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Are impatient farmers more risk-averse? Evidence from a lab-in-the-field experiment in rural Uganda

Are impatient farmers more risk-averse?
Evidence from a lab-in-the-field experiment in rural Uganda

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1. Introduction

Risk and time preferences are important factors in economic decision-making, particularly among farmers in developing countries (Binswanger, 1980, Yesuf & Bluffstone, 2009, Galarza, 2009). For instance, risk aversion has been shown to restrict farmers' willingness to participate in risky but potentially profitable activities such as money lending (Boucher *et al.*, 2008, Jacobson & Petrie, 2009). Risk-aversion has also been identified as a key feature preventing farmers from adopting new profitable technologies (e.g., Liu, 2008, Dercon & Christiaensen, 2011). Studies of time preferences in developing countries also find a high level of impatience, which may prevent farmers from making long-term investments (Tanaka *et al.*, 2010, Ashraf *et al.*, 2006, Duflo *et al.*, 2011).

Recent research suggests that risk and time preferences may be related: individuals who are more risk-tolerant may also be more patient (Anderhub *et al*., 2001, Burks *et al.*, 2009, Dohmen *et al.*, 2012, Carpenter *et al*., 2011, Benjamin *et al*., 2012). Precisely how they are related is still unclear, though some evidence suggests that they may share common genetic and behavioral roots. For instance, Carpenter *et al*. (2011) find that risk and time preferences are both related to the 7-repeat allele of the DRD4 gene that regulates dopamine uptake in the brain, while Dohmen *et al*. (2010) find that risk and time preferences both correlate with cognitive ability. Given these findings, as well as indirect evidence from lab experiments about the relationship between risk and time preferences provided by Halevy (2008), Epper *et al*. (2012), Andreoni and Sprenger (2012) and Bchir *et al.* (2013), field experiments are needed to shed light on their external validity.

We contribute to this literature by delivering new field evidence about the relationship between risk and time preferences via a method specifically designed for field settings: a simplified version of the Convex Time Budget method (CTB hereafter) first introduced by Andreoni & Sprenger (2012) (AS hereafter). Such a method is needed for two reasons. First, while the available laboratory evidence suggests that risk and time preferences are correlated, field data remains sparse because of methodological challenges. The standard method for eliciting time preferences based on multiple price lists (MPLs) has been criticized because it forces subjects to choose extreme budget allocations, which may partly explain why these methods yield high estimated individual discount rates (Frederick et al., 2002). Indeed, according to Andreoni & Sprenger (2012): the "experimenters' frequent assumption of linear utility … leads to upward-biased discount rate estimates if utility is concave". By contrast, the CTB exhibits several advantages relative to standard MPLs but requires some adjustments to be usable for field experiments. Second, almost all of the previous experimental studies were based on a specific combination of elicitation methods for risk and time preferences. With the exception of Carpenter et al. (2011), risk preferences were elicited by certainty equivalents for risky lotteries and time preferences were elicited with multiple price lists. The method based on certainty equivalents has some well-known limitations, such as the propagation of errors. Depending on the nature of the subject pool it is sometimes preferable to rely on a single lottery choice task as proposed by Binswanger (1980) and Eckel & Grossman (2008), rather than on the standard iterative methods implemented for narrowing down the certainty equivalents.

We develop and test a simplified version of the CTB, modified for implementation in a field setting, and illustrate its operation among farmers in rural Uganda. Our field-CTB restricts the set of feasible budget allocations between sooner and later payment dates to the options most frequently chosen when the standard CTB is implemented in the lab. Besides allowing for aggregate and individual estimates of subjective discount rates, the data generated by the field-CTB can also be used to estimate the curvature of the utility function. Therefore we can test directly the conjecture about the negative correlation between risk tolerance and impatience in individuals. We provide a robustness check for the existence of such a correlation by relying on a second and independent measure of risk preferences based on the method proposed by Binswanger (1980) and by Eckel & Grossman (2008), and which is particularly suitable for field experiments (Dave et al., 2010).

Based on our experimental field data which was obtained through a combination of our field- CTB and the Binswanger methods, we find evidence of a negative correlation between risk-tolerance and impatience. Because our study uses an unconventional sample for which a WEIRD[1] effect is unlikely, we increase both the robustness and the external validity of the alleged risk and time preference relationship.

The remainder of the paper is organized as follows: section 2 presents a brief overview of the literature, section 3 presents our experimental design, section 4 presents the results and section 5 concludes.

1. Relationship between risk and time preferences

Several recent experimental studies report a correlation between risk and time preferences (Anderhub et al., 2001, Carpenter et al., 2011, Dohmen et al., 2010, Burks et al., 2009). Albeit most find that risk-averse individuals are also more impatient, they also find that risk-tolerance is highly variable among individuals and can depend on individual characteristics, including gender, age, education, health status, risk-exposure, and religion. In parallel, recent genetic studies have found that the propensity to take risks is partly heritable

[1] Subjects from *Western, Educated, Industrialized, Rich and Democratic* countries (Henrich et al., 2010).

(Cesarini *et al*., 2009; Zhong *et al*., 2009). For instance, Carpenter *et al*. (2011) find that the propensity to choose risky lotteries is predicted by the presence of the 7 repeat allele of the dopamine receptor gene DRD4. They also find that the same allele predicts subjects' choices in an MPL designed to elicit time preferences.

In the experimental literature, Anderhub *et al*. (2001) elicit risk preferences by certainty equivalents for immediate lotteries and time preferences by certainty equivalents for delayed lottery. Similarly, Dohmen *et al.* (2009) rely on certainty equivalents for a lottery to elicit risk preferences and an MPL offering a series of choices between an immediate payment and a later payment. They find a strong negative correlation between individuals' propensity to take risks and their impatience: individuals who are more patient are less risk-averse. Dohmen *et al.*'s (2009) study uses a large (n > 1000) representative sample of the German population, which provides field evidence of the relationship between risk and time preferences but a major drawback is that the key result is based on a *between* subject analysis: subjects are either assigned to the time preference task or to the risk preference task. Their results therefore preclude conclusion that risk and time preferences are correlated *within* individuals. In contrast, and to facilitate a within subject analysis, Burks et al. (2009) ask their subjects to perform both tasks. They estimate a quasi-hyperbolic ($\beta-\delta$) discounting model with the data of the time preferences task and a CRRA parameter with the data of the risk preference task. They report a negative correlation with the estimated risk-aversion parameter and each of the time preferences parameters. Nevertheless, their data was obtained from a highly specialized sample: US trainee truckers, thus limiting its external validity. Interestingly, both Dohmen *et al*. (2009) and Burks *et al.* (2009) show that risk and time preferences are correlated to cognitive ability; individuals with higher cognitive skills are more patient and more risk-tolerant.

Additional methodological factors may explain the significance of previous findings related to risk and time preferences. Most importantly, all previous studies were based on standard MPLs to elicit time preferences, which are well known to overestimate discount rates (see Frederick et al., 2002, and Andersen et al., 2008). It is therefore important to test whether the relationship between risk and time preferences is robust to methodological factors, in particular to the way time preferences are elicited.

3. **Experimental design**

3.1 Sample

Risk and time preferences were elicited among subjects participating in a larger field experiment that examined the relationship between farmer preferences and their willingness to participate in an environmental conservation program in Uganda.[2] As such, our sample consists of farmers from Masindi District, western Uganda, where the program takes place (Figure 1). Farmers were recruited to participate in the experiment according to three criteria: land tenure, tribe, and language. The land tenure criterion ensured that participants had decision-making power over their land and thus could decide how to dedicate their land to farming and environmental conservation. Tribal affiliation and linguistics are important considerations because Uganda has 51 tribes and 31 languages, several of which are mutually unintelligible (Ladefoged, 1992). Within Masindi, we selected 13 villages in 5 sub-counties where ethnic Banyoro are the predominant tribal group and Runyoro is the most widely spoken language. [3]

INSERT FIGURE 1 ABOUT HERE

3.1 Risk preferences

Risk preferences were elicited using Eckel & Grossman's Gamble-Choice task (EG thereafter) (2008). In this task, subjects choose between six gambles (Table 1). Each gamble carries a 0.50 probability of a low outcome and a 0.50 probability of a high outcome. Gamble 1 offers a safe option involving a certain return with no risk. Gambles 2 to 5 increase linearly in both expected return and risk. Gamble 6 offers the same expected return as Gamble 5, but with more risk. Subjects were ranked on a scale of 1 to 6 according to their selected gamble: subjects who select Gamble 1 are classified as extremely risk-averse; subjects who select Gamble 6 are classified as risk-seeking.

INSERT TABLE 1 ABOUT HERE

3.2 Time preferences

Time preferences were elicited using a simplified version of AS's CTB task, which we adapted for implementation in the field. In this task, subjects work through three forms, each with five questions, concerning payments over near- and long-term time frames. Each question presents a payoff vector (x_t, x_{t+k})

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[2] See Clot & Stanton (2014).

[3] Banyoro are well represented in Kampala, Uganda's capital, where many students are fluent in both Runyoro and English, which facilitated the coordination of focus groups to test and translate our experimental protocol. Our protocol was adapted using double blind translation.

that offers a payment x_t at a sooner date t and a payment x_{t+k} at a later date $t+k$. In the first form, t=1 day and k= 35 days; in the second form, t=1 day and k=70 days, and in the third form, t=36 days and k=35 days. For each of the 15 questions, subjects choose between three payoff vectors corresponding either to an *extreme allocation* of a fixed budget at date t or date $t+k$, or to an *interior allocation* corresponding to an equal split of the fixed budget. A price ratio P measures the relative price of "consumption" at the sooner date: $P = 1+ r$, where r is the gross interest rate. Figure 2 presents a sample CTB form and Table 2 presents summary information of the 15 allocation questions. The sequence of questions is designed so that participants would initially choose the payoff vector (x_t,0) and eventually switch to (0, x_{t+k}), thereby revealing information about the curvature of their utility function. Following AS, varying the price ratio P allows estimation of the utility function curvature (α), varying k allows estimation of the discount factor (δ), and varying t allows estimation of present bias (β).

As in other field implementations of the CTB (Giné et al. (2012), Carvalho et al. (2013), Janssen et al. (2013), Clot and Stanton (2014), Sawada and Kuroishi (2015), we needed to adapt its original design to our field setting. In our experiment we introduced two important changes: first, we eliminated the intermediary budget allocation decision, instead requiring that subjects choose an inter-temporal payoff vector[4] directly. Second, we restricted the set of possible budget allocations from which subjects can choose. Critically, our restricted set of budget allocations contains the most frequently observed allocations in AS's unconstrained set (2012)[5]. Indeed, AS found that 37% of their subjects always choose extreme allocations, with the remaining subjects choose such extreme allocations only 50% of the time on average.[6]

INSERT TABLE 2 ABOUT HERE

3.3 Data

We collected data on 282 individuals across 13 villages. We conducted one experimental session per village. Each session involved between 20 and 24 subjects. Subjects were told that the study would take 4 hours and that they would earn approximately UGX 3500 (USD 1.35) plus a UGX 1500 thank-you payment, the average equivalent of two day's wages in rural Uganda.

[4] Our setting is nevertheless very close to AS because in their experiment subjects could directly see the final payoff vector corresponding to any allocation.
[5] Our choice set contrasts with Carvalho et al.'s (2013) who only allow for interior allocations.
[6] AS also found that subjects who choose interior allocations frequently select allocations that are close or equal to the mid-point.

INSERT FIGURE 2 ABOUT HERE

Subjects' socio-demographic characteristics were collected in a post-experiment survey. Table 3 reports summary statistics for the control variables used in our statistical analysis of the relationship between risk and time preferences. The average individual is 42 years old, has completed primary school, owns 10 hectares of land and lives less than one kilometer from a paved road. Men constitute 78% of the sample.

INSERT TABLE 3 ABOUT HERE

2. Results

We present our key findings in two subsections. Subsection 4.1 compares our field data to AS's data. There are two important differences between these data: first our data was generated by a highly simplified version of the CTB task, adapted to the field and second, in contrast to AS who run a controlled laboratory experiment with US students, our data was collected through a framed field experiment involving a heterogeneous subject pool of farmers in rural Uganda. Subsection 4.2 examines the within-subject relationship between risk and time preferences in two ways: (i) by investigating the correlation between the estimated parameters for risk tolerance and for patience based on the field-CTB data only, and (ii) by analyzing the correlation between a subject's risk preference category elicited with the EG method and time preferences elicited by the field- CTB task. For notational convenience we write $x_{t,+k}$ the amount of the sooner payment at date t, when the delay for the later payment equals k.

4.1 Laboratory versus field CTB data

We estimate individual parameters for approximately 72% of the subject pool (203 out of 282 individuals)[7]. Parameters are estimated as in Andreoni and Sprenger (2012) by assuming that an individual's preferences over experimental payoff vectors (x_t, x_{t+k}) are represented by a CRRA utility function combined with quasi-hyperbolic discounting (Laibson 1997, O'Donoghue and Rabin, 1999).

[7] AS (2012) provide estimates for 88% of their subjects (86 out of 97).

$$u(x_t, x_{t+k}) = \begin{cases} x_t^{\alpha} + \beta\delta^k x_{t+k}^{\alpha} & if\ t = 0 \\ x_t^{\alpha} + \delta^k x_{t+k}^{\alpha} & if\ t > 0 \end{cases} \tag{1}$$

The payoff vector that maximizes $u(x_t, x_{t+k})$ under the future value budget constraint $Px_t + x_{t+k} = B$ satisfies the first-order condition (for an interior solution) given by equation (2).

$$P = \frac{x_t^{\alpha-1}}{\alpha\beta\delta^k x_{t+k}^{\alpha-1}} \tag{2}$$

Rearranging and taking logarithm, we can rewrite the first-order condition as:

$$ln\left(\frac{x_t}{x_{t+k}}\right) = \frac{ln(\beta)}{\alpha-1} + \frac{kln(\delta)}{\alpha-1} + \frac{\ln(P)}{\alpha-1} \tag{3}$$

We rely on non-linear least squares in order to estimate α, β, δ. Increasing the gross interest rate r, all else equal, allows estimation of a subject's CRRA parameter α from his (x_t ,x_{t+k}) choices. Note that α also measures the curvature of the utility function. In a similar way we can estimate an individual's discount rate δ, by varying the delay k, all else equal. Finally, present bias β is estimated by comparing the choice (x_t ,x_{t+k}) when $t > 0$ to the choice (x_t ,x_{t+k}) when $t = 0$, all else equal. Strictly speaking, the elicitation of present bias requires an immediate cash payment because "present bias is a visceral response only activated when sooner rewards are actually immediate" (AS, 2012). However, for practical reasons such immediacy is not always feasible. For instance, in AS (2012), the payments are made several hours after a session in order to "equate transactions costs over sooner and later payments". For the same reason, we needed to include a front-end delay of one day in our experimental setting. By neutralizing transaction costs however, present bias may become undetectable[8].

For 79 of our subjects we could not provide meaningful parameters estimates because 76 subjects chose "flat[9]" or "quasi-flat[10]" allocation decisions and 3 subjects reported inconsistent answers[11]. The upper panel

[8] We refer to see AS (2012) for a thorough discussion about this issue.

[9] No variations in participants' decisions over the 15 CTB choice sets.
[10] No variations in participants' decisions over the 10 first CTB choice sets.
[11] Willing to wait longer for a smaller amount of money.

of Table 4 summarizes the estimates of the preference parameters for the 203 usable observations (*Field data* in Table 4). For comparison purposes the lower panel reports the AS estimates (*AS data* in Table 4). Figures 3 - 6 provide histograms of individual parameters for the two samples.

INSERT TABLE 4 ABOUT HERE

The histograms reveal both similarities and differences between our field data and AS's lab data. Similar to AS, the majority of our subjects exhibit low discount rates, limited present bias and moderate utility function curvature. Both α and β are mostly distributed around value 1. The median curvature estimate is $\alpha = 0.949$ (Table 2), which is closer to the median curvature estimate of AS than estimates reported in other papers (e.g., Andersen et al., 2008 found CRRA estimates below 0.5). The median time inconsistency parameter β equals 1, which is also close to AS's estimate. Further consistent with their findings, the null hypothesis of the absence of present bias ($\beta = 1$) cannot be rejected (t-test, $p = 0.000$) for our sample. More specifically, 36.45% of the subjects in our sample are categorized as 'time consistent'. Subjects are time consistent when they choose the same payoff for $t = 1$ and $k = 35$ ($x_{1,35}$) as for $t = 35$ and k=35 (i.e., $x_{1,35} = x_{35,35}$). Among the remaining 63.55% time-inconsistent subjects, 36.45% are present-biased (i.e. $x_{1,35} > x_{35,35}$, "impatient now and patient later") and 27.09% are future-biased (i.e. $x_{1,35} < x_{35,35}$, "patient now and impatient later"). In contrast to AS, however, our sample contains more time inconsistent individuals ($x_{1,35} \neq x_{35,35}$). In the AS sample 16.7% of the subjects are present-biased and 10.7% are future-biased. In this way, our results are similar to those of Ashraf *et al*. (2006), who observe about 35% of present-biased subjects and 19.8% of future-biased subjects in their Philippines sample. Another difference with AS is the large proportion of subjects who exhibit negative discount rates (88.7%) in our sample. We believe these subjects may be imposing a savings constraint on themselves by choosing to delay immediate consumption in favor of future consumption. In short, the comparison of our field data to the AS data reveals important similarities, including parameter estimates of α and δ, but also differences: a larger proportion of future-biased subjects and a very high proportion of subjects with negative discount rates. These two characteristics might be specific to our field context. However, an alternative interpretation is that students' preferences differ from those of field subjects, as suggested by the similarities of our findings with those of Ashraf *et al*. (2006).

INSERT FIGURES 3-6 ABOUT HERE

4.2 Correlation between risk and time preferences

In order to study the relationship between risk and time preferences we execute two independent analyses. First, we look for a correlation within subjects between their risk preferences, elicited with the EG task, and their time preference parameter δ, elicited with the field-CTB task. Second we study the correlation between the CRRA parameter estimates (α) and the time preference parameter estimate δ.

4.2.1 Correlation between risk preferences categories and the time preference parameter

The EG method allows us to categorize each subject as more or less risk-averse on a scale from 1 to 6 according to their selected gamble, where 1 corresponds to the most risk-averse category and 6 to the most risk-seeking. Table 5 shows the frequency of subjects in each category.

INSERT TABLE 5 ABOUT HERE

Before providing statistical support for the relationship between risk and time preferences based on our six risk-categories, we first give a graphical representation of this relationship based on a coarse categorization of subjects as follows: subjects who selected gamble 1 are classified as risk-averse, those who selected gambles 2 to 5 are classified as risk-neutral, and those who selected gamble 6 are classified as risk-seekers. As illustrated in Figure 7, risk-seekers are the most patient. The mean amount chosen for the earlier date is significantly lower for risk-seekers than for other risk-categories both for $x_{1,35}$ (Student t-test; t=1.6464, p=0.0999) as well as for $x_{36,35}$ (Student t-test; t=2.0787, p=0.0378). Figure 7 shows that our data is overall consistent with the hypothesis that risk tolerant individuals are also more patient, which aligns with previous findings (Anderhub et al., 2001, Carpenter et al., 2011, Dohmen et al., 2010, Burks et al., 2009). However, there is no difference when the delay is relatively long (k = 70) as illustrated by the case $x_{1,70}$.

INSERT FIGURE 7 ABOUT HERE

INSERT FIGURE 8 ABOUT HERE

Interestingly, Figure 8 shows that risk-seekers and risk-neutral individuals tend to be time-consistent ($x_{1,35}$ vs. $x_{35,35}$) while risk-averse subjects tend to be time-inconsistent. More specifically, risk-averse subjects are more likely to be future-biased than other subject-types. For t=1 day they choose a lower amount than for t=35 days. Risk-seekers seem to be sensitive to an increase in the delay k (all other things equal): they are less patient for higher values of k. They allocate lower amounts to the sooner date for k=35 days than for k=70 days. Interestingly, other risk categories are less sensitive to this parameter.

Tables 6 and 7 provide statistical support for the visual evidence reported in Figures 7 and 8. Table 6 summarizes the estimates of ordered probit regressions with the risk-preference category (coded 1 to 6, where 6 is the highest risk-tolerance category) as the dependent variable. The regressions support our conjecture about a negative correlation between risk and time preferences: δ affects negatively the probability that a subject belongs to a higher risk-tolerance category. The relationship between δ and the risk preference category remains robust after controlling for various factors, including demographic variables (*e.g.*, gender, age, education, etc.) and financial variables (*e.g.*, savings, outstanding loans, etc.).

We observe that the size of land ownership positively affects risk taking while age negative affects risk taking. Land ownership and cattle size are often good proxies for wealth in developing countries (Wik *et al*., 2004). For instance, individuals who own more land appear to be less risk averse, which is similar to decreasing risk-aversion with wealth. Our results about risk aversion confirm the results of other field experiments that rejected the hypothesis of constant relative risk aversion in favor of decreasing or increasing relative risk-aversion (e.g. Binswanger, 1981, Yesuf & Bluffstone, 2009)[12]. Larger land

[12] Our data, as well as the data of the cited papers, however do not allow for a direct test of CRRA, IRRA or DRRA. In contrast, the data of Holt & Laury (2002) which includes subjects" choices for different payoff scales provides the possibility of such a direct test. Their evidence, for US student subjects, is in favor of IRRA.

ownership increases the propensity to take risk as previously observed (Donkers *et al*., 2001; Hartog *et al*., 2002, Yesuf & Bluffstone, 2009). However, other studies found no correlation between risk-aversion and wealth (see e.g. Cardenas and Carpenter, 2013). We also observe that risk aversion increases with age, as in Tanaka *et al.* (2010). It is often found that education and gender significantly affect risk preferences (e.g., Tanaka *et al*., 2010, Croson and Gneezy, 2009). However, in our sample, which is mainly composed of educated men (for the purpose of testing the field -CTB task), we cannot study these variables.

4.2.2 Correlation between the parameter estimates of the CTB task

Table 7 summarizes the results of linear regressions between preference parameter estimates derived from the field-CTB task. The dependent variable is the curvature parameter a that accounts for relative risk aversion and the key explanatory variable is the time preference parameter δ. The regressions support our conjecture about a negative correlation between risk and time preferences: δ negatively affects α. Note that β is insignificant which is consistent with our previous result about the absence of present bias in our sample. The relationship between δ and the risk preference category is robust after controlling for demographic and financial variables. In the complete regression model, which includes all the control variables, the relationship between α and δ is highly significant. This result leads us to conclude that the negative correlation between impatience and the propensity to take risk is robust to multiple factors in our sample.

3. Concluding remarks

We designed a simplified field version of the CTB task to investigate the relationship between risk and time preferences in farmers participating in an environmental conservation program in Uganda. Compared to other elicitation strategies, which rely on a combination of tasks, the CTB task uniquely elicits both subjective discount factors and utility curvatures through a single experimental protocol. Notwithstanding our simplification of AS's original CTB method and our application to non-student subjects in a field setting, many of our findings are consistent with those of AS. Remaining differences, such as the higher frequency of time-inconsistent answers in our sample, are likely attributable to the nature of the subject pool since our sample has a lower level of education compared to the AS sample.

Using our field-CTB task, we find a negative correlation between time preferences and risk preferences: the more risk averse subjects discount more heavily delayed payments. This statement is established on two independent measures of risk tolerance: the risk aversion coefficient estimated from the CTB data, and the risk aversion category elicited with the EG method. The conclusion is therefore robust to the elicitation task as well as robust to several controls.

This key finding – that impatience and risk taking are negatively correlated – has two important implications. First, it provides new support for the previously documented relationship between risk and time preferences (Anderhub et al., 2001, Carpenter et al., 2011, Dohmen et al., 2010, Burks et al., 2009). This finding is robust both to a change in the elicitation method and to the field setting of a developing country context. Second, it reveals two facets of preferences that are important for designing efficient incentives to adopt conservation programs. Impatient, risk-averse individuals may favor investing in fast-growing crops that generate immediate cash compared to enrolling in long-term conservation contracts. Also, because of their collective dimension, conservation programs involve both the risk of short-term failure when potential participants expect a lack of involvement and the risk of a long-term benefit in case of success, but which is essentially collective. Therefore, impatient, risk-averse individuals may be reluctant to enroll for two reasons. Taking into account both the specificity of the relationship between impatience and risk aversion and the heterogeneity of preferences can provide new insights for designing more efficient incentives to enroll reluctant farmers into conservation programs and more generally, to involve individuals into targeted programs[13].

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[13] See Aycinema et al. (2015) for a case-study about the relevance of these dimensions for conditional cash transfer programs.

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TABLES

Table 1: Gamble-Choices task for measuring risk preferences

Gamble	Low Payoff	High Payoff	Expected value	SD	Implied CRRA[14] Range	Risk status
1	2800	2800	2800	0	3.46<r	Extremely risk-averse
2	2400	3600	3000	600	1.16< r <3.46	Strongly risk-averse
3	2000	4400	3200	1200	0.71< r <1.16	Risk-averse
4	1600	5200	3400	1800	0.50< r <0.71	Slightly risk-averse
5	1200	6000	3600	2400	0< r <0.50	Risk neutral
6	200	7000	3600	3400	r <0	Risk seeker

Table 2: Experimental Parameters for Convex Time Budget (CTB) task

Decision	***t (sooner date)***	***k (delay)***	***P (Price ratios)***	***Option 1***		***Option 2***		***Option 3***	
				a_t	a_{t+k}	a_t	a_{t+k}	a_t	a_{t+k}
1	1	35	1.00	4000	0	2000	2000	0	4000
2	1	35	1.05	3800	0	1900	2000	0	4000
3	1	35	1.11	3600	0	1800	2000	0	4000
4	1	35	1.25	3200	0	1600	2000	0	4000
5	1	35	1.43	2800	0	1400	2000	0	4000
6	1	70	1.00	4000	0	2000	2000	0	4000
7	1	70	1.05	3800	0	1900	2000	0	4000
8	1	70	1.11	3600	0	1800	2000	0	4000
9	1	70	1.25	3200	0	1600	2000	0	4000
10	1	70	1.43	2800	0	1400	2000	0	4000
11	36	35	1.00	4000	0	2000	2000	0	4000
12	36	35	1.05	3800	0	1900	2000	0	4000
13	36	35	1.11	3600	0	1800	2000	0	4000
14	36	35	1.25	3200	0	1600	2000	0	4000
15	36	35	1.43	2800	0	1400	2000	0	4000

[14] Preferences follow a Constant Relative Risk Aversion functional form, this is calculated as the range of '*r*' in the function $U=x^{(1-r)}/(1-r)$ for which each gamble is the utility-maximizing choice. (Eckel & Grossman, 2007)

Village	1	2	3	4	5	6	7	8	9	10	11	12	13	All sample
N	19	22	21	22	20	23	22	23	23	20	24	23	21	283
Age	52.526	41.636	41,00	40.318	40.25	40.739	45.773	48.391	36.045	37.85	48.042	35.348	41.333	42.22
	(3.2)	(3.167)	(2.77)	(2.59)	(2.59)	(3.445)	(2.859)	(3.425)	(2.364)	(1.952)	(2.676)	(2.274)	(3.909)	(0.844)
Gender (Male=1)	1	0.773	0.857	0.727	0.7	0.826	0.955	0.696	0.818	0.75	0.833	0.826	0.571	0.792
	(0)	(0.091)	(0.078)	(0.097)	(0.105)	(0.081)	(0.045)	(0.098)	(0.084)	(0.099)	(0.078)	(0.081)	(0.111)	(0.024)
Education †	0.263	0.5	0.619	0.454	0.55	0.347	0.318	0.478	0.695	0.4	0.416	0.478	0.571	0.468
	(0.103)	(0.109)	(0.108)	(0.108)	(0.114)	(0.101)	(0.101)	(0.106)	(0.098)	(0.112)	(0.102)	(0.106)	(0.110)	(0.029)
Land Area (Hectares)	23.444	14,00	13.25	10.813	4.425	7.429	8.024	5.87	5.262	4.363	6.083	8.522	16.881	9.655
	(10.315)	(5.589)	(3.722)	(2.933)	(0.58)	(1.963)	(1.27)	(0.77)	(0.907)	(0.648)	(1.584)	(1.635)	(12.178)	(1.325)
Income	23632.22	45170.47	28994.06	24742.05	73166.67	112934.8	50071.43	86188.41	70839.88	23708.33	36676.58	32206.15	42609.65	61799.17
	(7963.59)	(13449.87)	(5357.876)	(5995.235)	(12034.7)	(32264.28)	(9352.197)	(31434.8)	(23026.34)	(4779.298)	(6653.92)	(11022.58)	(17607.29)	(13678.41)
Household size	6.789	6.5	6.143	3.5	7.3	5.261	7.00	8.174	6.455	5.55	6.917	5.87	6.286	6.287
	(0.691)	(0.573)	(0.641)	(3.89)	(0.785)	(0.531)	(0.868)	(1.032)	(0.695)	(0.489)	(0.932)	(0.837)	(0.793)	(0.363)
Distance to market (Km)	2.516	3.75	2.643	0.98	3.205	5.122	2.414	3.326	4.518	1.181	2.85	7.413	4.838	3.483
	(0.424)	(0.492)	(0.356)	(0.235)	(0.475)	(0.697)	(0.349)	(0.275)	(0.533)	(0.268)	(0.362)	(0.705)	(0.482)	(0.160)
Distance to paved road (Km)	1.708	0.377	0.615	0.31	0.58	2.16	0.646	0.352	0.855	0.504	0.454	1.438	0.959	0.840
	(0.797)	(0.075)	(0.106)	(0.091)	(0.175)	(0.997)	(0.131)	(0.09)	(0.253)	(0.117)	(0.131)	(0.337)	(0.251)	(0.110)
Difficulty acquiring money††	0.578	0.181	0.523	0.5	0.45	0.260	0.136	0.434	0.347	0.35	0.291	0.173	0.428	0.352
	(0.116)	(0.084)	(0.111)	(0.109)	(0.114)	(0.093)	(0.074)	(0.105)	(0.101)	(0.109)	(0.094)	(0.080)	(0.110)	(0.028)
Outstanding loans (=1)	0.263	0.545	0.19	0.318	0.55	0.217	0.5	0.174	0.409	0.55	0.292	0.652	0.286	0.379
	(0.104)	(0.109)	(0.088)	(0.102)	(0.114)	(0.088)	(0.109)	(0.081)	(0.107)	(0.114)	(0.095)	(0.102)	(0.101)	(0.028)
Savings (=1)	0.526	0.727	0.286	0.409	0.6	0.478	0.864	0.478	0.636	0.85	0.625	0.739	0.619	(0.602)
	(0.118)	(0.097)	(0.101)	(0.107)	(0.112)	(0.106)	(0.075)	(0.106)	(0.105)	(0.082)	(0.101)	(0.094)	(0.109)	(0.029)

Table 3: Summary Statistics

Notes: Standard errors are in parentheses. †Education is coded as: primary level (=0), secondary level and above (=1). ††Difficulty Acquiring Money is coded as: easy (=0), difficult (=1).

Table 4: Individual Parameter Estimates

Parameter	N	Median	5th percentile	95th percentile
Field data				
α	203	0.949	-0.005	0.975
β	203	1	0.334	1.932
δ	203	1.004	0.991	1.031
r	203	-0.771	-0.999	22.58
AS data (AS, 2012)				
α	86	0.9665	0.7076	0.9997
β	86	1.0011	0.9121	1.1075
δ	86	0.9991	0.9948	1.0005
r	86	0.4076	-0.1784	5.618

Table 5: Frequency distribution of subjects in the risk task

Gamble	Implied CRRA[15] Range	Risk status	Fraction of Subjects (%)
1	3.46<r	Extremely risk-averse	16.25
2	1.16< r <3.46	Strongly risk-averse	16.61
3	0.71< r <1.16	Risk-averse	19.79
4	0.50< r <0.71	Slightly risk-averse	9.19
5	0< r <0.50	Risk Neutral	11.31
6	r <0	Risk Seeker	26.86

[15] Preferences follow a Constant Relative Risk Aversion functional form, this is calculated as the range of '*r*' in the function $U=x^{(1-r)}/(1-r)$ for which each gamble is the utility-maximizing choice. (Eckel & Grossman, 2007)

Table 6: Ordered Probit Regressions (dependent variable is risk category)

	(1) Critical variables		(2) Socio-economic variables		(3) Financial variables		(4) All variables	
Beta	-0.227*	(-1.47)	-0.143	(-0.86)	-0.232*	(-1.48)	-0.147	(-0.88)
Delta	-0.956***	(-2.00)	-0.785*	(-1.63)	-1.049***	(-2.14)	-0.830**	(-1.70)
Age			-0.0167***	(-2.78)			-0.0162***	(-2.66)
Gender			0.0962	(0.47)			0.0674	(0.32)
Education			-0.107	(-0.65)			-0.111	(-0.67)
Land Area			0.127**	(1.81)			0.123**	(1.83)
Income			0.00797	(1.34)			0.00813	(1.25)
Household size			0.00145	(0.13)			0.00226	(0.20)
Savings					0.231	(1.33)	0.0575	(0.31)
Outstanding loans					0.00559	(0.03)	-0.0531	(-0.30)
Difficulty acquiring money					0.124*	(1.46)	0.116	(1.29)
cut1								
_cons	-2.218***	(-3.79)	-2.525***	(-3.81)	-1.838***	(-2.91)	-2.238***	(-3.18)
cut2								
_cons	-1.636***	(-2.83)	-1.898***	(-2.90)	-1.245***	(-1.98)	-1.610***	(-2.31)
cut3								
_cons	-1.105**	(-1.91)	-1.380***	(-2.11)	-0.701	(-1.11)	-1.085*	(-1.56)
cut4								
_cons	-0.877*	(-1.51)	-1.134**	(-1.74)	-0.468	(-0.74)	-0.836	(-1.20)
cut5								
_cons	-0.596	(-1.03)	-0.830	(-1.27)	-0.183	(-0.29)	-0.530	(-0.76)
N	203		186		203		186	

t statistics in parentheses

* $p < 0.15$, ** $p < 0.10$, *** $p < 0.05$

Table 7: OLS Regression (dependent variable is α)

	(1) Critical variables		(2) Socio-economic variables		(3) Financial variables		(4) All variables	
Beta	0.0128	(0.30)	0.0206	(0.42)	0.0199	(0.46)	0.0282	(0.57)
Delta	-1.600***	(-12.72)	-1.593***	(-12.01)	-1.583***	(-12.54)	-1.579***	(-11.82)
Age			0.00147	(0.85)			0.00153	(0.86)
Gender			-0.0610	(-1.03)			-0.0578	(-0.97)
Education			-0.00203	(-0.04)			-0.00583	(-0.12)
Land area			0.00666	(0.70)			0.00778	(0.81)
Income			0.000363	(0.42)			0.000279	(0.32)
Household size			-0.00326	(-0.94)			-0.00292	(-0.84)
Savings					-0.0784	(-1.61)	-0.0606	(-1.12)
Outstanding loans					0.0382	(0.81)	0.0427	(0.84)
Difficulty acquiring money					0.000521	(0.02)	0.00273	(0.10)
Constant	2.413***	(15.68)	2.390***	(12.98)	2.423***	(14.38)	2.379***	(11.94)
N	203		186		203		186	

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

FIGURES

Figure 1: Location of Masindi district, Uganda

Figure 2: Sample Convex Time Budget Decision Form

TOMORROW and in 5 WEEKS Participant ID: ....

For ***each*** row below (1 to 5), decide how much money you would like **tomorrow AND in 5 weeks** by marking the corresponding box. ***Remember to mark 1 box PER ROW!***

If Game 2 is chosen as the game-that-counts, at the end of the study, I will draw a ball from this box. There are 15 balls in this box, numbered 1 to 15. The number on the ball that I draw will determine the decision according to which your actual earnings will correspond.

1	payment TOMORROW, 22/03/2013 ***and*** payment on 26/04/2013	4000 UGX 0 UGX ☐	2000 UGX 2000 UGX ☐	0 UGX 4000 UGX ☐
2	payment TOMORROW, 22/03/2013 ***and*** payment on 26/04/2013	3800 UGX 0 UGX ☐	1900 UGX 2000 UGX ☐	0 UGX 4000 UGX ☐
3	payment TOMORROW, 22/03/2013 ***and*** payment on 26/04/2013	3600 UGX 0 UGX ☐	1800 UGX 2000 UGX ☐	0 UGX 4000 UGX ☐
4	payment TOMORROW, 22/03/2013 ***and*** payment on 26/04/2013	3200 UGX 0 UGX ☐	1600 UGX 2000 UGX ☐	0 UGX 4000 UGX ☐
5	payment TOMORROW, 22/03/2013 ***and*** payment on 26/04/2013	2800 UGX 0 UGX ☐	1400 UGX 2000 UGX ☐	0 UGX 4000 UGX ☐

Figure 3a - Estimated Annual Discount Rates (Uganda sample)

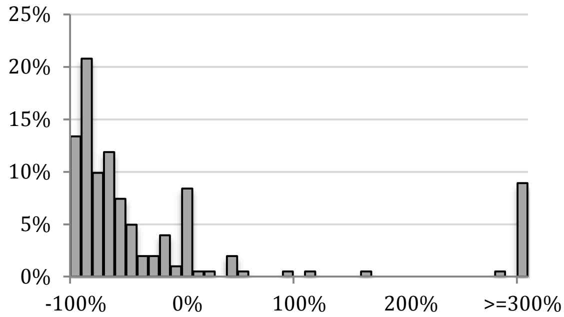

Figure 3b - Estimated Annual Discount Rates (AS 2012 sample)

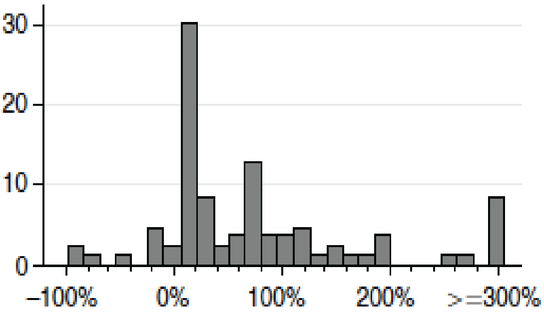

Figure 4a - Estimated Daily Discount Factor (delta) (Uganda sample)

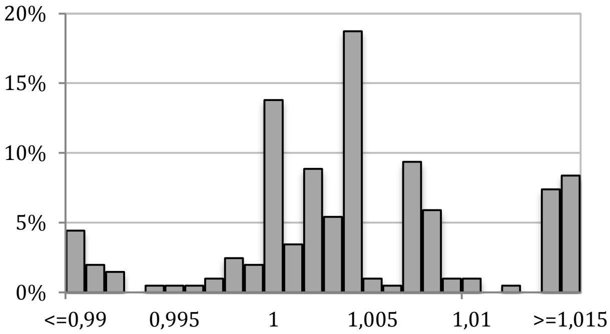

Figure 4b - Estimated Daily Discount Factor (delta) (AS 2012 sample)

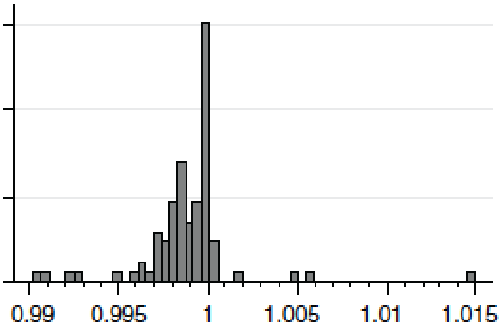

Figure 5a - Estimated Present Bias (beta) (Uganda sample)

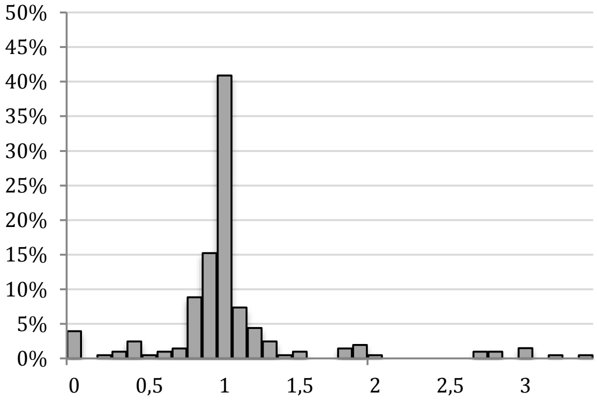

Figure 5b - Estimated Present Bias (beta) (AS 2012 sample)

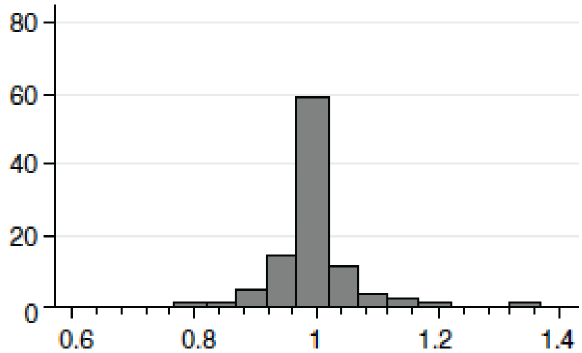

Figure 6a - Estimated Curvature Parameter (alpha) (Uganda sample)

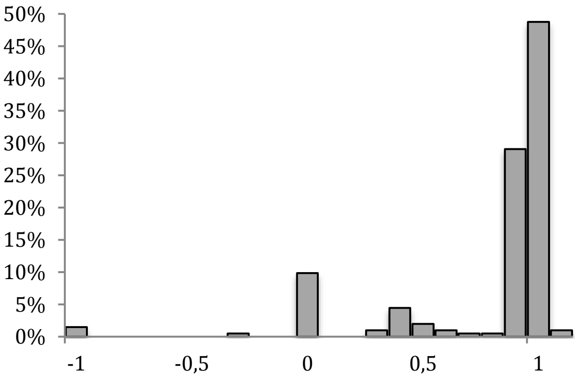

Figure 6b - Estimated Curvature Parameter (alpha) (AS 2012 sample)

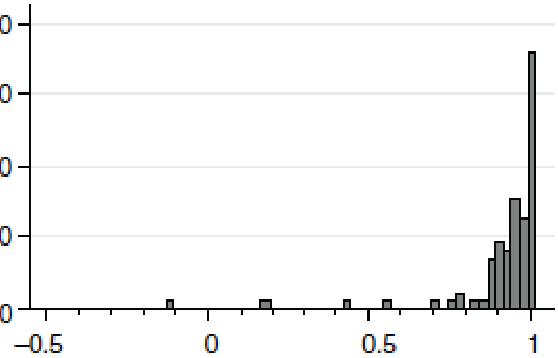

Figure 7: Mean Experimental Responses Over Time by Delay *k* and Sooner Payment *t*

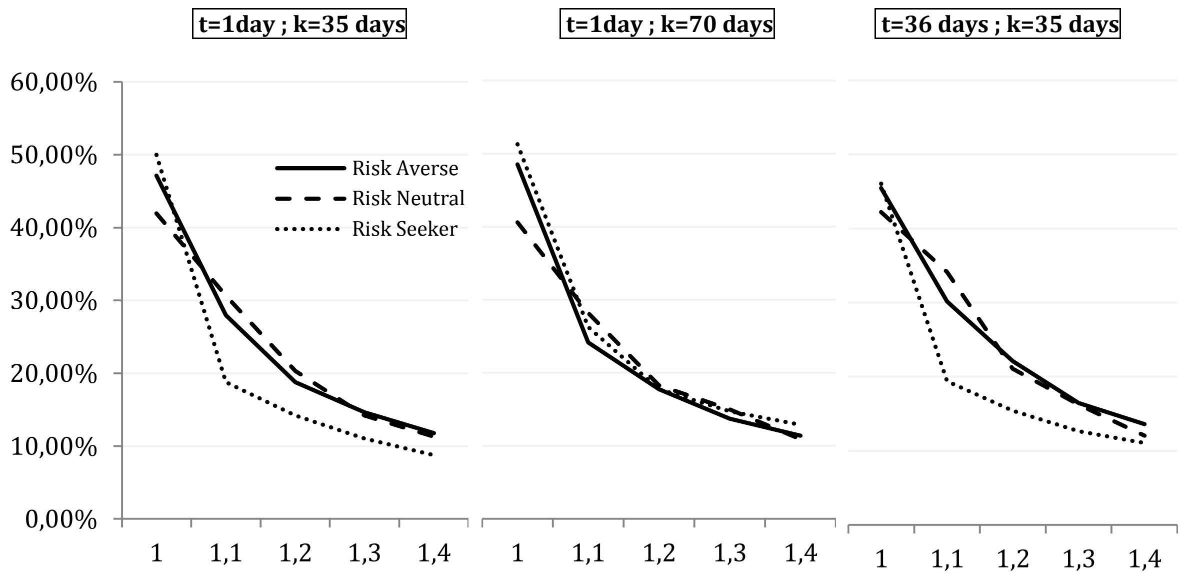

Figure 8 – Mean Experimental Responses Over Time by Risk Profile