UNICEF
Office of Research

Evidence from a Large-Scale Cash Transfer Programme

Subjective Well-being, Risk Perceptions and Time Discounting

Sudhanshu Handa, Bruno Martorano, Carolyn Halpern,
Audrey Pettifor, Harsha Thirumurthy

Office of Research Working Paper
WP-2014-02 | April 2014

INNOCENTI WORKING PAPERS

UNICEF Office of Research Working Papers are intended to disseminate initial research contributions within or relevant to the Centre's programme of work, addressing social, economic and other aspects of the realisation of the human rights of children. This paper has been subject to an extensive internal and external review process.

For further information and to download or order this and other publications, please visit the website at www.unicef-irc.org. The findings, interpretations and conclusions expressed in this paper are those of the author(s) and do not necessarily reflect the policies or views of UNICEF.

For readers wishing to cite this document we suggest the following form:

Handa, S., Martorano, B., Halpern, C., Pettifor, A., Thirumurthy, H. (2014). Subjective Well-being, Risk Perceptions and Time Discounting: Evidence from a large-scale cash transfer programme, *Innocenti Working Paper* No. 2014-02, UNICEF Office of Research, Florence.

ISSN: 1014-7837

THE UNICEF OFFICE OF RESEARCH

In 1988 the United Nations Children's Fund (UNICEF) established a research centre to support its advocacy for children worldwide and to identify and research current and future areas of UNICEF's work. The prime objectives of the Office of Research are to improve international understanding of issues relating to children's rights and to help facilitate full implementation of the Convention on the Rights of the Child in developing, middle-income and industrialized countries.

The Office aims to set out a comprehensive framework for research and knowledge within the organization, in support of its global programmes and policies. Through strengthening research partnerships with leading academic institutions and development networks in both the North and South, the Office seeks to leverage additional resources and influence in support of efforts towards policy reform in favour of children.

Publications produced by the Office are contributions to a global debate on children and child rights issues and include a wide range of opinions. For that reason, some publications may not necessarily reflect UNICEF policies or approaches on some topics. The views expressed are those of the authors and/or editors and are published in order to stimulate further dialogue on child rights.

The Office collaborates with its host institution in Florence, the Istituto degli Innocenti, in selected areas of work. Core funding is provided by the Government of Italy, while financial support for specific projects is also provided by other governments, international institutions and private sources, including UNICEF National Committees.

Correspondence should be addressed to:

UNICEF Office of Research - Innocenti
Piazza SS. Annunziata, 12
50122 Florence, Italy
Tel: (+39) 055 20 330
Fax: (+39) 055 2033 220
florence@unicef.org
www.unicef-irc.org

SUBJECTIVE WELL-BEING, RISK PERCEPTIONS AND TIME DISCOUNTING: EVIDENCE FROM A LARGE-SCALE CASH TRANSFER PROGRAMME

Sudhanshu Handa,[1,2] Bruno Martorano,[1] Carolyn Halpern,[2] Audrey Pettifor,[2] Harsha Thirumurthy[2]

[1] Social and Economic Policy, UNICEF Office of Research-Innocenti
[2] Carolina Population Center, University of North Carolina at Chapel Hill
Contact authors are Handa (shanda@unicef.org), Martorano (bmartorano@unicef.org) and Thirumurthy (harsha@unc.edu)

Abstract. The risk and time preferences of individuals as well as their subjective expectations regarding the future are likely to play an important role in choice behaviour. Measurement of these individual characteristics in large-scale surveys has been a recent development and empirical evidence on their associations with behaviour remains limited. We summarize the results of measuring individuals' attitudes towards inter-temporal choice, risk, and the future in a large-scale field survey in Kenya. We also examine the impact of a cash transfer programme on these preferences and expectations. We find very low rates of inconsistency in interpreting questions on time and risk preferences. Cash transfers alone do not appear to impact time discounting or risk aversion, but they do have an important impact on subjective well-being measures and on future perceptions of quality of life. These in turn may affect forward-looking decisions such as financial and human capital investment, although this is not explored in this paper and remains part of the future research agenda.

Keywords: cash transfers, subjective well-being, risk, field surveys

Acknowledgements: We are grateful to Ernst Fehr and Johannes Haushofer for their comments and suggestions. This research was funded by the U.S. National Institute of Mental Health through Grant Number 1R01MH093241 and by Eunice Kennedy Shriver National Institute of Child Health and Development R24 HD050924 to the Carolina Population Center.

TABLE OF CONTENTS

1. INTRODUCTION

Individuals' preferences and expectations play an important role in theoretical models of decision-making in various financial and non-financial domains. For example, an individual's risk preferences may influence whether or not that individual undertakes high-risk investments or engages in risky health behaviours such as smoking or excess drinking. Accurately measuring these individual characteristics can yield an improved understanding of various health and economic behaviours. In the field of development economics, there has been a tradition of measuring certain types of preferences and using them to explain behaviour (Binswanger 1980). More recently there has been a surge in efforts to measure subjective expectations regarding the future and using them to predict decision-making (Delavande et al 2011). There remains a limited evidence base, however, on the feasibility of measuring preferences and expectations in populations with low numeracy as well as the reliability and consistency of measures that are obtained in field surveys. In addition, the extent to which these preferences and expectations are shaped by one's economic interventions and various shocks, as opposed to being inherent traits of individuals, is still not clearly understood.

Two recent articles have reviewed the experience in eliciting information about individuals' subjective expectations, attitudes towards risk, and traits such as patience. Delevande et al (2011) argue that concepts such as probability and future expectations can be understood by respondents in field surveys and are relatively easy to collect, and thus should be considered in large scale field surveys. Cardenas & Carpenter (2008) in contrast focus on best-practice in the design of small-scale experiments meant to capture behavioural parameters, and conclude that while such initiatives are practical and of interest, they suffer from external validity due to small, unique samples. Both articles encourage the adoption of such measures in large population-based field surveys as a way of improving our understanding of individual decision-making in a range of spheres of interest to development policy.

While measuring preferences and expectations and then examining how those measures are associated with behaviours is one important line of inquiry, another relates to the factors that in turn shape these preferences and expectations. Specifically, only a few studies have examined the extent to which risk and time preferences are influenced by one's environment and the ways in which individuals form subjective expectations about the future. Cameron and Shah (2013), for example, find that individuals who experienced a natural disaster recently were more risk averse. The effect of various interventions and events on preferences and expectations has important implications for the extent to which we can assume that preferences and expectations are innate characteristics of individuals as opposed to time varying factors that are influenced by other variables. And despite the large literature on effects of cash transfers this paper is one of the few that looks at how fundamental decision-making parameters – people's risk and time preferences – are affected by the transfers.

This paper responds to the increased interest in these measures by reporting on the experience of collecting risk preferences, inter-temporal preferences and subjective expectations in a large field survey in Kenya, undertaken as part of the impact evaluation of the Government of Kenya's largest social protection programme, the Kenya Cash Transfer for Orphans and Vulnerable Children (CT-OVC). The objectives of the paper are thus two-fold. First, we report on the feasibility of collecting

such measures among low-income, mostly rural respondents in a developing country. We describe the pattern of responses, their main individual correlates, and their internal consistency. Second, we present results on the impact of a cash transfer programme on these measures using a randomized design. These impact estimates are identified through the random assignment at baseline of households to treatment and delayed-entry control status.

We find that there is in fact a great deal of internal consistency within each domain across the range of indicators that we measure. Moreover the few inconsistencies that we do observe are not systematically related to individual characteristics except possibly sex of the respondent. We also find impacts of programme participation on several of the measures, particularly current quality of life, subjective expectations about future risk, and quality of life.

The contribution of this paper to existing knowledge is two-fold. First, it is among the first papers to report on the results of collecting a wide range of preference and expectation measures in a large-scale household survey. The domains of measurement include risk preferences, time preferences, subjective expectations, and current quality of life. And it is one of only two studies that reports on the impact of a social protection programme (in this case, a cash transfer), on these parameters. This is of interest because it is still unclear whether risk aversion and time preference are permanent traits which condition decision-making but which themselves cannot be changed in the short run, or whether in fact they are malleable in the short run through public policy. Moreover, the impacts of cash transfer programmes on subject welfare and risk assessment are important because subjective well-being is both an end in itself and, like self-assessments of risk, an important determinant of other decisions that can affect an individual's welfare. As such, they represent benefits of cash transfer programmes that are typically not measured by most studies.

2. THE KENYA CASH TRANSFER PROGRAMMES FOR ORPHANS AND VULNERABLE CHILDREN

The context of our data collection is the impact evaluation of the Kenya CT-OVC, the country's largest social protection programme with a coverage of over 150,000 households as of mid-2013. The objective of the programme is to provide regular cash transfers to families living with OVC to encourage fostering and retention of children and to promote their human capital development. Eligible households, those who are ultra-poor (poorest 20 per cent) and contain an OVC, receive a flat monthly transfer of US$25 (KES 2000).[1] 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 currently no punitive sanctions for noncompliance with this responsibility; the CT-OVC, like the majority of such programmes in Africa, is thus an unconditional cash transfer programme.

When the evaluation was initiated in 2007, targeting of households for the programme was conducted in three stages.[2] In stage one, each Location (a Location is the fourth administrative level below province, district and division) formed an OVC Committee (LOC) that prepared a list of

[1] At the time of this study the transfer was only KES1500 which represented about 14 per cent of beneficiary consumption. It was raised in July 2011.

[2] Slight revisions to targeting have been made recently but the essentials of the process remain the same.

all potentially eligible households that met the demographic and poverty criteria. In stage two, the list of eligible households was sent to the programme's central office (located within the Ministry of Gender, Children and Social Development), which then administered a detailed socioeconomic questionnaire to assess poverty and confirm eligibility in order to rank households. The final number of households that enters the programme in each district depends on funding to that district, but approximately 20 per cent of the poorest households in each Location are enrolled in the programme. 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 programme reported very favorable targeting relative to other cash transfer programmes across the developing world (Handa, Huang et al., 2012).

3. STUDY DESIGN AND EMPIRICAL STRATEGY

3.1 The impact evaluation design

Prior to programme expansion of the CT-OVC in 2007, UNICEF designed a social experiment to track the impact of the programme 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 programme 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, the remaining two serving as control Locations for the study. Targeting of households was carried out in all Locations according to standard programme operation guidelines, and from the eligibility lists a sample of households was drawn at a rate of 2:1 treatment and control respectively. Sample size was based on power calculations for the key impact indicators of school enrollment and household consumption expenditures. Results from the original impact evaluation have been reported by the Kenya CT-OVC Evaluation Team (2012).

3.2 The follow-up survey

In 2011, through funding from the National Institute of Health, 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 on risk, time preference, subjective risk assessment and subjective well-being.[3] Enumerator training on the module was conducted as part of the routine training of the entire household questionnaire. As an introduction to the module, the study team first administered some components of the module to the enumerators themselves, as a way of helping them understand the intent of the questions, and to identify common mistakes in interpretation. For responses on a Likert Scale, a flash card was provided to enumerators with steps going from 1 (strongly disagree) to 5 (strongly agree) to aid in interpretation of responses. The lottery choices and time preference tasks were provided on flash cards to help respondents

[3] The 2011 study was approved by the UNC IRB and the Kenya Medical Research Institute Ethics Review Committee.

visualize the choices. For the lottery, a frown face was placed next to the loss amount and a happy face next to the winning amount to help respondents identify the pay-offs (see Appendix 1). Aside from this, no additional equipment or training was employed for this module. Based on interviewer observation by field supervisors, the module took less than 10 minutes to implement, though in some cases it took up to fifteen minutes if the respondent had difficulty understanding the choices. Feedback from the field teams indicated that respondents enjoyed thinking about the questions and that in fact they provided a nice break from the other more routine questions in the survey. The use of the visual aids for the time preference questions were seldom used, those questions being easy to communicate. On the other hand the card for the Likert Scale was used the most as it was easy for the respondents to indicate their choice by pointing to a step on the ladder. All questions were translated into Swahili and Luo.

3.3 Household attrition and balance between intervention and control arms

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 per cent 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 per cent. Table 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 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. (2014).

3.4 Differences in respondent characteristics across study arms

The figures in bold in Table 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 1. It is important to note that there is no element of self-selection into the programme; household eligibility was completely supply-driven and take-up was universal.

3.5 Empirical strategy

As noted above, the questions on preferences and expectations were administered to the main respondent, typically the household head. Table 2 shows mean characteristics of the individuals who were actually administered the expectations module in 2011. Excluding age, they are not statistically significant differences in characteristics. However, we control for individual and household characteristics (all measured at baseline) when estimating the effect of programme participation on the behavioural measures. We also estimate individual probability weights, calculated as the probability of being in the treatment group conditional on a set of individual and household characteristics, and weight the regression using the inverse probability weights (IPW) as a way of generating more robust (i.e. internally valid) estimates of the treatment effect. The regression used to derive the probability scores and associated weights as well as the graphs of the weighted (by the IPW) and unweighted probability scores are shown in Appendix 2. Application of the IPW clearly does a better job of aligning the distribution of the probability scores across respondents in the two arms and is thus our preferred method of estimating treatment effects, though we also report the unweighted regressions in Appendix 3. Our basic empirical approach is to relate the outcome of interest, typically a response on a question contained in the expectations module, to a set of individual characteristics (age, sex, education, health status at baseline), household characteristics (district of residence, household size and demographic composition at baseline, housing characteristics and per capita consumption expenditure both measured at baseline), and a dummy variable indicating treatment status:

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

In equation (1) the i subscript denotes individual level variables, the h subscript denotes household level variables, T equals 1 if individual lives in a treatment household, and X is a vector of either household or individual covariates. Among the individual covariates we include whether or not the individual was either disabled or chronically ill (both self-reported) at baseline. In the few cases where the individual that was administered the expectations module was not present at baseline, we use his/her health status from the first wave that s/he appears in the study. We apply inverse probability weights to this specification, use cluster robust standard errors (clustered at the Location level) and estimate (weighted) linear probability (for binary outcomes) or ordinary least squares models.

4. MEASURES

4.1 Inter-temporal Choice

To measure time preference, respondents were invited to make a choice between payment today and a payment one month from today. In particular, the question was asked as follows: "Suppose that you suddenly win money in the Lotto. If you could choose between these payment options which do you choose?" While the immediate monetary reward was the same for each question (KES1500 today), the delayed option payment changed. The six payment options were as follows:

KES1500 today or KES1250 in one month?

KES1500 today or KES1500 in one month?

KES1500 today or KES3000 in one month?

KES1500 today or KES4500 in one month?

KES1500 today or KES7000 in one month?

KES1500 today or KES9000 in one month?

While we have ordered the questions here from lowest to highest in terms of future money the questions were not actually asked in this order. The order of future payoffs was: 1500, 9000, 4500, 7000, 4500, 1250.

4.2 Risk aversion

To measure risk aversion, participants were asked to state their preference over a hypothetical choice of receiving KES 1500 for certain or playing a lottery that gave them a 50 per cent chance of winning and receiving a larger monetary reward or a 50 per cent chance of a smaller monetary reward. The five lottery options were:

A. 3000 or 0
B. 12000 or 0
C. 7000 or 1000
D. 8000 or 0
E. 2000 or 1000.

In two cases (A and E) the expected value of the lottery is the same as the certainty value but the loss is lower in Option E. Similarly the expected value of choices C and D are the same but the loss is lower in C, allowing us to see if loss-aversion plays a role in the decision process. Finally Option B provides an expected value that is significantly higher than the certainty equivalent and is designed to see if it induces respondents to take the lottery.

4.3 Subjective well-being: Quality of life

To measure the quality of life we asked respondents if they strongly agree (5) or disagree (1) with the following statements:

- I enjoy life
- I experience positive feelings in my life

- I feel positive about my future
- I am satisfied with my health
- I am satisfied with my life.

These questions are drawn from the domains of 'Positive Feeling' and 'Overall Life and Health' Domains of the WHO Quality of Life Scale (WHO 1998). Based on this information we compute a Quality of Life scale score by summing up the responses for each of the single indicators; the resulting scale thus ranges from 5 to 25.

4.4 Subjective Future Well-being and Risk Assessment

We measure subjective future well-being by asking respondents how they feel about their life in one, three and five years from now. For subjective future risk assessment, people were asked to express the likelihood that a certain event would happen in the near future. Respondents were shown the step ladder ranging from 1 (the lowest step) to 5 (highest) and it was explained that 5 indicated the event would occur for sure, and 1 that it would not occur at all; respondents were then asked to indicate how likely they thought the event would occur by pointing to a location on the scale. The questions were:

- In the next year what is the chance you will have a food shortage?
- In the next year what is the chance you will seek financial assistance from someone?
- In the next year what is the chance you will fall ill and not be able to conduct your daily activities?
- What is the chance someone else in your household will fall seriously ill and not be able to conduct daily activities?
- In the next year what is the chance somebody you know will die?

5. RESULTS

5.1 Inter-temporal choice

The literature on inter-temporal choice distinguishes between time preference and time discounting, the former referring to the inter-temporal elasticity of substitution (the discount rate) and the latter to any decision that involves a trade-off across time (Frederick, Loewenstein & O'Donoghue, 2002). The determinants of the latter will of course include the discount rate as well as other factors such as risk preference, affect (Ifcher & Zarghamee 2011), health status, and liquidity constraints. In the context of perfect capital markets rates of time preference should converge, but capital markets are far from perfect in developing countries, and these will in fact be the norm in the types of populations that we study here. Berg (2012) highlights the role of credit constraints in determining the time preference of poor households using data from South Africa. Beyond the level, new evidence highlights the role of income shocks. Haushofer et al (2013) report that a negative income shock provokes an increase of time discounting while Handa et al (2013) show that a targeted cash transfer in Zambia which is similar to the one studied here increases the propensity to wait for future money.[4] The results below on the inter-temporal choice task we administer reflect time discounting; whether or not they also reflect time preference depends on

4 Similar results are reported by Daly et al (2009) using data from Ireland. In particular, they find some association between economic discounting and non-monetary variables as psychological and biological traits.

whether or not we have managed to control for all other potential factors influencing the inter-temporal decision. However, it is necessary to highlight that tasks were not incentivized. Thus, we can hypothesis that liquidity constraints play a less important role in the decisions of participants.

5.1.1 Performance

The proportion of those willing to wait for each choice is shown in Figure 1 and depicts two important trends. First, the proportion willing to wait increases as the value of future money increases suggesting that respondents understood the questions. Second, there is a clear break at 3000, with a steep jump in the proportion willing to wait for KES1500 of 22 per cent to 78 per cent willing to wait for KES3000. In our econometric models below we thus classify individuals as 'patient' those who are willing to wait for KES1250 or KES1500 and 'impatient' those who never accept future money (about 16 per cent of respondents). The 18 per cent of respondents willing to wait for less money (KES1250) raises the question of whether these individuals did not understand the question and should be excluded from the analysis or whether they genuinely display positive time preference. During field work we probed some of these respondents about why they waited for less money and were told that they had no place to keep the money safely, and that they could use the one month period to plan how to use the money when they received it.

To further understand the degree of comprehension we assessed internal consistency for each respondent by checking whether there were any 'double switches' – cases where an individual agreed to wait for a particular value and then chose to not wait for a higher value. Table 3 shows that there are 140 inconsistent responses (7.8 per cent). In addition, it is interesting to observe that more than 70 per cent of them (100 out of 140) are associated with option A which might support the idea that these respondents did not understand the question, notwithstanding the anecdotal evidence cited above. Overall there is good internal consistency among these variables with a Cronbach's Alpha value of 0.86.

5.1.2 Programme effects on inter-temporal choice

We now turn to exploring the effect of participating in the CT-OVC on the inter-temporal choice task described above. Table 4 shows that the mean differences between the two groups are small. The smallest differences are for a future value of KES 1250 and a future value of KES 1500, while they are around four percentage points for the remaining options of payment. Distinguishing between patient and impatient people, Table 4 shows that there is no treatment effect. Indeed, the differences are small in both groups and never statistically significant.

Ordinary Least Squares (OLS) estimates of treatment effects, controlling for individual and household characteristics are shown in Table 5. Though most treatment effects are positive (and negative for impatience) none are statistically significant indicating no treatment effect on time discounting. Table 5 also shows that inconsistency is not related to treatment status. The individual correlates of time discounting are also of interest. Literacy appears to lead to a greater likelihood of delaying payment, while having a disability leads to impatience. We also re-estimated the models in Table 5 excluding inconsistent observations and did not find any differences in the average treatment effects.

To sum up, the results show that the programme does not generate any impact on the inter-temporal choice task tested here, which is in contrast to the one other study based on a national cash transfer programme, the Zambian Government's National Social Cash Transfer Programme (Handa et al 2013). One important difference between the two programmes is the size of the transfer, which represents 14 per cent of beneficiary pre-transfer consumption compared to 28 per cent in Zambia. Thus, it may be that the programme in Kenya is not able to sufficiently alleviate short-term liquidity constraint for participants compelling recipients to continue to prefer current consumption especially if they still have to satisfy basic needs. Finally, it is possible that time discounting is affected by other factors than household income level such as culture and institutions (see Havranek et al, 2013).

5.2 Risk preferences

In the framework of expected-utility theory, the rich are more risk tolerant than others, a rule that is believed to be valid in developed as well as in developing countries. For example, Yesuf and Bluffstone (2008) report a negative relationship between wealth level and risk aversion using experimental data from Ethiopia. As a consequence, it is suggested that high risk aversion traps low income households in the bottom of the distribution feeding a vicious cycle of low risk tolerance and persistence of poverty (Vieider et al, 2012). Nonetheless, not all scholars agree with this perspective. Using experimental data from Vietnam, Tanaka et al (2010) find a positive correlation between village income and risk tolerance but no significant correlation between household income and risk aversion. In one of the most influential works in this area, Binswanger (1980) reports similar results analyzing the risk attitude of farmers with different levels of wealth in rural India. Behaviour that deviates from expected-utility theory has also been noted in the literature, such as loss-aversion (Kahneman & Tversky 1979; Tversky & Kahneman 1991).

5.2.1. Performance

Figure 2 shows that less than 1 out of 4 people choose lottery A (i.e. 3000 or 0) while the favorite lottery is C (i.e. 7000 or 1000). However, the majority of people (65 per cent) do not pick any lottery. Note that the most popular choice is in fact the combination of the highest expected value and lowest loss, indicating that some degree of loss aversion may be important here.

Figure 3 explores the inconsistency in lottery choices to understand whether respondents understood the questions and could assess the relative expected values correctly. Lottery B has the highest expected value thus we expect that it is always preferred to the other lotteries. Figure 3 shows that there are inconsistent responses but not overwhelmingly so. The largest inconsistency occurs in respondents choosing C over B (5 per cent); as noted above, lottery C gives the 'best' combination of expected winnings and lowest loss suggesting that loss-aversion is playing a role in the decision process. Indeed five per cent also choose E (KES2000 vs. KES1000) over B, again providing some evidence of loss-aversion at work in this population. On the whole, the number of inconsistent responses is only 131 (about 7.3 per cent).

5.2.3. Programme effects on risk preference

Table 6 compares the mean differences between the treated and the control groups according to the different lotteries and we observe that differences are small and not statistically significant, with

the only exception of lottery A. Table 7 reports the results of regression equations for treatment effects on lottery choices and these confirm the results from the bivariate analysis – treatment effects are close to zero and never statistically significant, nor is inconsistency related to treatment status. Note also that risk tolerance is not affected by demographic characteristics while it is affected by health, which is similar to the results for inter-temporal choice. In particular, having a disability at baseline reduces significantly the preference for risk by 12-17 percentage points and increases the likelihood of not choosing any lottery by 18 points. There is a similar pattern for having a chronic illness at baseline though effect sizes are smaller.

Our results are consistent with those of Tanaka et al (2010) and of Binswanger (1980). In particular, the relationship between income level and risk tolerance is weak and in almost all the cases not statistically significant. This could again be related to the fact that the cash transfer is a relatively small share of consumption; it is also possible that beneficiaries perceive the transfers as a current income shock and are not sure about their future participation in the programme (though at this point participants had been in the programme for four years). Lastly but not less important, the results above could be explained by the fact that risk aversion is affected by other factors than household income level: for example, our results suggest that disabled and less educated people are less risk tolerant. Tanaka et al (2010) report positive correlation between income and risk taking attitude at the village level (but not at household level); Weber and Hsee (1999) provide a cross-cultural justification to the different degree of risk tolerance showing that people in a collectivistic society (e.g. Chinese) are less risk averse than people in an individualistic one (e.g. American).

5.3 Subjective well-being: Quality of Life

Subjective well-being is affected by many factors such as personal traits as well as environmental circumstances (Diener et al, 1995). For the latter, some scholars highlight the contribution of material conditions (e.g. Deaton, 2008; Stevenson and Wolfers 2008). In particular, more economic resources assure more opportunities in terms of consumption, which in turn make people happier increasing their quality of life. Although there is not a general consensus about the validity of this rule in high income countries (see Easterlin 1974; Frey and Stutzer, 2003), the positive relationship between economic conditions and quality of life appears more robust in developing countries. This idea follows Maslow's (1943) theory of a "hierarchy of needs" according to which the quality of life of poor people is strictly related to the satisfaction of basic needs.

As a consequence – if the human component is strictly related to nature and nurture – public policy has space to affect subjective well-being by altering external conditions. However, operationalizing the meaning of subjective well-being is not straightforward. Usually, a single measure is used to capture how people perceive their life overall (Diener, 2000). Nonetheless, there is a growing consensus toward the need to complete this assessment with information related to the eudemonic (see Ryff and Singer, 1998) and affective well-being (see Tinkler and Hicks, 2011). In a recent study, Haushofer and Shapiro (2014) demonstrate that an unconditional cash transfer generated a positive impact on psychological well-being of poor people living in Kenya.

5.3.1 Performance of quality of life indicators

Figure 4 shows that scores on the Quality of Life composite scale are above the middle value. People report a middle/high value for life (3.2) and health satisfaction (3.2). Positive values are also reported in terms of "enjoying life" (3.3) and "positive feelings" (3.4) while the highest values are reported for "positive about my future" (3.4). About 6.2 per cent of people report the highest value, while less than 2 per cent the lowest value; the Cronbach alpha score is 0.86 and all two-way covariances are above 0.70 except for 'I am satisfied with my health' and 'I experience positive feelings in my life' which has a covariance of 0.68. The highest pairwise covariance (0.98) is between 'I enjoy life' and 'I am satisfied with my life'. In general the health question has the lowest correlation with the other items in the scale suggesting that satisfaction related to health may be determined somewhat differently than the other items.

5.3.2 Programme effects on subjective quality of life

We convert each component of the scale to a binary indicator equal to 1 if the respondent agreed or strongly agreed with the statement. Table 8 shows that the mean differences for each of these binary indicators among the two groups are small but statistically different.

Table 9 reports the results of the OLS regression estimates of treatment effects. Treatment status coefficients are always positive and statistically significant at 10 per cent or better in all cases except for health. Point estimates are around 6 percentage points for the four domains and respondents in treated households score on average 0.76 points higher on the overall Quality of Life scale (column 6). Reporting a chronic illness at baseline reduces quality of life overall by 1.41 points on the scale score as well as in all individual items except Health (where it is significant at 10 per cent); in contrast, having a disability only affects the health item and to a lesser degree (and at 10 per cent significance only) on positive feelings. Those with a partner in the household also tend to report higher quality of life.

The overall results suggest that income level is an important factor in determining subjective quality of life in poor countries as suggested by Maslow's (1943) hierarchy of needs theory.

5.4 Subjective future expectations

As Delavande et al. (2011) point out, most economic decisions involve some type of assessment about a situation in the future, thus eliciting expectations about future circumstances would seem important for predicting current human behaviour. Here we report on two dimensions of future expectations: future subjective well-being and perceptions about future risks.

5.4.1 Performance

Figure 5 shows the proportion of respondents who believe their life will be better in the future. First, 38 per cent of people think that their life will be better in one year. Second, this percentage increases to 42 per cent when they think about their life in 3 or 5 years. Third, about 33 per cent of people report being more optimistic about their future in the short (one and three years) as well as in the medium time (better in five years). Lastly, 29 per cent of people are more pessimistic believing that their life will not get better in the future. To assess the internal consistency of these reports we expect that a person who is positive about his/her life in one year as well as in 5 years

from now, will also feel better about his/her life in three years from now. Nine people report an inconsistent response representing less than 1 per cent of the overall sample. The Cronbach alpha for the three indicators is a very high 0.92.

Figure 6 shows that the chance of death of acquaintances is evaluated above the middle at 2.7 meaning that for respondents this event is somewhat more likely to occur than not occur. The highest scores are associated with the events of food shortage (3.5) and the need of financial assistance (3.7). In contrast to the previous area of research, these indicators are not as strongly associated with each other, the alpha score being 0.61. A principal components analysis clearly identifies two factors, the first related to illness and death and the second related to financial and food shortage. The alpha analysis for the three health related items is 0.73 but only 0.54 for the two items on food and finance. A cross-tabulation of these two variables indicates that 14 per cent of responses are 'off diagonal'. Since most households are own producers of food it is possible not to have a food shortage but still seek financial help.

5.4.2 Programme effects on future perceptions

We recode each of the variables described above into binary indicators. For the 'will your life be better' questions we code 1 if the respondent says his/her life will be better and 0 if the same or worse. For the other indicators which are measured on the 5 point scale, we code 1 if the respondent believes there is no chance the event will occur and 0 otherwise. Table 10 reports the mean comparison between the treated and the control group on the different outcomes of interest. For all indicators differences are large and statistically significant. Looking at the chance of a food shortage or the chance that they will need financial assistance, the differences between the two groups are smaller than 2 points and not statistically significant. The treated and the control group report opposite responses. In particular, the former group appears less likely to think they will experience a food shortage while the latter group is less inclined to the probability that they need financial assistance. Lastly, differences are large but statistically different for the remaining indicators on future risk assessment.

Table 11 reports regression estimates to test for a treatment effect on perceptions of the future. The Table shows that people in the treatment group are more optimistic about their future than those in the control group. In particular, they feel that their life will be better in one, three as well as in five years from now, though the latter is significant at 10 per cent only. This result could be explained by the increasing uncertainty over a longer time period, as well as the continuation of the programme. Indeed, Handa et al (2013) find similar results analyzing the impact of Zambia's cash transfer programme. With respect to the other indicators, the treated group is less likely to believe they will fall ill (8 points) and less likely to believe they will know someone else who will either fall ill or die (significant at ten per cent only). Indeed, the treated group thus appears to be more optimistic than the control group. The coefficient associated with an inconsistent response is positive and statistically significant (Table 11 – Model 10); nonetheless, only nine people report an inconsistent response representing less than 1 per cent of the overall sample, and when we exclude these nine from the regressions in columns 1-9 the results remain the same.

Note that those who are disabled at baseline are less likely to believe their life will be better in the future, and those who are chronically ill are more likely to think they will fall ill, or to know

someone who will fall ill or even die. Thus baseline health status continues to have an important relationship with reporting on almost all domains explored in this paper.

To sum up, we observe a positive impact of the programme on subjective future well-being, which in turn may affect decision-making, especially those that involve a time dimension. However, we do not observe treatment effects on future perceptions of risk of different events in the food/financial spheres, but do for own illness, where treatment individuals are less likely to feel certain they will fall ill.

6. CONCLUSIONS

This paper provides an assessment of efforts to measure individuals' expectations and preferences in a large-scale field survey and assess the impact of a large cash transfer programme on these measures.

We integrated the preferences and expectations questions into the field survey at very low cost and the performance of the indicators was quite promising. The rate of inconsistency was low for both lottery choices and the inter-temporal choice task at 8 per cent, though some of the inconsistency on the latter may be related to genuine decisions to delay for less money because of other reasons such as inability to safely store the money. Individuals in this sample were quiet risk averse with about 65 per cent refusing to ever select a lottery choice. However there is suggestive evidence of loss aversion, with the most popular lottery being that with the combination of highest expected value and lowest loss. Indeed a lottery with an expected value of 6000 and a maximum loss of 1500 was not preferred to one with an expected value of 1500 but with a maximum loss of 500 in about 7 per cent of the sample—these cases are considered inconsistent but they may in fact be displaying loss-aversion. Hence it is likely that our 8 per cent inconsistency in these two sets of questions is actually much lower, providing further evidence that these questions can be asked in large scale population-based surveys at minimal time cost and with measurement error that is probably no worse than questions in other areas such as consumption, investment and production with are routinely asked.

Impacts of the cash transfers on these indicators is somewhat mixed. We uncovered no impacts of the programme on time discounting nor on risk aversion (as measured by lottery choices). This may be because the value of the transfer was quite low at the time of our survey, only 14 per cent of mean consumption. On the other hand it could be that these characteristics are more permanent and cannot be changed in the short or medium term through small increases in income. However a comparable study which referred to the Zambia cash transfer programme did find effects on a similar inter-temporal choice task, though the value of the transfer in that case was almost twice as large as a share of beneficiary consumption.

On the other hand we find strong and positive effects of the cash transfer on current subjective well-being and perceptions about future well-being. Thus respondents living in households that are in the programme are 6 percentage points more likely to believe their life will be better in one and three years' time. These respondents are also more likely to feel happy and to feel positive about the future, and they score 0.76 points higher on the overall scale score for quality of life. These impacts are not only important outcomes in their own right, but also for their potential in influencing decisions in other domains. For example, optimism about the future is crucial in the

investment decision-making process, which opens the possibility that the programme could promote not only individual well-being but also the process of economic development for the society as a whole.

In terms of the research agenda, our next step is to explore the interactions between the behavioural measures we have reported on here. On the one hand, happier people may be more risk tolerant. On the other hand, it is possible that patient people are also more optimistic about their future. There is some evidence for example that risk-aversion and time preference are inter-related, while the relationship between affect, emotion and risk-taking has also been established (Loewwenstein et al. 2003, Tanaka et al. 2010). If public policy with an equity objective such as the cash transfers could affect present and future well-being it might also alter (indirectly) investment decisions. Understanding these relationships is crucial in order to identify 'win-win' policies that promote equity as well as growth.

REFERENCES

Berg, E. (2012). “Are poor people credit-constrained or myopic? Evidence from a South African panel”, Journal of Development Economics, doi:10.1016 / j.jdeveco.2012.10.002

Binswanger, H. P. (1980). “Attitudes toward Risk: Experimental Measurement in Rural India.” American Journal of Agricultural Economics, 62(3): 395–407.

Cameron, L. & Shah, M. (2013). "Risk-Taking Behavior in the Wake of Natural Disasters," NBER Working Papers 19534, National Bureau of Economic Research, Inc.

Cardenas, J. C., & Carpenter, J. (2008). “Behavioural development economics: Lessons from field labs in the developing world”, Journal of Development Studies, 44(3), 311-338.

Daly, M., Delaney, L., Harmon, C. P. (2009). "Psychological and Biological Foundations of Time Preference," Journal of the European Economic Association, MIT Press, vol. 7(2-3), pages 659-669, 04-05.

Deaton, A. (2008). “Income, Health and Well-being around the World: Evidence from the Gallup World Poll”, Journal of Economic Perspectives, 22(2): 53-72.

Diaz, J. J. & Handa, S. (2006). “An Assessment of Propensity Score Matching as a Non Experimental Impact Estimator: Evidence from Mexico’s Progresa Program,” Journal of Human Resources Vol. 41(2): 319-345.

Delavande, A, Gine, X. and McKenzie, D. (2011). “Measuring subjective expectations in developing countries: A critical review and new evidence,” Journal of Development Economics, 94(2): 151-163.

Diener, E. (2000). “Subjective well-being: The science of happiness and a proposal for a national index”, American Psychologist, 55(1), 34–43.

Diener, E., Suh, E. M., Smith, H. and Shao, L. (1995). “National differences in reported subjective well-being: Why do they occur?,” Social Indicators Research, 34 (1), 7-32.

Easterlin, R. (1974). “Does Economic Growth Improve the Human Lot?”, in David P.A. and M.W. Reder (eds.), Nations and Households in Economic Growth: Essays in Honour of Moses Abramowitz, Academic Press, New York and London.

Frederick, S., Loewenstein, G. and O’Donoghue, T. (2002). “Time discounting and time preference: a critical review.” Journal of Economic Literature. Vol. XL, pp 351-401.

Frey, B. S. and Stutzer, A. (2003). “Testing Theories of Happiness”, IEW Working Paper No. 147, University of Zurich.

Handa, S., et al., (2014). “The Government of kenya’s Cash Transfer program Reduces the Risk of sexual Debut among Young People Age 15-25,” PLoS ONE 9(1): e85473. doi:10.1371/journal.pone.0085473.

Handa, S., et al., (2012). “Targeting Performance in Three African Cash Transfer Programs,” Journal of Development Effectiveness, Vol.4 (1):78-108.

Handa, S. & Maluccio, J. (2010). “Matching the Gold Standard: Comparing Experimental and Nonexperimental Evaluation Techniques for a Geographically Targeted Program,” Economic Development & Cultural Change, Vol. 58(3): 415-447.

Handa, S., Seidenfeld, D. and Tembo, G. (2013). "The Impact of a Large Scale Poverty Targeted Cash Transfer Program on Inter-temporal Choice," Carolina Population Center, University of North Carolina at Chapel Hill.

Harrison, G. W., Morten I. L., and Melonie B. W. (2002). "Estimating Individual Discount Rates in Denmark: A Field Experiment." American Economic Review, 92(5): 1606–17.

Haushofer, J. & Shapiro, J. (2013), "Household Response to Income Changes: Evidence from an Unconditional Cash Transfer Program in Kenya," Working Paper, available at: http://web.mit.edu/joha/www/publications/haushofer_shapiro_uct_2013.11.16.pdf

Haushofer, J., Fehr, E. & Schunk, D. (2013), "Negative Income Shocks Increase Discount Rates," Working Paper, available at: http://web.mit.edu/joha/www/publications/Haushofer_Schunk_Fehr_2013.pdf

Havranek, T., Horvath, R., Irsova, Z., & Rusnak, M. (2013). "Cross-Country Heterogeneity in Intertemporal Substitution," William Davidson Institute Working Papers Series wp1056, William Davidson Institute at the University of Michigan.

Heckman, J., Ichimura, H. & P. Todd (1997). "Matching as an Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Program." Review of Economic Studies. 64: 605-654.

Heckman, J., Ichimura, H. & P. Todd (1998). "Matching as an Econometric Evaluation Estimator." Review of Economic Studies. 65: 261-294.

Hotelling, H. (1931). "The Economics of Exhaustible Resources, Journal of Political Economy 39: 137–75.

Ifcher, J. & Zarghamee, H. (2011). "Happiness and Time Preference: The Effect of Positive Affect in a Random-Assignment Experiment," American Economic Review Vol. 101(7): 3109-3129.

Kahneman, D. & Tversky, A. (1979). "Prospect Theory: An Analysis of Decision Under Risk," Econometrica 47, pp. 263–92.

Kenya CT-OVC Evaluation Team (2012). "The impact of Kenya's Cash Transfer for Orphans and Vulnerable Children on human capital," Journal of Development Effectiveness, Vol.4 (1): 38-49.

Kirby, K. N., Petry, N. M., & Bickel, W. K. (1999). "Heroin addicts have higher discount rates for delayed rewards than non-drug-using controls," Journal of Experimental Psychology: General, 128, 78–87.

Loewenstein, G. (1996). "Out of control: Visceral influences of behavior," Organizational Behavior and Human Decision Processes, 65, 272–292.

Loewenstein, G. (2005). "Hot–cold empathy gaps and medical decision making," Health Psychology, 24(Suppl. 4), S49–S56.

Loewenstein, G., Read, D., & Baumeister, R. F. (eds.) (2003). Time and decision: Economic and psychological perspectives on intertemporal choice. New York: Russell Sage Foundation.

Maslow, A. H. (1943). "A theory of human motivation," Psychological Review, 50, 370 –396.

Mischel, W., Shoda, Y. & Rodriguez, M. (1989). Delay of Gratification in Children. Science, May 26.

Rae, J. M. C. W. (1905). *The Sociological Theory of Capital*. New York: Macmillan.

Ryff, C. D., & Singer, B. H. (1998). “The contours of positive human health”, Psychological Inquiry, 9, 1-28.

Rosenbaum, P. & Rubin, D. (1983). “The Central Role of the Propensity Score in Observational Studies for Causal Effects.” Biometrica 70: 41–50.

Samson, M., Heinrich, C., Kaniki, S., Regalia, F., Mac Quene, K., Muzondo, T., et al. (2011). Impacts of South Africa's Child Support Grant. In S. Handa, S. Devereux & D. Webb (Eds.), Social Protection for Africa's Children. New York: Routledge.

Samuelson, P. A. (1937). A note on measurement of utility. The Review of Economic Studies, 4(2), 155-161.

Schultz, T.P. (2004). “School Subsidies for the Poor: Evaluating the Mexican Progresa Program,” Journal of Development Economics 74(1): 199-250.

Smith, A. (1776). An Inquiry into the Nature and Causes of the Wealth of Nations. London: W. Strahan and T. Cadell.

Stevenson, B. & Wolfers, J. (2008). “Economic Growth and Subjective Well-Being: Reassessing the Easterlin Paradox”, at: http://www.uvm.edu/~pdodds/files/papers/others/2008/stevenson2008a.pdf

Strathman, A., Gleicher, F., Boninger, D. & Edwards, S. (1994). “The Consideration of Future Consequences: Weighing Immediate and Distant Outcomes of Behavior,” Journal of Personality and Social Psychology, 66, 742–752.

Tanaka, T., Camerer, C & Nguyen, Q. (2010). “Risk and Time Preference: Linking Experimental and Household Survey Data from Vietnam,” American Economic Review Vol 100(1): 557-571.

Tinkler, L., & Hicks, S. (2011). Measuring Subjective Well-being. London: Office for National Statistics.

Tversky, A. & Kahneman, D. (1991). “Loss Aversion in Riskless Choice: A Reference Dependent Model,” Quart. J. Econ.106, pp. 1039–61.

Vieider, F.M., Chmura, T., & Martinsson, P. (2012). "Risk attitudes, development, and growth: Macroeconomic evidence from experiments in 30 countries," Discussion Papers, WZB Junior Research Group Risk and Development SP II 2012-401, Social Science Research Center Berlin (WZB).

Vuchinich, R. E., & Simpson, C. A. (1998). “Hyperbolic temporal discounting in social drinkers and problem drinkers,” Experimental and Clinical Psychopharmacology, 6, 292–305.

Warner, J. T. & Pleeter, S. (2001). "The Personal Discount Rate: Evidence from Military Downsizing Programs," American Economic Review, 91(1), pp. 33-53.

Weber, E. U. & Hsee, C. K. (1999). “Models and mosaics: Investigation of cultural differences in risk perception and risk preference,” Psychonomic Bulletin and Review. 6, 611-617.

World Bank (2009). Conditional Cash Transfers: Reducing Present and Future Poverty, Washington DC.

WHO (1998). WHO Quality of Life User Manual, Department of Mental health and Prevention of Substance Abuse, World Health Organization, Geneva.

Yesuf, M. & Bluffstone, R. (2008). “Wealth and time preference in rural Ethiopia,” Environment for Development Discussion Paper Series DP 08-16.

TABLES AND FIGURES

Table 1: 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. (KES)	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
Observations	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.

Table 2: Mean characteristics of respondents of behavioural module

	T	C	p-value difference in means
Age in years	57.3	59.1	0.03
Female	79.3	77.3	0.57
Partner in household	34.5	33.5	0.68
Can read	29.9	29.9	0.91
Chronically ill (baseline)[1]	14.9	17.8	0.14
Disabled (baseline)[1]	6.3	6.29	0.98
Observations	1280	525	

Control group mean weighted using the Inverse Probability Weight. [1] Self-reported.

Figure 1. Per cent who will wait one month by future value

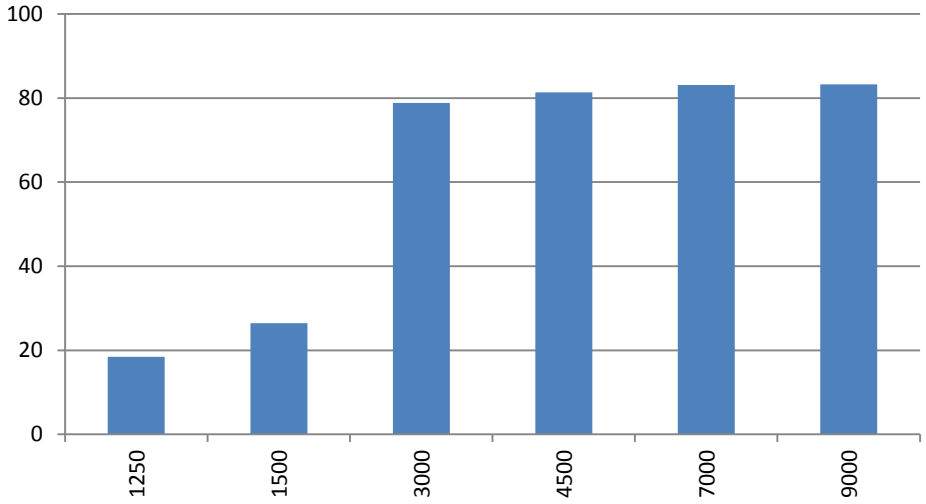


Table 3. Inconsistent inter-temporal choice responses

Future value	Consistent (N)	*%*	Inconsistent (N)	*%*	Total
1250	233	*70.0*	100	*30.0*	333
1500	229	*94.2*	14	*5.8*	243
3000	844	*97.8*	19	*2.2*	863
4500	46	*86.8*	7	*13.2*	53
7000	24	*100.0*	0	*0.0*	24
9000	5	*100.0*	0	*0.0*	5
Impatient (never wait)	284	*100.0*	0	*0.0*	284
Observations	1665	*92.2*	140	*7.8*	1805

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

Would wait 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
patient	31.8	32.3	0.85
impatient	16.0	19.2	0.11
Observations	1280	525	

Control group mean weighted using the Inverse Probability Weight

Table 5: Determinants of Time Discounting with Inverse Probability Weights

	Is willing to wait one month for KES:								
	wait9000	wait7000	wait4500	wait3000	wait1500	wait1250	Patient[1]	Impatient[2]	Inconsistent[3]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(10)
Treated	0.0336	0.0418	0.0361	0.0360	0.006	0.001	-0.000	-0.0297	-0.000
	(1.31)	(1.60)	(1.35)	(1.30)	(0.20)	(0.04)	(-0.01)	(-1.17)	(-0.00)
Age (x100)	-0.186	-0.266	0.267	-0.139	0.639	0.544	0.596	0.208	-0.186
	(-0.41)	(-0.58)	(0.55)	(-0.29)	(1.27)	(1.13)	(1.12)	(0.47)	(-0.60)
Age squared (x1000)	-0.0071	-0.00052	-0.0448	-0.00084	-0.0531	-0.0446	-0.0532	0.00268	0.0119
	(-0.16)	(-0.01)	(-0.95)	(-0.02)	(-1.06)	(-0.95)	(-1.04)	(0.06)	(0.42)
Female	0.0367	0.0232	0.0211	0.0356	-0.0592	-0.0164	-0.0193	-0.0372	0.0420
	(0.90)	(0.57)	(0.50)	(0.85)	(-1.50)	(-0.44)	(-0.47)	(-0.92)	(1.73)
Partner in household	-0.0301	-0.0179	-0.0300	-0.0185	**-0.0757**	-0.0158	-0.0610	0.0147	0.0181
	(-1.01)	(-0.58)	(-0.90)	(-0.55)	(-2.07)	(-0.46)	(-1.61)	(0.50)	(0.69)
Able to read	**0.0675**	**0.0628**	0.0589	**0.0785**	0.0389	0.0526	0.0591	**-0.0613**	0.0150
	(2.19)	(2.07)	(1.89)	(2.40)	(1.01)	(1.37)	(1.47)	(-2.03)	(0.48)
Chronically ill	0.00496	0.0106	0.0255	0.0409	0.00902	0.00487	0.0245	-0.000604	0.00383
	(0.12)	(0.25)	(0.60)	(0.96)	(0.20)	(0.12)	(0.51)	(-0.01)	(0.16)
Disabled	-0.150	-0.156	-0.146	-0.145	-0.0941	-0.0825	**-0.117**	0.163	-0.0294
	(-1.80)	(-1.87)	(-1.74)	(-1.70)	(-1.72)	(-1.86)	(-2.10)	(1.95)	(-1.39)
Observations	1,805	1,805	1,805	1,805	1,805	1,804	1,805	1,805	1,805
R-squared	0.079	0.081	0.076	0.082	0.059	0.031	0.054	0.080	0.033

Notes: Linear probability OLS regressions with robust standard errors and inverse probability weights. Also included in model but not reported are indicators for district, rural residence, 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, crowding index, and baseline per capita household consumption expenditure. Coefficients in bold are statistically significant at 5 per cent. [1] Will wait for KES1250 or kES1500. [2] Will never wait for any amount offered. [3] Responses inconsistent.

Figure 2. Per cent who choose to take a lottery (different options)

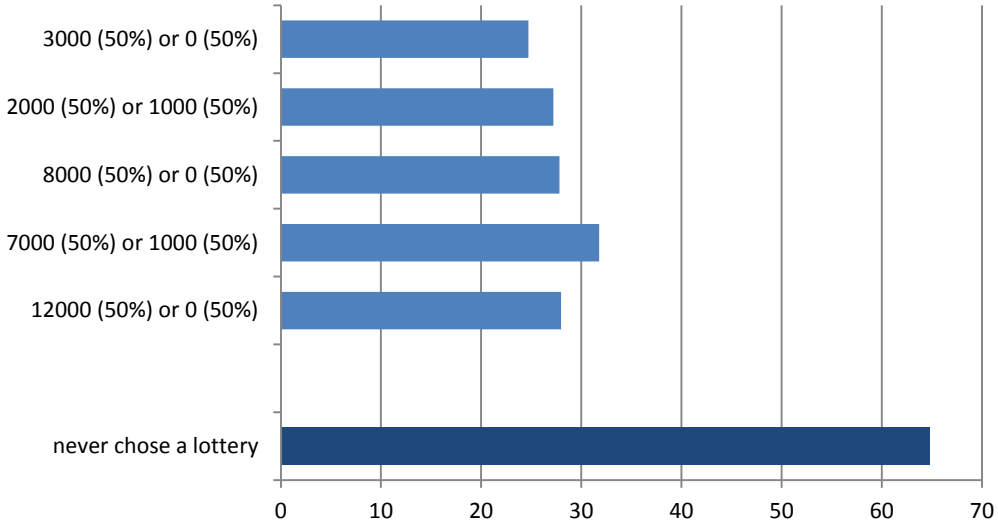


Figure 3. Consistency in Lottery Choices

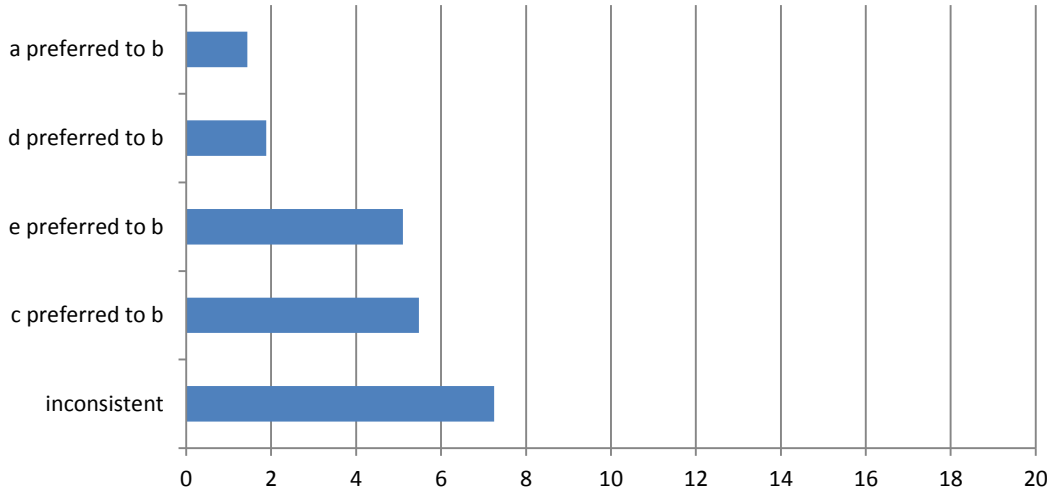


Table 6. Comparison of Lottery Choices by Study Arm

	T	C	p-value difference in means
B: 12000 (50%) or 0 (50%)	26.8	28.6	0.44
C: 7000 (50%) or 1000 (50%)	31.4	30.0	0.57
D: 8000 (50%) or 0 (50%)	27.2	28.5	0.58
E: 2000 (50%) or 1000 (50%)	26.6	27.3	0.74
A: 3000 (50%) or 0 (50%)	23.6	30.0	0.02
Never chose a lottery	65.6	63.4	0.36

Control group mean weighted using the Inverse Probability Weight

Table 7: Determinants of Risk Aversion with Inverse Probability Weights

	Will play the following lottery instead of taking KES1500 for certain:						
	3000 or 0 Lottery A	12000 or 0 Lottery B	7000 or 1000 Lottery C	8000 or 0 Lottery D	2000 or 1000 Lottery E	Never plays lottery	Inconsistent
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treated	-0.0490	-0.0205	0.00781	-0.0164	-0.0102	0.0236	-0.00311
	(-1.64)	(-0.70)	(0.26)	(-0.55)	(-0.35)	(0.76)	(-0.17)
Age (x100)	-0.173	-0.189	-0.580	-0.169	-0.392	0.692	-0.503
	(-0.35)	(-0.39)	(-1.24)	(-0.34)	(-0.79)	(1.34)	(-1.63)
Age squared (x1000)	0.0018	-0.0005	0.0019	-0.0007	0.0016	-0.005	0.005
	(0.39)	(-0.11)	(0.44)	(-0.14)	(0.35)	(-0.94)	(1.76)
Female	-0.0116	0.0198	-0.0356	0.00526	-0.00607	0.00830	-0.0281
	(-0.29)	(0.50)	(-0.86)	(0.13)	(-0.15)	(0.19)	(-1.16)
Partner in household	-0.00476	0.0296	0.0213	0.0228	0.0194	0.00906	**-0.0387**
	(-0.13)	(0.78)	(0.55)	(0.60)	(0.50)	(0.23)	(-1.97)
Able to read	0.0680	0.0758	0.0378	0.0521	0.0360	-0.0845	0.00863
	(1.60)	(1.87)	(0.89)	(1.26)	(0.88)	(-1.93)	(0.31)
Chronically ill	-0.0282	-0.0603	-0.0749	**-0.0776**	**-0.0986**	0.0430	0.0173
	(-0.64)	(-1.53)	(-1.79)	(-1.98)	(-2.58)	(0.96)	(0.49)
Disabled	**-0.172**	**-0.146**	**-0.158**	**-0.147**	**-0.124**	**0.180**	-0.0336
	(-4.54)	(-3.82)	(-3.69)	(-3.83)	(-3.00)	(4.04)	(-1.42)
Observations	1,805	1,805	1,805	1,805	1,805	1,805	1,805
R-squared	0.069	0.070	0.087	0.065	0.062	0.088	0.065

Notes: Linear probability OLS regressions with robust standard errors and inverse probability weights. Also included in model but not reported are indicators for district, rural residence, 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, crowding index, and baseline per capita household consumption expenditure. Coefficients in bold are statistically significant at 5 per cent.

Figure 4. Quality of life indicators (1=strongly disagree; 5=strongly agree)

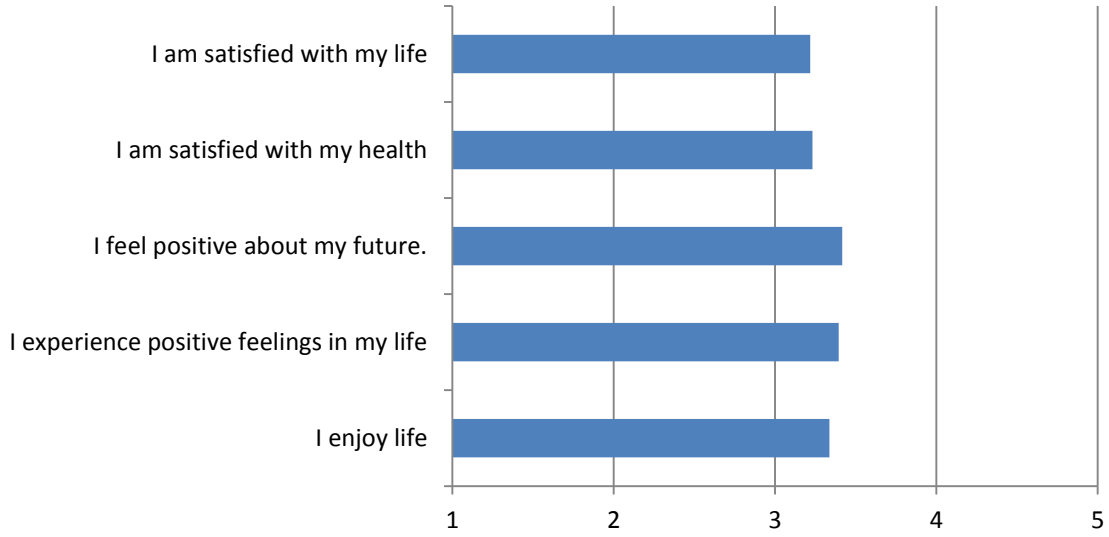


Table 8: Mean Differences by Study Arm in Quality of Life Items

	T	C	p-value difference in means
Enjoy life	49.6	42.2	0.00
Positive feelings	49.5	43.4	0.02
Future feelings	49.2	41.9	0.00
Health satisfaction	44.5	39.7	0.06
Life satisfaction	44.4	38.6	0.02

Variables take value of 1 if respondent strongly agrees or agrees with statement. Control group mean weighted using the Inverse Probability Weight.

Table 9: Determinants of Quality of Life with Inverse Probability Weights

	Happy	Positive Feelings	Future Feelings	Health	Life	Overall Scale Score
	(1)	(2)	(3)	(4)	(50)	(6)
Treated	**0.0717**	0.0562	**0.0623**	0.0368	0.0557	**0.763**
	(2.24)	(1.87)	(1.96)	(1.17)	(1.76)	(2.51)
Age (x100)	-0.284	0.0405	0.136	**-1.31**	-0.385	-5.75
	(-0.56)	(0.08)	(0.28)	(-2.25)	(-0.71)	(-1.12)
Age squared (x1000)	-0.00732	-0.0431	-0.0751	0.0683	0.0152	-0.0285
	(-0.15)	(-0.89)	(-1.62)	(1.22)	(0.29)	(-0.06)
Female	0.0726	0.0495	0.0340	-0.00850	**0.135**	0.488
	(1.74)	(1.22)	(0.83)	(-0.19)	(3.28)	(1.22)
Partner in household	0.0771	**0.104**	**0.0833**	**0.127**	**0.129**	**1.144**
	(1.92)	(2.77)	(2.21)	(3.19)	(3.22)	(3.02)
Able to read	0.0556	**0.0836**	0.0544	0.0392	0.0692	0.589
	(1.29)	(2.06)	(1.31)	(0.92)	(1.59)	(1.28)
Chronically ill	**-0.101**	**-0.0961**	**-0.143**	-0.0974	**-0.102**	**-1.409**
	(-2.19)	(-2.25)	(-3.00)	(-1.90)	(-2.25)	(-2.74)
Disabled	-0.0224	-0.101	0.000108	**-0.126**	0.0122	-0.628
	(-0.31)	(-1.91)	(0.00)	(-2.21)	(0.17)	(-1.26)
Observations	1,805	1,805	1,805	1,805	1,804	1,805
R-squared	0.076	0.123	0.117	0.119	0.076	0.124

Notes: Linear probability OLS regressions with robust standard errors and inverse probability weights. Also included in model but not reported are indicators for district, rural residence, 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, crowding index, and baseline per capita household consumption expenditure. Coefficients in bold are statistically significant at 5 per cent.

Figure 5. Percentage of people that think their life will be better in 1, 3 and 5 years

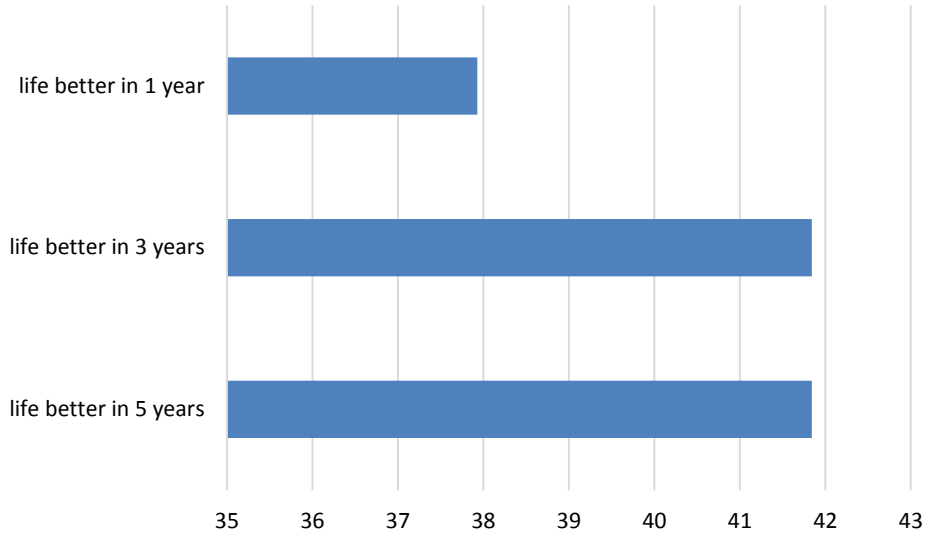


Figure 6. Risk assessment indicators (1=least likely, 5=most likely)

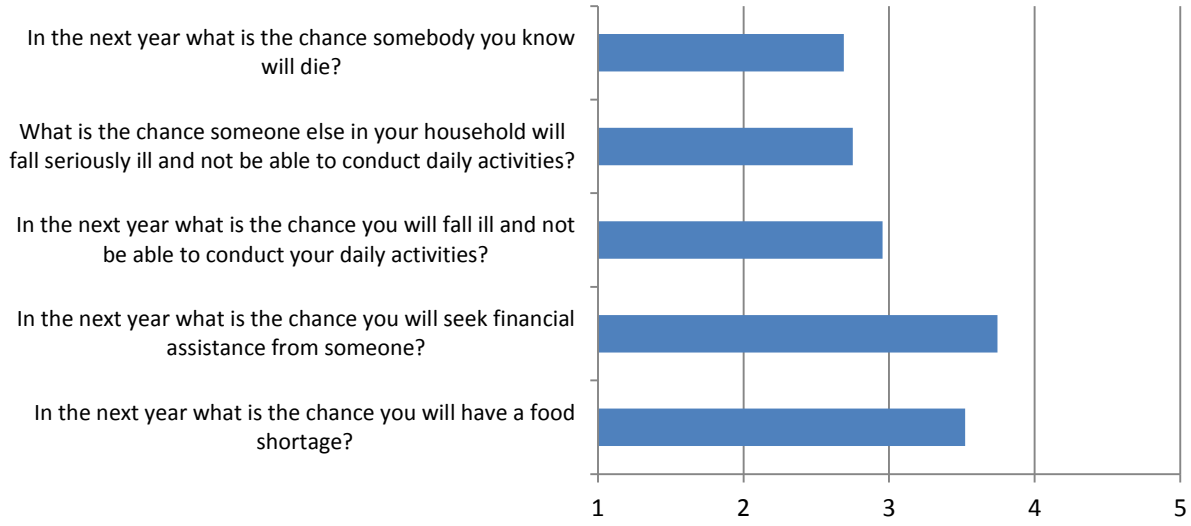


Table 10: Comparison of future perceptions by study arm

	T	C	p-value difference in means
Life will be better in the future			
life better in 1 year	40.1	33.7	0.01
life better in 3 years	43.1	36.1	0.01
life better in 5 years	43.0	36.9	0.02
Future risk assessment			
Food	11.1	9.5	0.30
Financial	8.1	9.9	0.25
Illness	14.6	21.8	0.00
Someone else ill	19.2	23.7	0.04
Someone else die	26.9	31.3	0.06

In the first three rows, 1 indicates respondent believes life will be better in the future, and 0 if the same or worse. Future risk assessment is coded 1 if respondent believes there is *no chance* the event will happen in the next year. Control group mean weighted using the Inverse Probability Weight.

Table 11: Determinants of Future perceptions with Inverse Probability Weights

	Yes life will be better in:				Strongly disagree that in next year will:					
	One year	Three years	Five years	Yes on all three	Have food shortage	Have financial problems	Fall ill	Know someone else who will fall ill	Know someone who will die	Inconsistent[1]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Treated	**0.0657**	**0.0638**	0.0546	0.0371	0.0148	-0.0134	**-0.0810**	-0.0515	-0.0532	**0.00470**
	(2.16)	(2.10)	(1.72)	(1.27)	(0.71)	(-0.68)	(-3.03)	(-1.82)	(-1.73)	(1.97)
Age (x100)	-0.449	-0.733	-0.949	-0.703	-0.0029	-0.534	**-1.54**	**-1.98**	**-1.49**	0.0099
	(-0.84)	(-1.39)	(-1.80)	(-1.33)	(-0.01)	(-1.33)	(-3.06)	(-3.80)	(-2.69)	(0.27)
Age squared (x1000)	-0.00967	0.00457	0.0197	0.0183	-0.000593	0.0343	**0.117**	**0.176**	**0.116**	-0.00234
	(-0.19)	(0.09)	(0.39)	(0.37)	(-0.02)	(0.94)	(2.54)	(3.51)	(2.14)	(-0.74)
Female	-0.0219	-0.0113	-0.00281	-0.00177	0.0390	-0.0122	0.0239	-0.0282	-0.0376	-0.00210
	(-0.52)	(-0.28)	(-0.07)	(-0.04)	(1.37)	(-0.40)	(0.70)	(-0.76)	(-0.94)	(-0.51)
Partner in household	0.0108	0.0144	-0.0166	0.0212	0.00301	0.0298	-0.0380	-0.0632	-0.0542	0.00310
	(0.28)	(0.40)	(-0.42)	(0.59)	(0.10)	(1.04)	(-1.16)	(-1.88)	(-1.46)	(0.94)
Able to read	0.0290	0.0260	0.0391	0.0239	0.00890	-0.00501	0.00153	-0.0160	**-0.0748**	-0.00348
	(0.67)	(0.64)	(0.93)	(0.60)	(0.38)	(-0.18)	(0.05)	(-0.49)	(-2.01)	(-1.01)
Chronically ill	0.0506	0.0425	0.0237	0.0434	-0.0271	-0.0110	**-0.103**	**-0.0806**	**-0.119**	-0.00125
	(0.97)	(0.86)	(0.46)	(0.86)	(-1.07)	(-0.44)	(-3.02)	(-2.12)	(-2.76)	(-0.43)
Disabled	**-0.119**	**-0.131**	**-0.115**	**-0.109**	0.0523	-0.0131	-0.0390	0.0384	-0.0296	0.00327
	(-2.47)	(-2.73)	(-2.44)	(-2.48)	(1.09)	(-0.42)	(-1.19)	(0.63)	(-0.46)	(0.50)
Observations	1,793	1,802	1,802	1,805	1,803	1,805	1,805	1,805	1,800	1,805
R-squared	0.098	0.122	0.121	0.097	0.045	0.063	0.104	0.070	0.061	0.011

Notes: Linear probability OLS regressions with robust standard errors and inverse probability weights. Also included in model but not reported are indicators for district, rural residence, 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, crowding index, and baseline per capita household consumption expenditure. Coefficients in bold are statistically significant at 5 per cent. [1] Inconsistent response on 'life will be better' questions'.

APPENDIX 1

Visual Aid for Lottery Choices

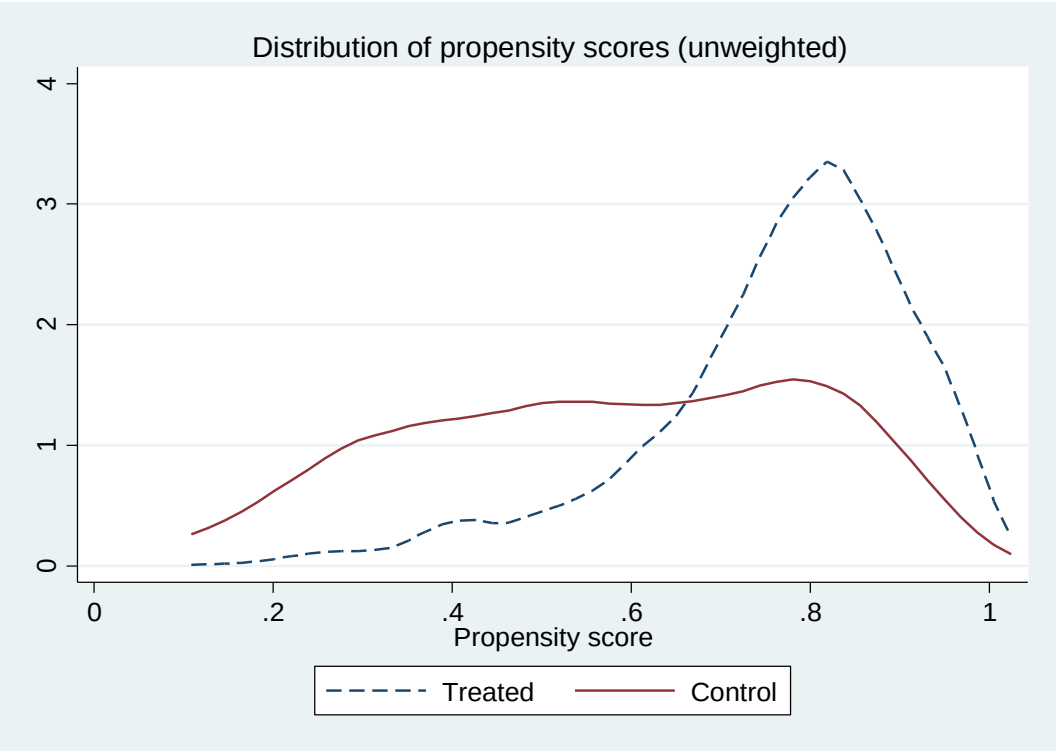
		
A	3000	0
B	12000	0
C	7000	1000
D	8000	0
E	2000	1000

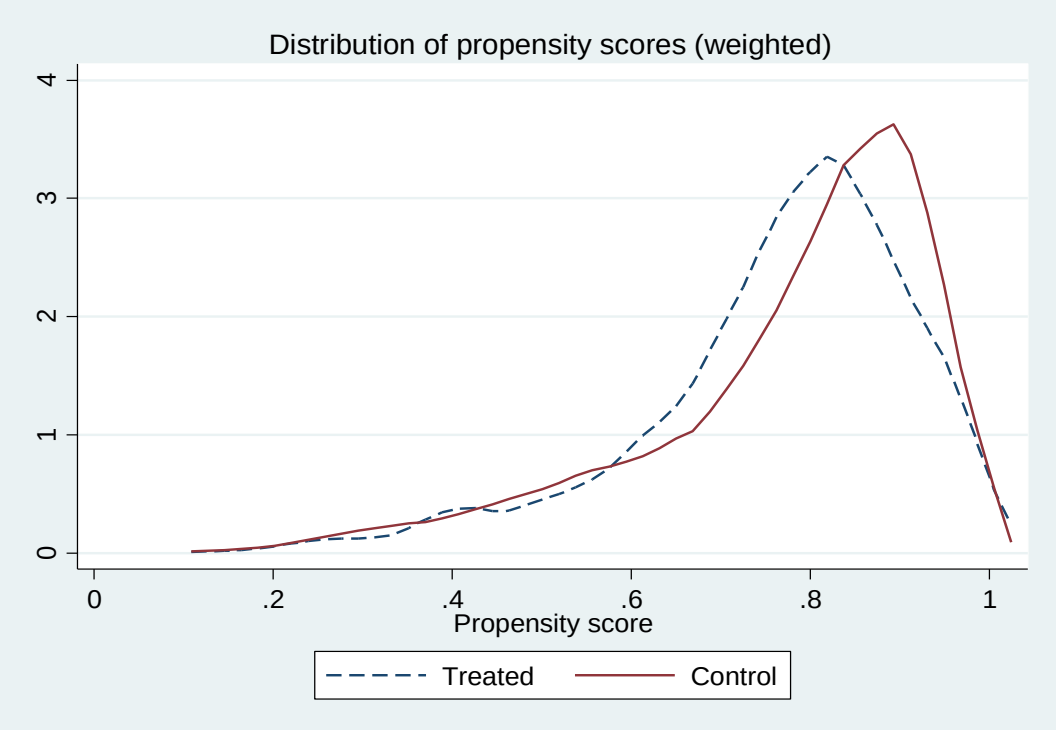
Table A1: Probit estimates of probability of being in treatment group

	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.

Distribution of probability scores





Appendix 2: OLS Regression Results without Inverse Probability Weights

Table A1: OLS Determinants of Time Discounting

	Is willing to wait one month for KES:								
	9000	7000	4500	3000	1500	1250	Patient[1]	Impatient[2]	Inconsistent[3]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treated	0.0233	0.0292	0.0184	0.00842	-0.000509	0.0122	-0.00422	-0.0177	-0.000834
	(1.14)	(1.42)	(0.87)	(0.38)	(-0.02)	(0.57)	(-0.16)	(-0.90)	(-0.06)
Age (x100)	0.045	0.042	0.345	0.095	**0.967**	**0.828**	**1.00**	-0.082	-0.151
	(0.14)	(0.13)	(1.00)	(0.27)	(2.58)	(2.68)	(2.55)	(-0.03)	(-0.71)
Age squared (x1000)	-0.022	-0.022	-0.046	-0.016	**-0.09**	**-0.068**	**-0.089**	0.015	0.025
	(-0.73)	(-0.73)	(-1.41)	(-0.49)	(-2.50)	(-2.23)	(-2.36)	(0.50)	(1.02)
Female	-0.00304	-0.00437	0.00342	0.0189	-0.0523	-0.00534	-0.0177	-0.00435	**0.0478**
	(-0.13)	(-0.18)	(0.14)	(0.71)	(-1.84)	(-0.21)	(-0.59)	(-0.19)	(2.91)
Partner in household	0.00565	0.0125	0.0229	0.0182	-0.0445	-0.0119	-0.0254	-0.0191	0.0213
	(0.28)	(0.61)	(1.05)	(0.78)	(-1.74)	(-0.53)	(-0.93)	(-0.96)	(1.34)
Able to read	**0.0536**	**0.0530**	**0.0520**	**0.0742**	-0.0128	0.0110	0.00192	**-0.0525**	0.0135
	(2.65)	(2.65)	(2.47)	(3.34)	(-0.49)	(0.49)	(0.07)	(-2.68)	(0.83)
Chronically ill	**0.0511**	**0.0539**	**0.0709**	**0.0690**	0.0326	0.0324	0.0466	**-0.0491**	0.00556
	(2.29)	(2.42)	(3.13)	(2.82)	(1.06)	(1.18)	(1.44)	(-2.26)	(0.31)
Disabled	-0.0620	-0.0712	-0.0579	-0.0516	-0.0129	-0.0544	-0.0397	0.0723	-0.0269
	(-1.43)	(-1.63)	(-1.32)	(-1.14)	(-0.28)	(-1.42)	(-0.83)	(1.67)	(-1.22)
Observations	1,805	1,805	1,805	1,805	1,805	1,804	1,805	1,805	1,805
R-squared	0.034	0.035	0.033	0.036	0.029	0.020	0.023	0.032	0.021

Notes: Linear probability OLS regressions with robust standard errors. Also included in model but not reported are indicators for district, rural residence, 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, crowding index, and baseline per capita household consumption expenditure. Coefficients in bold are statistically significant at 5 per cent. [1] Will wait for KES1250 or KES1500. [2] Will never wait for any amount offered. [3] Responses inconsistent.

Table A2: OLS Determinants of Risk Aversion

	Will play the following lottery instead of taking KES1500 for certain:						
	3000 or 0	12000 or 0	7000 or 1000	8000 or 0	2000 or 1000	Never picks lottery	Inconsistent
	Lottery A	Lottery B	Lottery C	Lottery D	Lottery E		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treated	-0.0168	-0.0116	0.0175	0.00746	-0.000147	-5.53e-05	0.0117
	(-0.70)	(-0.47)	(0.70)	(0.30)	(-0.01)	(-0.00)	(0.83)
Age (x100)	-0.199	0.0502	-0.143	0.0627	0.070	0.302	-0.352
	(-0.51)	(0.13)	(-0.35)	(0.15)	(0.17)	(0.73)	(-1.38)
Age squared (x1000)	0.005	-0.003	-0.002	-0.003	-0.003	0.000	0.003
	(0.14)	(-0.92)	(-0.52)	(-0.81)	(-0.74)	(0.07)	(1.33)
Female	-0.0241	0.00662	-0.0424	-0.0166	-0.0166	0.0326	**-0.0392**
	(-0.85)	(0.23)	(-1.39)	(-0.56)	(-0.56)	(1.05)	(-2.15)
Partner in household	0.0119	0.0203	-0.00584	0.0143	-0.00530	0.0162	**-0.0365**
	(0.46)	(0.76)	(-0.21)	(0.53)	(-0.20)	(0.57)	(-2.25)
Able to read	0.0119	0.0416	0.0449	0.0248	0.0250	**-0.0556**	0.0140
	(0.46)	(1.55)	(1.62)	(0.92)	(0.93)	(-1.97)	(0.93)
Chronically ill	-0.00510	0.0175	-0.00621	-0.00438	-0.0515	0.0113	-0.0288
	(-0.18)	(0.58)	(-0.20)	(-0.15)	(-1.80)	(0.36)	(-1.86)
Disabled	**-0.0937**	**-0.0810**	-0.0693	**-0.0812**	-0.0405	0.0772	0.00376
	(-2.50)	(-2.05)	(-1.60)	(-2.05)	(-0.96)	(1.74)	(0.14)
Observations	1,805	1,805	1,805	1,805	1,805	1,805	1,805
R-squared	0.039	0.057	0.062	0.049	0.039	0.066	0.031

Notes: Linear probability OLS regressions with robust standard errors. Also included in model but not reported are indicators for district, rural residence, 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, crowding index, and baseline per capita household consumption expenditure. Coefficients in bold are statistically significant at 5 per cent.

Table A3: OLS Determinants of Quality of Life

	Happy	Positive Feelings	Future Feelings	Health	Life	Overall Scale Score
	(1)	(2)	(3)	(4)	(5)	(6)
Treated	0.0328	0.0326	**0.0644**	**0.0532**	**0.0588**	**0.708**
	(1.21)	(1.23)	(2.44)	(2.03)	(2.20)	(2.82)
Age (x100)	-0.502	0.101	0.184	-0.828	-0.185	-4.82
	(-1.16)	(0.25)	(0.46)	(-1.94)	(-0.42)	(-1.18)
Age squared (x1000)	0.0222	-0.0551	**-0.0772**	0.0142	0.003	-0.107
	(0.54)	(-1.44)	(-2.08)	(0.35)	(0.07)	(-0.28)
Female	0.0312	0.00375	0.00367	-0.00628	**0.0817**	0.166
	(0.97)	(0.12)	(0.12)	(-0.20)	(2.59)	(0.56)
Partner in household	0.0154	0.0444	0.0412	**0.0638**	**0.113**	**0.703**
	(0.53)	(1.55)	(1.45)	(2.26)	(3.92)	(2.62)
Able to read	**0.0852**	**0.0922**	**0.0806**	**0.0785**	**0.0706**	**0.858**
	(2.90)	(3.18)	(2.79)	(2.72)	(2.42)	(3.06)
Chronically ill	-0.0440	-0.0317	-0.0419	**-0.102**	-0.0314	**-0.711**
	(-1.31)	(-0.94)	(-1.26)	(-3.18)	(-0.95)	(-2.13)
Disabled	-0.0175	-0.0628	-0.0497	**-0.116**	-0.0248	-0.632
	(-0.33)	(-1.23)	(-0.98)	(-2.42)	(-0.47)	(-1.39)
Observations	1,805	1,805	1,805	1,805	1,804	1,805
R-squared	0.041	0.069	0.085	0.097	0.041	0.087

Notes: Linear probability OLS regressions with robust standard errors. Also included in model but not reported are indicators for district, rural residence, 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, crowding index, and baseline per capita household consumption expenditure. Coefficients in bold are statistically significant at 5 per cent.

Table A4: OLS Determinants of Future Perceptions

	Yes life will be better in:				Strongly disagree that in next year will:					
	One year	Three years	Five years	Yes on all three	Have food shortage	Have financial problems	Fall ill	Know someone else who will fall ill	Know someone who will die	Inconsistent[1]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Treated	**0.113**	**0.104**	**0.103**	**0.0801**	**0.0359**	0.00968	-0.0303	-0.0189	-0.0123	**0.00727**
	(4.38)	(3.96)	(3.94)	(3.19)	(2.21)	(0.61)	(-1.41)	(-0.84)	(-0.50)	(2.09)
Age (x100)	-0.618	-0.566	-0.564	-0.62	-0.0627	-0.447	**-0.738**	**-0.996**	**-0.892**	0.0204
	(-1.49)	(-1.43)	(-1.43)	(-1.54)	(-0.24)	(-1.68)	(-2.07)	(-2.57)	(-2.23)	(0.42)
Age squared (x1000)	0.000982	-0.0195	-0.0229	0.0017	-0.000637	0.0348	0.0385	**0.0787**	0.0605	-0.00381
	(0.03)	(-0.52)	(-0.62)	(0.05)	(-0.03)	(1.41)	(1.23)	(2.20)	(1.63)	(-0.90)
Female	-0.0223	-0.0145	0.000932	0.00159	0.00558	0.00526	0.00857	-0.0118	-0.0109	-0.00167
	(-0.72)	(-0.47)	(0.03)	(0.05)	(0.26)	(0.28)	(0.35)	(-0.45)	(-0.38)	(-0.33)
Partner in household	0.00436	0.00459	-0.0135	0.00674	-0.0167	0.0314	-0.0173	**-0.0493**	-0.0382	0.00340
	(0.15)	(0.16)	(-0.48)	(0.24)	(-0.82)	(1.74)	(-0.77)	(-2.10)	(-1.46)	(0.78)
Able to read	-0.0171	0.0108	0.0450	0.00790	0.00317	0.00205	0.0359	0.0251	-0.0127	-0.00382
	(-0.60)	(0.38)	(1.58)	(0.29)	(0.18)	(0.13)	(1.64)	(1.07)	(-0.50)	(-0.91)
Chronically ill	0.0348	0.0357	0.0199	0.0300	-0.00340	0.0239	**-0.0746**	-0.0362	**-0.0669**	-0.00185
	(1.05)	(1.09)	(0.61)	(0.94)	(-0.17)	(1.18)	(-3.54)	(-1.39)	(-2.40)	(-0.46)
Disabled	-0.0585	-0.0675	-0.0569	-0.0616	0.0254	-0.0206	-0.00421	0.0255	0.00140	0.00493
	(-1.20)	(-1.39)	(-1.21)	(-1.38)	(0.76)	(-0.82)	(-0.13)	(0.61)	(0.03)	(0.51)
Observations	1,793	1,802	1,802	1,805	1,803	1,805	1,805	1,805	1,800	1,805
R-squared	0.068	0.092	0.107	0.067	0.020	0.028	0.067	0.042	0.037	0.011

Notes: Linear probability OLS regressions with robust standard errors. Also included in model but not reported are indicators for district, rural residence, 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, crowding index, and baseline per capita household consumption expenditure. Coefficients in bold are statistically significant at 5 per cent. [1] Inconsistent response on 'life will be better' questions'.