market Access in a Large Scale Cash Transfer Program[1]

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Summary

Time preference, the weight that individuals give to future over current consumption, is a characteristic that is thought to influence decision-making in almost every sphere of life, including personal finances, diet, exercise, sexual behavior and the environment. In this article we provide evidence on whether a national poverty alleviation program in Kenya can affect inter-temporal decisions. We administered a preferences module as part of a large-scale impact evaluation of the Kenyan Government's Cash Transfer for Orphans and Vulnerable Children. Four years into the program we find that individuals randomized to the treatment group are only marginally more likely to wait for future money. However among the poorest households for whom the value of transfer is still relatively large we find significant program effects on the propensity to wait. We also find strong program effects among those who have access to credit markets and are thus less liquidity constrained to begin with, though the program itself does not improve access to credit. The results demonstrate a unique and potentially powerful way in which large-scale unconditional cash transfers can contribute to economic development in Africa. And the external validity of the results is likely high given the similarity of the Kenyan program to other national programs in the region.

Keywords: Time preference, credit constraints, cash transfers, Kenya

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1. Introduction

Time preference, the relative importance individuals give to present versus future consumption, is a topic that has long captured the interest of economists, sparked by the belief that the time preference parameter is a crucial determinant of a wide range of decisions in virtually every sphere imaginable, from risky sex to entrepreneurship, human capital investment and even obesity. The study of time preference has a long history in psychology where it is linked to self-control and emotional states (Damasio 1994; Bechara and Damasio 1997). In economics on the other hand the origins of time preference can be traced back to models of savings, growth and development (Rae 1905; Samuelson 1937; Smith 1776). More recently economists have begun to use both laboratory and small scale field experiments to understand whether time preference affects financial decisions and the role of income or wealth in determining inter-temporal choice. This paper contributes to this literature by evaluating the impact of a large national cash transfer program on inter-temporal choice using a field survey in which households were randomly assigned to treatment or delayed entry control status. The fact that our results are derived from an actual program which currently reaches 170,000 households in Kenya and is similar in design features to many other such programs in the region implies a degree of external validity which distinguishes this study from previous work that relates economic circumstances to time preference.

In the face of perfect capital markets the individual marginal rate of substitution for present over future consumption should converge to the market interest rate. However in developing countries such markets are far from perfect and so differences in marginal rates of substitution can persist even if preferences are the same. Moreover the empirical literature suggests that the individual discount rate itself, that is, the preference parameter that determines an individual's own marginal rate of substitution, may vary for a variety of reasons beyond simple liquidity constraints (Bradford et al 2014). For example there is evidence that the discount rate is affected by age (Handa et al 2014b), gender (Harrison et al. 2009), education (Perez-Arce, 2011), health (Handa et al 2014a), marital status (Bradford 2010) and even household size (Holden et al. 1998). The economics literature has been particularly interested in the role of income or wealth in determining inter-temporal choice and

many analyses show that the poor discount more than the rich in both developed (Hausman, 1979; Lawrence, 1991; Harrison et al, 2002) as well as in developing countries (Pender and Walker, 1990; Yesuf and Bluffstone, 2008; Carvalho, 2010; Holden, 2013). Nonetheless, not all scholars agree on this conclusion. For example, Ogaki and Atkeson (1997) argue that wealth and the discount rate are not correlated while Haushofer et al (2013) sustain that only income *changes* matter--a negative shock has a significant impact on people's time discounting shifting preferences toward present gratification but a positive shock does not have the opposite effect. Similarly, using randomized data from Vietnam, Tanaka et al (2010) report that a whether shock - leading to an income loss - provokes an increase of discount rates while in rural Ethiopia, di Falco et al (2011) find that people living in areas affected by drought discount more than others. Finally, Holden (2013) shows that negative income shocks provoke an increase of discount rates ranging between 40 and 50 per cent. In contrast, Harrison et al. (2005) report that the discount rate decreased for Danish people reporting improvement in their economic conditions while Giné et al. (2013) do not find any relationship between shocks – proxied by a death of family members or an income shocks - and inter temporal choices though the size of their shock; Meier and Sprenger (2010) report a similar result for the US.

A crucial question is why poverty conditions or negative income shocks lead individuals toward present gratification. According to one strand of the literature, the relationship between economic conditions and time preferences is mediated by neurobiological and psychological factors. In particular, poverty status could limit cognitive functions (Shah et al, 2012; Mani et al 2013) or augment stress leading people toward bad decisions (Chemin et al 2013; Cornelisse et al. 2013).[2] Another explanation is that the poor discount more than the rich just because they cannot afford to do differently (Duflo, 2003). Indeed, since marginal rates of substitution should not vary across the population under perfect capital markets, the role of credit constraints is considered to be a key factor determining inter-temporal choice in developing countries, explaining the higher propensity to choose present over future consumption among the poor in particular (Holden et al. 1998; Yesuf and Bluffstone, 2008; Carvalho et al. 2014; Dean and Sautmann, 2014). Morduch (1990) shows that among poor rural farmers in India, consumption changes are mainly driven by

[2] On the other hand, Handa et al (2013) show that a positive income shock increased subjective wellbeing which lead to a reduction of time discounting.

variation in current income. Similarly, Karlan and Zinman (2008) and Berg (2012) show that consumption jumped when poor elderly received a basic pensions in South Africa.

While there may be some deficit in the cognitive process affecting preferences of the poor (Bertrand et al. 2004), the evidence cited above support the idea that a major issue concerns the environment where poor live and in which they process decisions about consumption and/or investment, opening up the policy space for interventions to influence inter-temporal choice behavior. Indeed, Banerjee et al (2013) report evidence in this regard using randomized data from India, showing that women experiencing access to microcredit increase expenditure on durable goods and reduce expenditure on items associated with instantaneous utility. Studying the impact of an unconditional cash transfer targeted to poor people living in rural Kenya, Haushofer and Shapiro (2013) show that people receiving a lump sum are more inclined to invest in durable goods while those benefitting from monthly transfers are present biased (i.e. are credit and saving constrained). Handa et al (2013) find that an unconditional cash transfer program implemented in Zambia increases the propensity to wait for future money.

Building on the literature addressing the link between economic circumstances and inter-temporal choice, we investigate the impact of the Kenya Cash Transfer for Orphans and Vulnerable Children (CT-OVC) on beneficiaries' time discounting using data that was collected for the evaluation of the CT-OVC, currently the Kenyan Governments largest poverty alleviation program. A special module on preferences and expectations was administered during the 3rd wave of the evaluation to approximately 1800 respondents, one-third of who were randomly assigned to a delayed entry control arm. In a companion paper (Handa 2014a), we present evidence on the experience in implementing these hypothetical and probabilistic questions in a large scale field survey in a poor population and show that the responses have high internal consistency indicating that respondents understood the questions. Building on this work, and given the importance given in the literature to wealth and credit constraints in determining inter-temporal choice, the aim of this paper is to investigate the interaction between receipt of the transfer and the position of individuals in the credit market. The cash transfer could influence time discounting by alleviating credit constraints and thus allowing beneficiaries to save and plan for

the future. Alternatively an individual's credit market position may itself be unaffected by the program but may act as a moderator, leading to a heterogeneous treatment effect whereby access to credit plus the additional cash available from the program together lead people to be more patient.

The paper thus contributes to the existing literature in several ways. Firstly, it provides evidence about the role of credit constraints in determining time discounting. Secondly, it is one of the few papers that investigate the impact of a cash transfer program on time discounting and how that impact varies by the beneficiary's credit market position. Finally, it is only one of two studies to investigate these questions within the context of a large scale national cash transfer program, thus contributing directly to the public policy literature on how poverty alleviation programs may affect time preference.

2. The Kenya CT-OVC

The Kenya CT-OVC currently reaches 170,000 households and over 300,000 OVC across the country as of mid-2013. The program began as a pilot in 2004 with technical assistance from UNICEF, and was subsequently integrated into the national budget and began phased expansion in 2007. The objective of the program is to provide regular cash transfers to families living with orphans and vulnerable children (OVC) to encourage fostering and retention of children and to promote their human capital development. Eligible households, those who are ultra-poor (poorest 20 percent) and contain an OVC, receive a flat monthly transfer of $25 (U.S.) (KES2000). An OVC is defined as a household resident between 0 to17 years old with at least one deceased parent, or who is chronically ill, or whose main caregiver is chronically ill. Beneficiary households are informed that, in exchange for the cash payment, the care and protection of the resident OVC is their responsibility though there are no punitive sanctions for noncompliance with this responsibility.

Targeting of households for the program is conducted in three stages. In stage one each Location (a Location is the fourth administrative level below province, district and division) forms an OVC Committee (LOC) that prepares a list of all potentially eligible households in the Location that meet the demographic and poverty criteria. In stage two, the list of eligible households is sent to the program's central office

(located within the Ministry of Gender, Children and Social Development), which then administers a detailed socioeconomic questionnaire to assess poverty and confirm eligibility in order to rank households. The final number of households that enters the program in each district depends on funding to that district, but approximately 20 percent of the poorest households in each Location are enrolled in the program. In cases where more households meet the eligibility criteria than funds are available, households are prioritized with child-headed households receiving the first priority (of which there are very few), followed by elderly-headed households. An evaluation of the targeting performance of the program reported very favorable targeting relative to other cash transfer programs across the developing world (Handa, Huang et al., 2012).

3. Data and study design

Impact evaluation design: Prior to program expansion of the CT-OVC in 2007, UNICEF designed a social experiment to track the impact of the program on a range of household welfare indicators including food security, child health, and schooling. The evaluation was contracted to Oxford Policy Management (OPM), and entailed a cluster randomized longitudinal design, with a baseline household survey conducted in 2007 and a 24-month follow-up in 2009. The ethical rationale for the design was that the program could not expand to all eligible Locations at the same time, so Locations whose entry would occur later in the expansion cycle could be used as control sites to measure impact. Thus within each of seven districts across the country (Kisumu, Homa Bay, Migori, Suba, Nairobi, Garissa, and Kwale), four Locations were identified as eligible, and two were randomized for immediate implementation and two were randomized for deferred expansion, serving as control Locations. Targeting of households was carried out in all Locations according to standard program operation guidelines, and from the eligibility lists a sample of households was drawn, two-thirds from intervention Locations and the remaining third from control sites. Sample size was based on power calculations for the key impact indicators of school enrollment and household consumption expenditures. Results from the impact evaluation have been reported by the Kenya CT-OVC Evaluation Team (2012a, b).

In 2011, we returned to the households in the original evaluation sample that had been re-interviewed in 2009 and administered the same household survey plus an

additional module covering preferences and expectations that was administered to the main respondent. Since this module was only administered in 2011, we do not have baseline information on these variables. The 2011 study was approved by the UNC IRB and the Kenya Medical Research Institute Ethics Review Committee.

Household attrition[3]: The initial study period coincided with a time of political turmoil in Kenya resulting from the disputed national elections in December 2007. Over 1000 people died and approximately 400,000 people were internally displaced at this time. Consequently, attrition between baseline and the first follow-up in 2009 was 17 percent and concentrated in Kisumu and Nairobi, the two Locations in the study that experienced the most election-related unrest. Attrition between the 2009 and 2011 rounds was only 5 percent. Table A1 in Appendix 1 shows means of selected demographic and poverty measures for households in each arm across the three waves. Means for these indicators were stable across the three waves despite the relatively high attrition rate between 2007 and 2009, indicating that the representativeness of the sample remained intact.

To further explore the potential for selective attrition we estimated the probability of attriting between 2007 and 2009 using baseline values for the variables reported in Table 1. The only statistically significant variables out of the 26 total variables in this regression were the indicators for Kisumu and Nairobi, the number of residents age 12-17, (log of) household size and unprotected water source. The probability of attriting was 19 and 9 percentage points higher for households in Nairobi and Kisumu respectively (relative to the reference), while households in the intervention group were 8 points less likely to be lost at follow-up relative to the control group. To assess whether there was any *differential* determinant of attrition between the two groups we re-estimated this model interacting each regressor with the indicator for intervention status. In only two cases (out of a possible 26) was there a statistically significant interaction effect (the indicator for residence in Kwale, and the number of residents age 6-11). Based on the stability of characteristics in each arm across the waves, the fact that the two most important determinants of attrition stem from residence in Kisumu and Nairobi, which were disproportionately affected by the election violence relative to other study sites, and the minimal differences in the determinants of

[3] This section is based on Handa (2014a).

attrition across arms, we believe that selective attrition is not a concern in the subsequent analysis. The results on the determinants of attrition are available from the authors upon request and are also reported in Handa et al. (2014a).

Baseline balance: The figures in bold in Table A1 (see Appendix 1) indicate statistical significance between intervention and control arms of the study in each wave. The poverty-related variables are balanced across arms in each wave, but there are statistically significant differences in the age, sex and schooling levels of household heads across arms. This is due to the prioritization process that occurred at the central Ministry because the number of households on the list exceeded the budget. Due to the small number of child-headed households, the prioritization process effectively gave the most weight to elderly-headed households. Since the final prioritization process was not conducted in control Locations, households in the control arm of the study were drawn from a slightly larger eligibility list than those from the intervention arm resulting in the differences in heads' characteristics observed in Table A1 (see Appendix 1). It is important to note that there is no element of self-selection into the program; household eligibility was completely supply-driven and take-up was universal.

4. Empirical strategy and measures

Empirical strategy: To measure the impact of the program on people's time preferences, we estimate the following regression model:

$$y_i = \alpha + \beta_1 T_h + \beta_2 X_i + \beta_3 X_h + \varepsilon_i \qquad (1)$$

where *y* defines individual time discounting, T the treatment status and X a set of control variables measured at both the individual (*i*) and household (*h*) level. The preferences module was administered to the main respondent of the household and there are small differences across study arms due to the prioritization process of the CT-OVC driven by an inability to serve everyone on the initial eligibility lists (see above). To control for these differences we re-weight the control group sample using the method of inverse probability weighting (IPW), which entails estimating the probability of being in the treatment group using a set of covariates measured at baseline, deriving the predicted probability and then weighting the control sample by

the inverse of this probability. Results of the estimating equation to derive the probabilities are shown in the Appendix 2, as is the distribution of predicted probabilities before and after weighting, which show that the two distributions become much more similar after applying the weights. Table 1 reports means of selected characteristics of the respondents to the preferences module by study arm and as can be seen in Column (3), once the weights are applied the characteristics of the individual respondents in the control group move towards those of the treatment group with only the difference in mean age being statistically significant. In equation (1) we continue to include a full set of control variables to absorb this and any other difference between the two groups. Given the supply-driven nature of program enrollment, the randomization to study arm, and the additional balance constructed through the IPW procedure, the internal validity of the results we present is strong.

[TABLE 1 HERE]

Inter temporal choice: In order to measure time preferences, we invited participants to carry out an inter-temporal choice task entailing a choice between an immediate versus a future payment. While the former was fixed at KES 1500, the one month future values were varied as follows: KES 1500, 3000, 4500, 7000 and 9000 (Figure 1) (note that the questions were not asked in this order, nor was any actual payment involved).[4] We also included a KES1250 option as a check to see if people understood the question. Based on these responses we build two variables to capture impatience: an ordinal variable ranging from 1 (will wait for KES 1250) to 7 (will never wait for any amount) and a dichotomous variable indicating people who are never willing to wait for money.

Figure 1 reports the percentage of participants willing to wait for each option of payments. As expected, the percentage of participant that is willing to wait rises as the future value of the payment increases. Moreover, a substantial proportion of participants switch their preference from immediate money to future payments at KES 3000. In particular, the share of people willing to wait one month increased from 26 per cent to near 79 per cent. Figure 1 also shows that more than 80 per cent of participants would wait one month for a future value of KES 9000. Lastly, it is interesting to observe

[4] All instruments used in this study are available at www.cpc.unc.edu/projects/transfer.

that about 16 per cent of people "always" prefer immediate money than future payments.

[FIGURE 1 HERE]

In previous work we have reported on the internal consistency of the responses as a way of assessing whether the respondents understood the question (Handa 2014a). Only 8 per cent of respondents report a 'double switch', where they are willing to delay at a specific amount and then later do not delay for a larger amount. About a third of these inconsistent respondents are those who would wait for less money. We exclude inconsistent respondents from our analysis but include those who would delay for less money, though results are not sensitive to the exclusion of this latter group.

Access to credit: In the 2011 survey we included a small set of questions on access to credit, capturing whether the household currently had any outstanding loans, whether they had sought a loan, and if they had not sought a loan, why not. We defined households as credit constrained if they had sought a loan and were rejected, or if they had not sought a loan for a reason that indicated they felt they could not obtain a loan (lack of collateral for example), or because they did not know where to go or how to get one (transaction cost constrained). As a result, about 1 out of 4 individuals in our sample are defined as having access to credit (are not credit constrained).

To see how credit constraints interact with receiving treatment and initial wealth we estimate the relationship between baseline per adult equivalent household consumption expenditure and the probability of being credit constrained using local linear regressions (lowess) by study arm. The relationship between credit constrained and wealth is surprisingly flat except for very low levels of consumption (below KES 1000) and treated households appear slightly more credit constrained than control households. Note that credit constraints are measured 4 years after program implementation so these results suggest there was no program impact on credit constraints of households. The relatively flat relationship in Figure 2 may be simply a function of the unique sample of households, all of whom are potentially eligible for the program and so are quite poor. Mean consumption in the sample is 60 US cents per person per day, and even the highest consumption levels depicted in the graph only represent $US2 per person per day.

[FIGURE 2 HERE]

To investigate more carefully the determinants of access to credit we estimate regressions using a set of individual and household level covariates and also include treatment status—results are shown in Table 2 using both OLS and probit specifications, both of which are weighted using the IPW. Having a partner in the household or being literate seem to be important determinants of credit access. In contrast, those living in larger households appear to be more credit constrained while individuals with a chronic illness are less so.

[TABLE 2 HERE]

If credit constraints are an important determinant of time preference we might expect to see a relationship between our measure of credit access and the inter-temporal choice task we administered. Table 3 confirms that people without credit constraints appear more inclined to wait for future money. At every value of future money except for KES1250 (which is lower than the instantaneous option of KES1500) those with access to credit appear significantly more likely to wait (IES).

[TABLE 3 HERE]

Mean comparisons between treated and control group: Beyond controlling for access to credit, the aim of this paper is to investigate the impact of the program on time discounting. Thus – as a first step – we compare the responses between participants in the program (treated group) and the others (control group) across the different payment options. As can be seen in Table 4, people in these two groups seem to respond in a similar way. The share of people willing to wait rises as the future value of the payment increases in both groups. A future value of KES 3000 represents a switch point in time preferences for people in the treated as well as for those in the control group. Overall, the mean differences between these two groups are smaller than five points and statistically significant only for future values KES 9000, 4500 (at 10 per cent) and 7000 (at 5 per cent).

[TABLE 4 HERE]

As before, we estimate local linear regressions to trace the relationship between propensity to wait and household wealth using (baseline) per adult equivalent household consumption. Figure 3 shows some evidence that even in this very poor sample, higher wealth is somewhat related to an increased propensity to wait for future money, and this pattern is stable across the two study arms. The proportion of households designated with access to credit is 22.5 percent in each arm.

[FIGURE 3 HERE]

We next check participant responses between treated and control group controlling for access to credit. As shown in Table 56, the mean differences are small and not statistically significant between treatment and control groups without access to credit. However differences are slightly larger between study arms among those having access to credit. Indeed, the mean differences are statistically significant for KES3000, KES 7000 (at 10 percent) and the ordinal indicator of impatience, an initial suggestion that the treatment effect may indeed depend on one's credit market position.

[TABLE 5 HERE]

5. Results

Full sample: Table 6 presents multiple regression estimates of the determinants of each of our 5 inter-temporal choice tasks. We also include estimates in the last 2 columns of the ordinal and dichotomous indicators for impatience described earlier. The first row of Table 6 indicates that beyond the threshold value of KES3000 individuals in the program display a 3-5 point higher likelihood of waiting for future money but this is statistically significant only for KES7000 and only at the 10 percent confidence level. Access to credit generally leads to a greater likelihood of waiting for future money, and less likelihood of never waiting no matter what the amount. Other results portray an interesting story about the determinants of inter-temporal decision-making. Literacy is strongly associated with delaying payment (by 8-9 points) while having a disability has an even stronger effect in the opposite direction, both intuitive results. In the Appendix 3, we show results for the full sample, including the 8 percent

of individuals who had inconsistent responses; results are similar to those shown in Table 6.

[TABLE 6 HERE]

Results by baseline consumption levels: The CT-OVC seems to have weakly positive effects on making people choose to wait for future money even after controlling for credit constraints. This may in part be due to the relatively low value of the transfer at the third round when the preferences module was fielded. At baseline the value of the transfer as a share of beneficiary consumption was 23 percent. With inflation its value eroded to 18 percent in 2009 down to 11 percent by 2011. Consistent with the drop in the real value of the transfer, the significant impacts of the program on consumption (Kenya CT-OVC Evaluation Team 2012a) had dissipated by 2011 (Romeo, Dewbre et al 2014). It could be then that the weak effects of the program reflect in part the erosion in the 'intensity of the treatment', the fact that the transfer does not represent a large enough increase in income to alleviate liquidity constraints and induce an impact on the propensity to wait for future money.

We test this hypothesis by estimating program impacts on the poorest 50 percent of our sample, among whom median daily consumption is 34 US cents per person per day and the transfer share is 22 percent of baseline consumption. Results in the top panel of Table 7 show that in fact the program impact is about twice as high on this set of individuals than it is in the full sample and several of the point estimates are now statistically significant. For example the program increases the likelihood of waiting for KES 4500 or 7000 by 8 percentage points and reduces the ordinal impatience score by 0.392 (Table 7). The association between credit access and waiting for future money is also twice as high among this sample and also now statistically significant in several instances.

[TABLE 7 HERE]

The bottom panel of Table 7 shows results for individuals in households with baseline adult equivalent consumption above the median for the sample. In contrast to the top panel of Table 8 here the program does not have any impact in delaying payment though access to credit does generally support individuals to delay payment,

particularly for KES 7000 and 9000 and credit access significantly reduces the likelihood of never choosing to delay at any payment level.

Heterogeneous treatment effects by credit access: Earlier we showed that there is no program effect on credit access hence this variable is not on the causal pathway between the cash transfer and the propensity to wait for future money. Moreover program effects are stronger among the poorest households for whom the transfer is larger as a proportion of baseline consumption and this group is also slightly more credit constrained than richer households (21 versus 23 percent). If liquidity constraints in the face of imperfect capital markets affect inter-temporal choice and the cash transfer itself is not big enough to eliminate liquidity constraints, than the cash transfer combined with credit access may together be large enough to overcome liquidity constraints and lead to impact on the choice task. We test this hypothesis by interacting the treatment dummy with the credit access variable. Initial estimates showed no differential impact by credit access among the control group so we drop the dummy variable for credit access (which measures the difference among the control group) and estimate the following model:

$$y_i = \alpha + \beta_1 T_h + \beta_2 T_h * (Credit\ Access) + \beta_3 X_i + \beta_4 X_h + \varepsilon_i \qquad (2)$$

In this framework β_2 measures the differential treatment effect by credit access among the treated group only while the coefficient of the treatment dummy (β_1) measures the difference between the treated group without credit access and the entire control group. The constant term in this model shows the mean value of the dependent variable among the control group as a whole. Table 8 shows a significant heterogeneous treatment effect of the CT-OVC by credit access on the order of 6 percentage points with slightly larger effect sizes for larger values of future money. Moreover the difference between the treated group without credit access and the control group, given by the coefficient of treatment dummy, is not significantly different. The two bottom panels of Table 8 show results by baseline adult equivalent consumption. These reveal that in fact for both groups, there is a positive treatment effect on the propensity to wait for future money in the presence of credit access with effect sizes of roughly equal magnitude. It seems then that the combination of the increased cash from the CT-OVC program and increased access to liquidity through

the credit market work together to affect inter-temporal choice leading individuals to be more willing to wait for future money.

[TABLE 8 HERE]

Using the model based on propensity to wait for KES7000 we show the predicted probabilities of waiting for those with and without credit access among the treated group by baseline consumption. The program effect is about 6 points larger on average among those with credit access, but increases to almost 10 points at the top of the consumption distribution, presumably where liquidity constraints are least binding.

[FIGURE 4 HERE]

6. Discussion and Conclusions

Liquidity constraints due in part to lack of access to credit are a major barrier to consumption smoothing and investment in developing countries (Bardhan and Udry, 1999; Ghosh et al 2000; Rosenzweig and Wolpin 1993). Median consumption among households eligible for the Kenyan government's largest poverty alleviation program is 60 cents per day and 77 percent are credit constrained. Program participation had an important initial impact on consumption, but this impact dissipated by the fourth year as the value of the transfer eroded with inflation (Kenya CT-OVC Evaluation Team 2012a). Our analysis of the link between program participation and inter-temporal choice shows that the program has only a weak positive impact on the propensity to wait for future money after four years. However this impact doubles in magnitude among the very poorest for whom the transfer still represents a relatively large portion of total consumption, suggesting that the transfer helps alleviate liquidity constraints and allows individuals to place more weight on the future. And when we focus on individuals that are not credit constrained, we find large and statistically significant impacts of the program compared to households that are credit constrained. Among those with credit access the program increases the propensity to wait for KES3000 or more by 6 percentage points, and reduces the likelihood of never waiting for any sum of money by the same magnitude. Our interpretation of this effect is that the combination of the transfer and credit access is enough to relax the liquidity constraint for individuals and allows them to place more weight on the future.

Have we identified an actual change in time preference? The literature in this field distinguishes between time preference (the preference for current versus future utility as embodied in the utility function) and time discounting, which refers to any reason for caring less about the future (Frederick, et al 2002), including time preference (the shape of the utility function), emotions and liquidity constraints. We have established that program participants are more willing to wait for future money after controlling for liquidity constraints, and that impacts are larger among those who are likely to be less constrained. And given the rigorous study design, a cluster randomized trial to evaluate the CT-OVC, we have been able to account for other major factors that determine inter-temporal choice. However without imposing a structural behavioral model on the data we cannot provide further evidence on the degree to which our results represent a change in underlying preferences. What we can say is that a major national unconditional cash transfer program contributes significantly to inducing beneficiaries to be more future oriented in financial decisions.

Our results support the existing evidence that economic conditions or wealth affect inter-temporal choice though our study differs from the previous literature in that it is based on a large field study rather than a small laboratory or field experiment and thus has greater external validity. However the results reported here are probably most exciting from a policy perspective, taken as they are from a rigorous impact evaluation of the Kenyan government's largest poverty alleviation program. They imply that rather than any deficit in cognitive functioning, the way poor people perceive and discount their future is influenced by their environment and it is possible to promote forward looking decision-making by modifying these conditions through public policy. The Kenya CT-OVC has been shown to break the transmission of poverty across generations by promoting physical and human capital accumulation (Kenya CT-OVC Evaluation Team 2012b; Asfaw et al 2014). Those results, together with the ones presented in this paper suggest that an unconditional poverty targeted cash transfer program implemented on a large scale can contribute to economic development in multiple ways, supporting social and economic protection on the one hand and forward-looking decision-making on the other.

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Table 1: Mean characteristics of respondents of behavioral module

	T	C (unweighted)	C (weighted)	p-value difference (1) vs. (3)
	(1)	(2)	(3)	(4)
Age in years	57.3	49.2	59.1	0.03
Female	79.3	72.2	77.3	0.57
Partner in household	34.5	40.4	33.5	0.68
Can read	29.9	44.0	29.9	0.91
Chronically ill (baseline)[1]	14.9	14.1	17.8	0.14
Disabled (baseline)[1]	6.3	4.0	6.3	0.98
N	1280	525	525	

1/ Self-reported. Estimates in column (3) weighted by inverse probability weight.

Table 2: Determinants of the access to the credit

	OLS	Probit
	(1)	(2)
T	-0.00315	-0.0339
	(-0.16)	(-0.50)
Age 25-59 years	-0.0386	-0.133
	(-0.68)	(-0.74)
Age 60+ years	-0.0813	-0.298
	(-1.41)	(-1.61)
Female	0.0421	0.135
	(1.52)	(1.40)
Has partner	**0.0667**	**0.250**
	(2.72)	(3.04)
Can read	**0.0635**	**0.187**
	(2.53)	(2.31)
Has chronic illness	**0.0534**	**0.173**
	(1.99)	(1.97)
Disabled	-0.00452	-0.0101
	(-0.11)	(-0.07)
Log consumption	0.0170	0.0701
	(0.89)	(1.07)
Cattle	-0.00383	-0.0203
	(-1.21)	(-1.36)
Goats	-0.00103	-0.0100
	(-0.76)	(-1.04)
Sheep	0.00216	0.0236
	(0.60)	(1.24)
Poultry	0.00227	0.00803
	(1.54)	(1.63)
log household size	**-0.0635**	**-0.202**
	(-2.58)	(-2.44)
Rural	-0.0326	-0.152
	(-0.70)	(-0.84)
Observations	1,804	1,804
R-squared	0.043	

Notes: Coefficients or probit marginal effects reported with t-statistics in parentheses. Also included in model but not reported are indicators for district. Coefficients in bold are statistically significant at 10 percent.

Table 3: Mean differences in per cent willing to wait by study arm and amount

Is willing to wait one month for KES:	**no access to credit**	**access to credit**	p-value difference in means
1250	18.30	19.01	0.742
1500	25.25	30.28	0.046
3000	77.07	84.50	0.000
4500	79.75	86.38	0.001
7000	81.28	88.97	0.000
9000	81.35	89.44	0.000
Impatient: Ordinal	3.27	2.94	0.001
Impatient: Dichotomous	17.58	9.86	0.000
N	1378	426	1804

Table 4: Mean differences in per cent willing to wait by study arm and amount

Is willing to wait one month for KES:	**T**	**C**	p-value difference in means
1250	19.1	19.5	0.84
1500	26.4	26.3	0.96
3000	78.4	75.0	0.13
4500	81.1	77.5	0.09
7000	83.1	78.7	0.03
9000	83.1	79.6	0.09
Impatient: Ordinal	3.2	3.3	0.14
Impatient: Dichotomous	16.0	19.2	0.11
N	1280	525	

Control group mean weighted using the Inverse Probability Weight

Table 5: Mean differences in per cent willing to wait by study arm and amount

	Not having access to credit			**Access to credit**		
Is willing to wait one month for KES:	**C**	**T**	p-value difference in means	**C**	**T**	p-value difference in means
1250	21.98	19.07	0.237	11.16	19.1	0.026
1500	25.77	25.60	0.95	28.36	29.17	0.863
3000	74.99	76.71	0.505	74.80	84.03	0.032
4500	76.71	79.74	0.227	80.15	85.76	0.159
7000	77.51	81.35	0.119	82.79	89.24	0.083
9000	77.95	81.35	0.165	85.17	89.24	0.252
Impatient: Ordinal	3.34	3.25	0.471	3.34	2.97	0.046
Impatient: Dichotomous	20.64	17.64	0.21	14.34	10.42	0.262
N	386	992	1378	138	238	426

Control group mean weighted using the Inverse Probability Weight

Table 6: Determinants of Propensity to Wait for Future Money

	Is willing to wait one month for KES:					Impatience	
	9000	7000	4500	3000	1500	Ordinal[1]	Dichotomous[2]
	(1)	(2)	(3)	(4)	(5)	(7)	(9)
T	0.0320	**0.0459**	0.0434	0.0471	-0.00257	-0.176	-0.0320
	(1.17)	(1.65)	(1.52)	(1.60)	(-0.09)	(-1.31)	(-1.17)
Access to credit	**0.0603**	0.0484	0.0357	0.0196	0.0272	-0.157	**-0.0603**
	(1.88)	(1.44)	(1.02)	(0.52)	(0.71)	(-0.99)	(-1.88)
Age 25-59 years	0.0522	0.0483	0.0960	0.0656	0.0608	-0.414	-0.0522
	(0.89)	(0.82)	(1.51)	(1.03)	(0.96)	(-1.53)	(-0.89)
Age 60+ years	0.0161	0.00997	0.0670	0.0461	0.0643	-0.311	-0.0161
	(0.27)	(0.16)	(1.02)	(0.70)	(0.96)	(-1.09)	(-0.27)
Female	0.0351	0.0294	0.0236	0.0339	-0.0581	-0.00586	-0.0351
	(0.80)	(0.68)	(0.53)	(0.77)	(-1.40)	(-0.03)	(-0.80)
Has partner	-0.0174	-0.0208	-0.0307	-0.0273	**-0.0923**	0.228	0.0174
	(-0.53)	(-0.61)	(-0.85)	(-0.75)	(-2.43)	(1.40)	(0.53)
Can read	**0.0834**	**0.0887**	**0.0874**	**0.0944**	0.0493	**-0.445**	**-0.0834**
	(2.49)	(2.64)	(2.56)	(2.67)	(1.27)	(-2.67)	(-2.49)
Has chronic illness	-0.00789	-0.000595	0.0123	0.0300	0.00887	-0.0335	0.00789
	(-0.18)	(-0.01)	(0.28)	(0.67)	(0.19)	(-0.16)	(0.18)
Disabled	**-0.163**	**-0.155**	**-0.150**	-0.145	-0.0932	**0.766**	**0.163**
	(-1.85)	(-1.77)	(-1.70)	(-1.62)	(-1.57)	(1.89)	(1.85)
Rural	0.0603	0.0557	0.0721	0.0890	0.0784	-0.396	-0.0603
	(0.89)	(0.83)	(1.08)	(1.37)	(1.41)	(-1.22)	(-0.89)
Log consumption	-0.00786	-0.00219	0.00510	0.00735	0.0280	-0.0268	0.00786
	(-0.32)	(-0.09)	(0.20)	(0.28)	(0.91)	(-0.22)	(0.32)
Observations	1,664	1,664	1,664	1,664	1,664	1,664	1,664
R-squared	0.084	0.081	0.077	0.087	0.065	0.084	0.084

Notes: OLS regressions with robust standard errors and inverse probability weights; inconsistent responses excluded. Also included in model but not reported are indicators for district, log household size, number of residents in each of six age categories, quality of roof, floor, walls, toilet facility, type of cooking fuel used, electricity, and crowding index. Coefficients in bold are statistically significant at 10 percent. 1/ Higher values indicate that individual needs increasingly higher amount of money to wait. 2/ Will never wait for any amount offered.

Table 7: Determinants of Propensity to Wait for Future Money by Baseline Consumption

	Is willing to wait one month for KES:					Impatience	
	9000	7000	4500	3000	1500	Ordinal[1]	Dichotomous[2]
	(1)	(2)	(3)	(4)	(5)	(7)	(9)
			Below median consumption				
T	0.0601	**0.0772**	**0.075**	**0.0746**	0.0534	**-0.392**	-0.0601
	(1.51)	(1.88)	(1.79)	(1.74)	(1.43)	(-2.10)	(-1.51)
Access to credit	**0.0851**	0.0697	0.0688	0.0436	**0.121**	**-0.43**	**-0.0851**
	(1.93)	(1.45)	(1.42)	(0.84)	(2.57)	(-2.02)	(-1.93)
Observations	824	824	824	824	824	824	824
R-squared	0.123	0.117	0.109	0.120	0.076	0.112	0.123
			Above median consumption				
T	-0.00556	0.00709	0.00696	0.0128	**-0.0582**	0.0691	0.00556
	(-0.22)	(0.27)	(0.26)	(0.45)	(-1.81)	(0.53)	(0.22)
Access to credit	**0.0586**	0.0489	0.0249	0.0196	-0.0173	-0.0703	**-0.0586**
	(1.97)	(1.62)	(0.80)	(0.60)	(-0.46)	(-0.47)	(-1.97)
Observations	841	841	841	841	841	841	841
R-squared	0.131	0.129	0.125	0.131	0.115	0.133	0.131

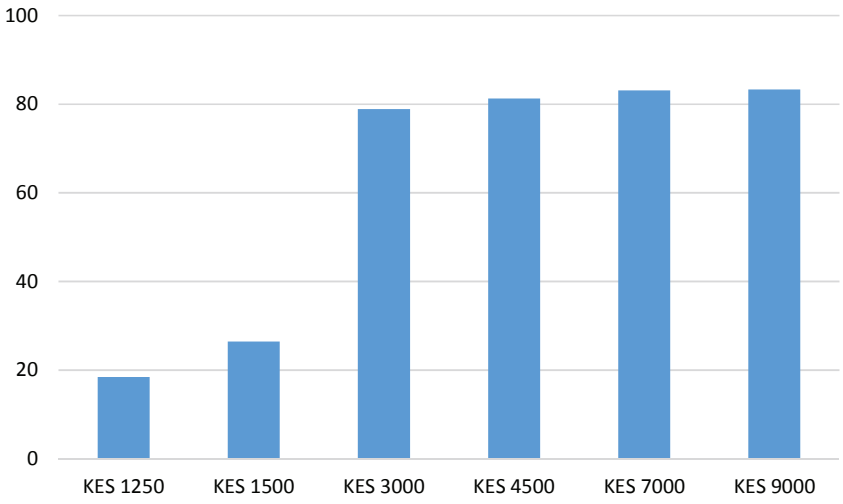
Notes: OLS regressions with robust standard errors and inverse probability weights; inconsistent responses excluded. Also included in model but not reported are indicators for Age 25-59 years, Age 60+ years, Female, Has partner, Can read, Has chronic illness, Disabled, Rural, Log consumption as well as indicators for district, log household size, number of residents in each of six age categories, quality of roof, floor, walls, toilet facility, type of cooking fuel used, electricity, and crowding index. Coefficients in bold are statistically significant at 10 percent. 1/ Higher values indicate that individual needs increasingly higher amount of money to wait. 2/ Will never wait for any amount offered.

Table 8: Interaction of treatment status and credit access on propensity to wait for future money

	Is willing to wait one month for KES:					Impatience	
	9000	7000	4500	3000	1500	Ordinal[1]	Dichotomous[2]
	(1)	(2)	(3)	(4)	(5)	(6)	(8)
T	0.0180	0.0324	0.0325	0.0352	-0.0112	-0.116	-0.0180
	(0.63)	(1.11)	(1.10)	(1.15)	(-0.36)	(-0.83)	(-0.63)
T*access to credit	**0.0594**	**0.0578**	**0.0463**	**0.0513**	0.0368	**-0.259**	**-0.0594**
	(2.50)	(2.43)	(1.79)	(1.87)	(1.10)	(-2.09)	(-2.50)
Constant	**0.548**	**0.506**	0.292	0.231	-0.131	**5.394**	**0.452**
	(2.54)	(2.26)	(1.25)	(0.96)	(-0.51)	(5.11)	(2.09)
Observations	1,664	1,664	1,664	1,664	1,664	1,664	1,664
R-squared	0.082	0.081	0.077	0.088	0.064	0.084	0.082
			Below median consumption				
T	0.0438	0.0621	0.0634	0.0620	0.0288	-0.294	-0.0438
	(1.05)	(1.45)	(1.45)	(1.39)	(0.73)	(-1.50)	(-1.05)
T*access to credit	**0.0663**	**0.0625**	0.0469	0.0541	**0.101**	**-0.405**	**-0.0663**
	(1.83)	(1.72)	(1.21)	(1.32)	(2.05)	(-2.19)	(-1.83)
Constant	**0.969**	**0.901**	0.67	**0.846**	0.0226	**3.22**	0.0314
	(2.38)	(2.12)	(1.55)	(1.86)	(0.05)	(1.64)	(0.08)
Observations	824	824	824	824	824	824	824
R-squared	0.118	0.114	0.105	0.119	0.068	0.108	0.118
			Above median consumption				
T	-0.0204	-0.00776	-0.00618	-0.00113	-0.0558	0.115	0.0204
	(-0.59)	(-0.22)	(-0.17)	(-0.03)	(-1.26)	(0.64)	(0.59)
T*access to credit	**0.0641**	**0.0636**	0.0556	0.0585	-0.0106	-0.195	**-0.0641**
	(1.87)	(1.85)	(1.52)	(1.50)	(-0.23)	(-1.13)	(-1.87)
Constant	0.359	0.276	-0.0692	-0.377	**1.021**	**5.102**	0.641
	(0.87)	(0.65)	(-0.15)	(-0.78)	(1.67)	(2.33)	(1.55)
Observations	841	841	841	841	841	841	841
R-squared	0.129	0.129	0.126	0.133	0.114	0.134	0.129

Notes: OLS regressions with robust standard errors and inverse probability weights; inconsistent responses excluded. Also included in model but not reported are indicators for Age 25-59 years, Age 60+ years, Female, Has partner, Can read, Has chronic illness, Disabled, Rural, Log consumption as well as indicators for district, log household size, number of residents in each of six age categories, quality of roof, floor, walls, toilet facility, type of cooking fuel used, electricity, and crowding index. Coefficients in bold are statistically significant at 10 percent. 1/ Higher values indicate that individual needs increasingly higher amount of money to wait. 2/ Will never wait for any amount offered.

Figure 1: Percent who will wait one month by future value



Note: the specific question was: "Suppose that you suddenly win money in the Lotto. If you could choose between these payment options which do you choose?"

Figure 2: Relationship between household wealth and the probability of being credit constrained, by study arm

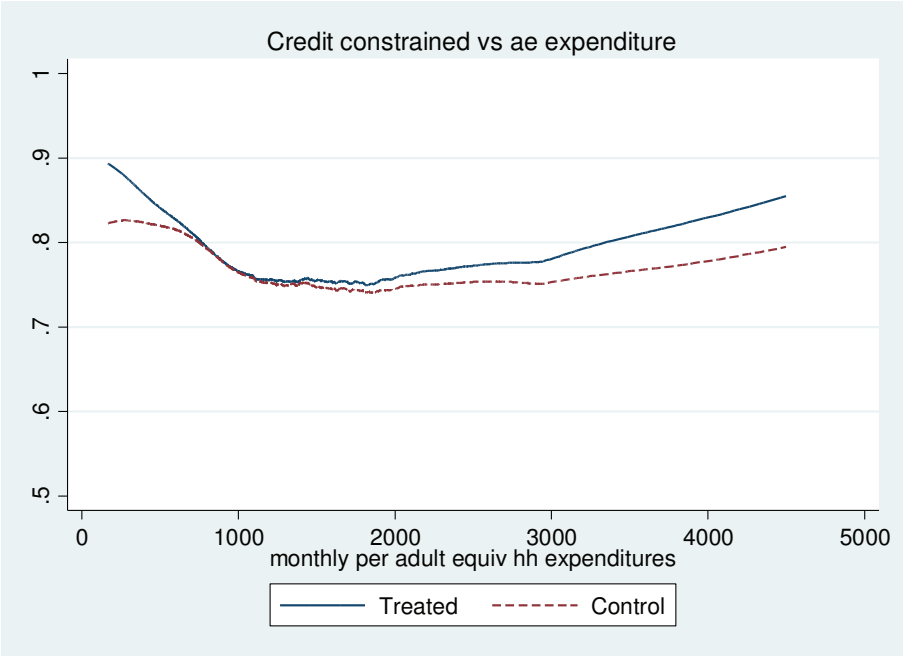


Figure 3: Relationship between time preference and household wealth, by study arm

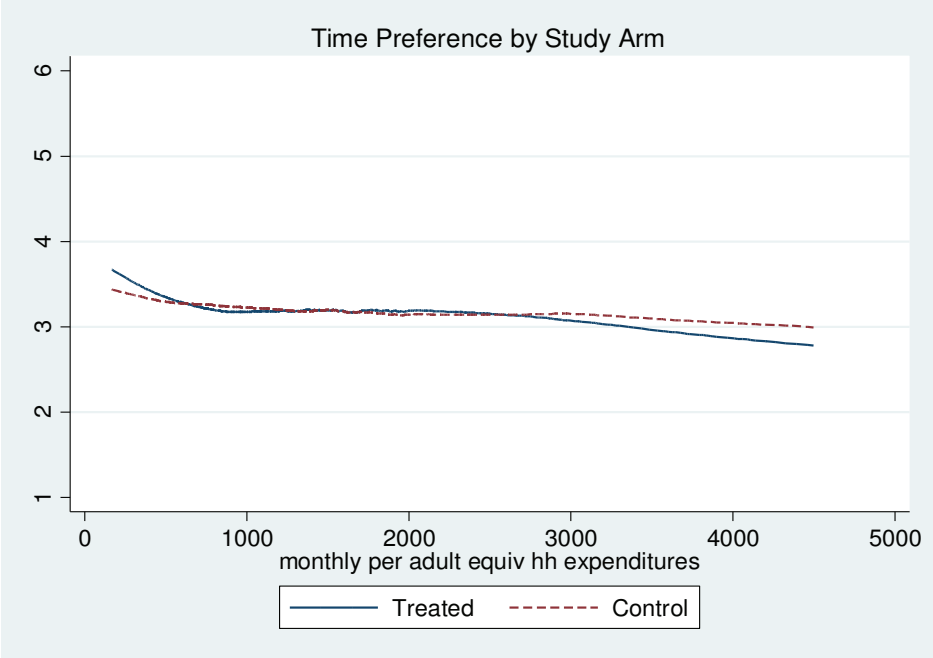
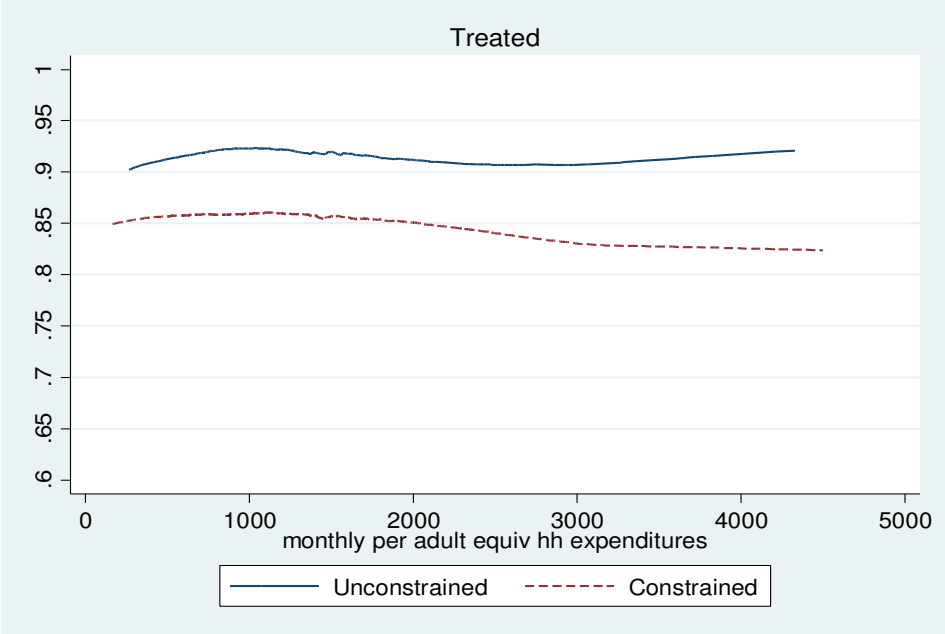


Figure 4: Probabilities of waiting for those with and without credit access among the treated group by baseline consumption



Appendix 1

Table A1: Household characteristics by wave and intervention status in the CT-OVC Evaluation Sample

Sample:	2007		2009		2011	
	T	C	T	C	T	C
Demographics						
Household size	5.48	5.79	5.54	5.81	5.53	5.82
Residents 0-5 years	0.66	**0.86**	0.68	0.85	0.67	**0.86**
Residents 6-11 years	1.21	**1.33**	1.23	1.32	1.23	1.31
Residents 12-17 years	1.40	1.38	1.40	1.39	1.40	1.40
Residents 18-45 years	1.12	**1.45**	1.13	**1.46**	1.13	**1.46**
Residents 46-64 years	0.59	**0.36**	0.60	**0.37**	0.60	**0.38**
Residents 65+ years	0.51	0.42	0.50	0.41	0.51	0.41
Female head	0.65	**0.57**	0.65	**0.59**	0.65	**0.59**
Age of head in years	62.34	**56.06**	62.21	**56.20**	62.55	**56.55**
Head not completed primary	0.53	**0.38**	0.53	**0.38**	0.53	**0.38**
Poverty						
Per adult equiv. monthly exp. (Ks)	1533.30	1501.25	1541.77	1459.94	1550.14	1441.99
Walls of mud/dung/grass/sticks	0.75	0.84	0.75	0.86	0.74	0.87
Roof of mud/dung/grass/sticks	0.23	0.22	0.23	0.23	0.22	0.22
Floor of mud/dung	0.66	0.74	0.65	0.77	0.66	0.79
No toilet	0.55	0.56	0.55	0.56	0.54	0.56
Unprotected water source	0.62	0.68	0.61	0.70	0.61	0.70
Region						
Garissa	0.10	0.06	0.11	0.06	0.09	0.05
Homa Bay	0.12	0.13	0.12	0.13	0.12	0.14
Kisumu	0.18	0.23	0.18	0.22	0.18	0.22
Kwale	0.08	0.09	0.08	0.10	0.08	0.11
Migori	0.23	0.23	0.22	0.25	0.22	0.26
Nairobi	0.13	0.10	0.13	0.07	0.13	0.06
Suba	0.15	0.16	0.16	0.16	0.17	0.17
N	1540	754	1325	583	1266	545

Statistically significant (at 10%) differences of t-test between Treatment (T) and Control (C) within each wave shown in bold. Thirty-three new households at follow-up not included in table.

Appendix 2

Table A2: Probit estimates of probability of being in treatment group

	Marginal Effect	Std. Error
Female	0.0413	0.0312
Partner in household	-0.0262	0.0283
Able to read	-0.0246	0.0277
Chronic illness	-0.00150	0.0325
Disabled	0.0729	0.0418
Rural area	**0.242**	0.0594
Per capita consumption (x10000)	-0.0111	0.027
Residents age 0-5	-0.00576	0.0305
Residents age 6-11	0.00601	0.0298
Residents age 12-17	0.00637	0.0290
Residents age 18-45	**-0.0817**	0.0503
Residents age 46-64	**0.121**	0.0686
Residents age 65+	0.0214	0.0376
Log household size	-0.00398	0.128
Crowding	-0.0113	0.00842
Walls of mud/dung/grass/sticks	**-0.120**	0.0387
Roof of mud/dung/grass/sticks	0.0188	0.0394
Floor of mud	-0.0479	0.0362
Cooking fuel biomass	**0.250**	0.0586
Electricity	-0.0730	0.0778
No toilet	-0.00278	0.0264
Nairobi	**0.234**	0.0503
Homa Bay	**-0.333**	0.0868
Migori	**-0.335**	0.0843
Kisumu	**-0.360**	0.0856
Suba	**-0.269**	0.0876
Kwale	**-0.201**	0.0891
Age <30	**-0.128**	0.0651
Age 31-40	**-0.345**	0.0651
Age 41-45	**-0.359**	0.0730
Age 46-50	**-0.190**	0.0675
Age 51-55	**-0.151**	0.0626
Age 56-60	**-0.105**	0.0581
Age 61-65	-0.0284	0.0564
Age 66-75	0.0132	0.0469
Residents age 18-45*residents 46-64	0.0238	0.0198
Household size*residents 18-45	**0.00597**	0.00342
Household size*residents 46-64	-0.00710	0.00946
Log likelihood	-916.14	
Chi square (38)	292.2	
Psuedo R-square	0.16	
Observations	1,805	

Estimates are used to derive probability scores for inverse probability weight calculation. See text for explanation.

Figure A2. Distribution of probability scores

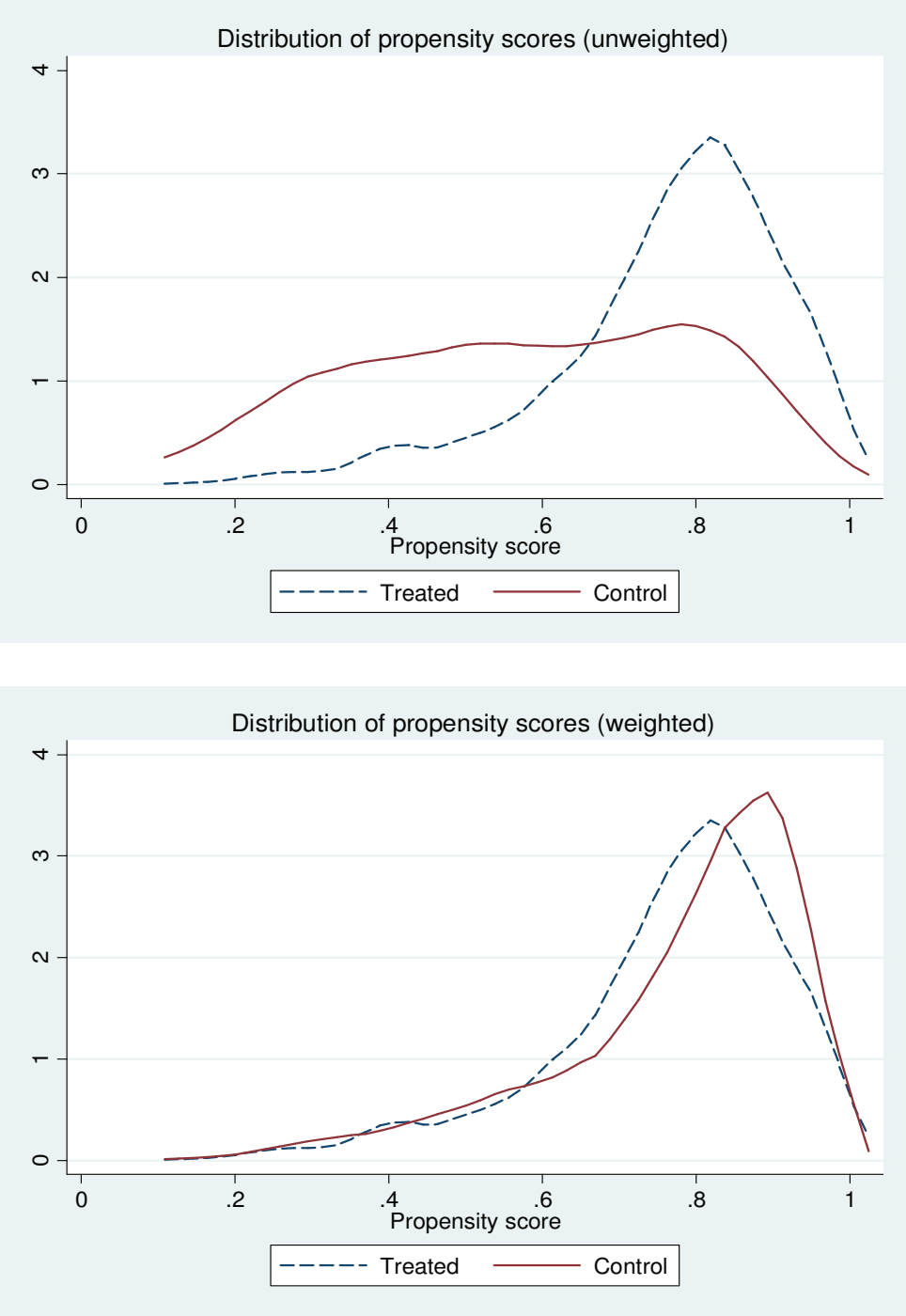


Table A3: Determinants of Time Discounting – full sample including inconsistent observations

	Is willing to wait one month for KES:					Impatience	
	9000	7000	4500	3000	1500	Ordinal[1]	Dichotomous[2]
	(1)	(2)	(3)	(4)	(5)	(7)	(9)
T	0.0351	0.0436	0.0394	0.0373	0.00555	-0.165	-0.0312
	(1.34)	(1.64)	(1.45)	(1.33)	(0.19)	(-1.26)	(-1.21)
Access to credit	**0.0564**	0.0445	0.0278	0.0195	0.0306	-0.0614	-0.0489
	(1.84)	(1.39)	(0.84)	(0.54)	(0.81)	(-0.41)	(-1.62)
Age 25-59 years	0.0185	0.0121	**0.114**	0.0221	0.0597	-0.273	-0.0254
	(0.33)	(0.22)	(1.82)	(0.36)	(1.06)	(-0.96)	(-0.46)
Age 60+ years	-0.0236	-0.0268	0.0747	0.00589	0.0606	-0.164	0.0114
	(-0.41)	(-0.46)	(1.14)	(0.09)	(1.01)	(-0.53)	(0.20)
Female	0.0408	0.0282	0.0229	0.0378	-0.0618	-0.112	-0.0402
	(0.98)	(0.69)	(0.54)	(0.90)	(-1.56)	(-0.54)	(-0.98)
Has partner	-0.0253	-0.0115	-0.0263	-0.0159	**-0.0839**	0.136	0.0106
	(-0.82)	(-0.36)	(-0.79)	(-0.47)	(-2.29)	(0.87)	(0.35)
Can read	**0.0828**	**0.0803**	**0.0769**	**0.0910**	0.0305	**-0.442**	**-0.0765**
	(2.68)	(2.62)	(2.44)	(2.80)	(0.80)	(-2.73)	(-2.51)
Has chronic illness	0.00170	0.00799	0.0249	0.0383	0.0149	-0.101	0.00270
	(0.04)	(0.19)	(0.59)	(0.89)	(0.34)	(-0.48)	(0.06)
Disabled	**-0.152**	**-0.157**	**-0.148**	**-0.143**	-0.0888	**0.813**	**0.164**
	(-1.78)	(-1.84)	(-1.74)	(-1.65)	(-1.55)	(2.10)	(1.93)
Rural	0.0647	0.0616	0.0928	0.0940	0.0572	-0.510	-0.0646
	(1.02)	(0.97)	(1.48)	(1.52)	(1.09)	(-1.63)	(-1.01)
Log consumption	-0.00894	-0.000786	-0.00531	0.00307	0.0307	-0.00582	0.00981
	(-0.40)	(-0.03)	(-0.22)	(0.12)	(1.08)	(-0.05)	(0.44)
Observations	1,804	1,804	1,804	1,804	1,804	1,804	1,804
R-squared	0.078	0.077	0.075	0.080	0.059	0.077	0.079

Notes: OLS regressions with robust standard errors and inverse probability weights. Also included in model but not reported are indicators for district, log household size, number of residents in each of six age categories, quality of roof, floor, walls, toilet facility, type of cooking fuel used, electricity, and crowding index. Coefficients in bold are statistically significant at 10 percent. 1/ Higher values indicate need increasingly higher amount of money to wait. 2/ Will never wait for any amount offered.