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Stein T. Holden and Mesfin Tilahun

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By

Stein T. Holden[1] and Mesfin Tilahun[1,2]

[1]School of Economics and Business

Norwegian University of Life Sciences

P. O. Box 5003, 1432 Ås, Norway.

[2]Mekelle University, Mekelle, Tigray, Ethiopia.

Email: stein.holden@nmbu.no; mesfin.tilahun.gelaye@gmail.com

Abstract

Risk and time preferences are fundamentally important for financial decisions. We study such preferences for business group members based on field experiments in Ethiopia. The relationship between risk preferences and time preferences has been subject to intensive research and debate among behavioral and experimental economists lately. We aim to contribute to this literature based on a Double Multiple Choice List approach used in an incentivized field experiment. First, we provide strong evidence of diminishing impatience in our data that cannot be explained by present bias. Next, we assess whether measures of diminishing impatience can be associated with measures of risk aversion and probabilistic sensitivity. We also assess whether measurement error in the risk experiment could be the culprit and create spurious correlations between measures of risk aversion and discount rate elasticities with respect to time horizon. Using a random coefficient model, we find strong evidence of diminishing impatience and large and highly significant individual variation in discount rate elasticities with respect to time horizon. We find only weak support for the idea that diminishing impatience is explained by probabilistic sensitivity due to uncertainty about delayed payouts in the discount rate experiments.

Risk aversion and optimism/pessimism were unrelated to model noise. More pessimistic and more risk averse respondents had more hyperbolic time preferences and these results were not sensitive to measurement error. Surprisingly, more consistent responses in the risk experiments (lower measurement error) were found for respondents with more hyperbolic time preferences and respondents with higher probabilistic insensitivity.

Key words: Time preferences, risk preferences, diminishing impatience, probability weighting.

JEL codes: C93; D83.

1. Introduction

Risk and time preferences are fundamentally important for financial decisions. We study such preferences for business group members based on field experiments in Ethiopia. Risk and time preferences have been subject to intensive research and debate in recent years. This started with the important contribution by Anderssen et al. (2008) who used a Double Multiple Choice List[1] (DMCL) approach to elicit risk and time preferences of a sample of adult Danes through a incentivized field experiment. They proposed that earlier estimates of discount rates were upward biased because they ignored risk aversion, which implied diminishing marginal utility of larger future amounts compared to smaller near future amounts based on time-separable utility functions. They estimated discount rates that were adjusted for individual risk aversion based on a constant relative risk aversion (CRRA) utility function in a discounted expected utility framework with constant individual discount rates.

Andreoni and Sprenger (2012a; b; 2015; Andreoni et al. 2015) used a Convex Time Budget (CTB) approach to estimate individual discount rates. The CTB approach allows intermediate mixes between near future and far future amounts with varying “exchange rates” while the MCL approach requires corner solutions between more near future smaller and far future larger amounts. Andreoni et al. (2015) compared the DMCL and CTB approaches and found that the CTB resulted in lower estimates of risk aversion (less concave utility functions), and for that reason, higher discount rates.

Abdellaoui et al. (2019) estimated risk and time preferences jointly based on a sample of 100 students in Berlin using a MCL approach that combined risky prospects with varying delays. This facilitated joint estimation of probability weighting and discount functions. They found that a rank dependent utility model and hyperbolic or quasi-hyperbolic discount function to most accurately represent their data. Estimation with an expected utility model with constant discount rate gave an annual discount rate of 5.9% while a rank dependent utility model with constant discount rate more than doubled the estimated discount rate to 14.1%.

Abdellaoui et al. (2013) proposed a new method for measuring utility over time and compare utility over time and risk including for gains, for losses and for mixed prospects. Based on two sets of experiments, one hypothetical (68 students in Rotterdam) and one real (52 students in Paris), they found utility over time and over risk to be different. For gains, utility over risk was concave while it was convex to linear for losses. For time, utility was close to linear both for gains and for losses. Utility over risk and time were also uncorrelated.

[1] Often called Price List instead of Choice List. We prefer the term Choice List as such lists typically contain more than prices.

In this study we aim to assess the relationship between measured risk preferences and time preferences to test a number of hypotheses. Risk and time preferences are latent variables that only can be measured with error. Measurement error is therefore a complicating factor that makes it hard to separate such errors from eventual causal relationships or correlations between the underlying latent variables. First, we take probability weighting into account in the estimation of risk preferences. It is possible that the relative risk aversion coefficient based on expected utility theory is confounded with variable probabilistic sensitivity that may be captured with a Rank Dependent utility (RDU) function (Quiggin 1982; Abdellaoui et al. 2019). We limit our study to experiments with gains only and therefore do not include loss aversion in our study.

Second, hyperbolic discounting and magnitude effects are commonly found in time preference studies (Wang et al. 2016; Holden and Quiggin 2017; Grijalva et al. 2018). Many studies have attributed hyperbolic time preferences to present bias and have therefore assumed that the quasi-hyperbolic discounting model of Laibson (1997) is taking care of the phenomenon. Andreoni et al. (2015) allowed for quasi-hyperbolic time preferences but found little evidence of present bias in their study with undergraduate students using monetary gambles. Andersen et al. (2011) investigated the importance of magnitude effects. They used an incentivized experiment (10% probability of payout) with two magnitude levels where the large amount is the double of the small amount. The experiment took place in Denmark with a sample of adult Danes. They found a small but significant magnitude effect but the effect disappeared when they used only delayed payouts. Holden and Quiggin (2017) found highly significant hyperbolic and magnitude effects in an incentivized field experiment with a DMCL approach in rural Malawi where the largest magnitude level was 20x the lowest and present bias could not explain the strongly hyperbolic responses.

The choice of assumptions related to the degree of asset integration in the estimation of risk and time preferences is another issue where there is no concensus. This relates to the puzzle associated with positive risk aversion in small gambles and the utility function implications for risk preferences in large risk gambles, the so-called calibration problem of Rabin (2000). Several experimental studies have found limited asset integration in risk experiments (Binswanger 1981; Wik et al. 2004). Andreoni et al. (2015) alternatively assumed no asset integration or estimated the prospect money as additional in a Stone-Geary utility function. Andersen et al. (2008) assumed that prospect amounts are integrated with a daily wage rate (limited asset integration). Holden and Quiggin (2017) proposed that hyperbolic and magnitude effects can be explained by limited and variable asset integration such that longer time horizons and larger magnitudes lead to higher levels of asset integration. They analyzed data from a field experiment that fits well with this explanation.

Halevy (2008) and Epper et al. (2011) proposed another reason for hyperbolic (falling) discount rates with time. They related it to non-linear probability weighting and uncertainty about future payouts. Epper et al.

(2011) used a two-parameter Prelec 2 type of probability weighting function and found that the estimated alpha parameter, capturing the degree of inverted S-shape of the probability weighting function, is strongly correlated with the (hyperbolic) reduction in discount rates in a discount rate experiment with a two months versus a four months delay. They used a sample of 112 students from Zurich University and combined the incentivized time preference experiments with risk preference experiments that allowed them to derive probability weighting as well as utility function curvature parameters. While the cumulative uncertainty associated with more delayed payouts should lead to higher rather than lower discount rates, they proposed that this effect is more than countered by sub-proportionality affecting the weighting of this future uncertainty. We investigate the external validity of this interesting finding in their relatively small student sample within our relatively large and more heterogeneous youth and young adult sample through an incentivized field experiment in rural Ethiopia.

Abdellaoui et al. (2011) estimated probability weighting functions in an intertemporal setting. In their study they used a sample of 52 undergraduate economics students from Bogazici University in Turkey to assess how a delay in the risk game affected their risky decisions and how this was related to the curvature of the utility function and the probability weighting function. They found that a delay changed the responses in the risk game through changes in the probability weighting function making it less non-linear and more optimistic (elevated). We think that such an effect of delay on the probability weighting function should also be relevant for the relationship between probability weighting and hyperbolic discounting if such hyperbolic discounting is due to uncertainty associated with delayed payment like suggested by Halevy (2008) and Epper et al. (2011). These studies attempting to explain hyperbolicity as a result of uncertainty about future payouts were based on laboratory experiments with relatively small student samples. We think that the issue is worthy more comprehensive studies to examine both the internal and external validity of the findings. Our paper is a contribution in this direction.

We study the correlation between risk preferences and time preferences with a rank dependent utility (RDU) (Quiggin 1982) framework using two sets of incentivized multiple price list (DMCL) experiments to facilitate estimation of risk and time preference parameters with a within-subject design. For the risk preference MPLs we use a certainty equivalent approach to jointly estimate the utility function curvature and a Prelec 2-parameter probability weighting function for our sample of 980 rural youth and young adults that are members of youth business groups in northern Ethiopia. These groups are investing in joint natural resource based businesses. The time preference MCLs allowed for estimation of individual time and magnitude discount rate elasticities in form of random coefficient parameters. We test whether the strength in the individual sub-proportionality or common ratio effect is correlated with the time elasticity of individual discount rates, based on the hypothesis and findings of Halevy (2008) and Epper et al. (2011).

Another strand of the literature has investigated the relationship between cognitive ability and risk and time preferences. Several studies have found that cognitive ability is positively correlated with risk tolerance and patience (Frederick 2005; Burks et al. 2009; Dohmen et al. 2010; Benjamin et al. 2013). Some studies have also found that cognitive ability is associated with more consistent choices in experiments (Frederick 2005; Oechssler et al. 2009; Benjamin et al. 2013). We therefore use measurement error in our risk experiment as an indicator of cognitive ability. To our knowledge, this is the first study to assess whether this type of measurement error variation can explain the variation in hyperbolicity. This would imply that hyperbolicity can be an artifact resulting from limited cognitive ability.

A complicating issue is that measurement error may be associated not only with cognitive ability but also with measured risk aversion in risk preference experiments. Andersson et al. (2016) found that variation in cognitive ability could lead to bias in risk preference estimation with a MCL approach due to the specific design of MCLs, and more frequently committed random errors by respondents with weaker cognitive ability. The link between cognitive ability and risk tolerance could therefore potentially be spurious or at least potentially biased for this reason. Our MCL approach allows us to test for such potential bias in estimated risk aversion and thereby assess the robustness of the relationship between risk aversion and hyperbolicity. Still, we should be very careful about drawing causal implications due to the potential endogeneity of cognitive ability, risk preference measures and time preference measures (Dohmen et al. 2018). We therefore cautiously assess the correlations between the imperfectly measured risk and time preferences when testing a number of hypotheses derived from theory and earlier studies.

We elaborate on the theory and hypotheses to be tested in part 2. The experimental designs and sample are presented in part 3, and estimation methods in part 4. Descriptive statistics are presented in part 5, the main results and discussion in part 6, before we conclude.

2. Theory and hypotheses

Diminishing impatience was first inspected closely by Strotz (1955). Since then it has been subject to many experimental studies with Thaler (1981) being one of the first. The dominant explanation of diminishing impatience has been present bias associated with immediate pleasure, addiction, self-control problems (procrastination) and liquidity constraints (Laibson 1997). We will in this study, however, focus on an alternative explanation for the diminishing impatience, that of the degree of uncertainty associated with prospects received at alternative future points in time, based on Halevy (2008) and Epper et al. (2011).

Certainty can only be guaranteed at present. The degree of confidence in future outcomes may depend on how far into the future the outcome is to materialize, the trust in the provider, the kind of assurances or guarantees that can be given, and the hazard of mortality of the receiver. However, standard linear probability models would only lead to higher discount rates for future more uncertain or risky prospects. For diminishing impatience to be explained by uncertainty about future payouts, there must be present bias and/or non-linear weighting of future uncertain outcomes. Such uncertainty combined with non-linear probability weighting may explain some experimental evidence in line with this (Keren and Roelofsma 1995; Weber and Chapman 2005; Halevy 2008; Epper et al. 2011). Such non-linear weighting also explains the common ratio effect associated with Allais' paradox (Allais 1953). It is the specific inverted S-shape of the probability weighting function that potentially may explain diminishing impatience. The probability weighting function must be convex and have increasing elasticity to account for diminishing impatience (Halevy 2008). It is, however, an empirical question whether this can be the explanation for observed diminishing impatience.

We start from a probability weighting function that has typically been used to assess atemporal risk. It captures the behavioral phenomenon that decision makers typically overweight low probabilities and underweight high probabilities. To capture this we use a two-parameter Prelec 2 function (Prelec 1998):

(1) $$w(p) = \exp\left(-\beta(-\ln p)^{\alpha}\right), \alpha > 0, \beta > 0$$

This is a strictly increasing and continuous function $w\left(p\right):\left[0,1\right]\rightarrow\left[0,1\right]$ with an inverse, w^{-1}, that is also a probability weighting function. We study the probability weighting function associated with gains only as our experiments include gains only[2]. Our analysis therefore is restricted to the context of Rank Dependent Utility (RDU) (Quiggin 1982), which is consistent with Cumulative Prospect Theory (Tversky and Kahneman 1992) in the gains domain.

The α parameter captures the degree of (inverted) S-shape of the weighting function. If $\alpha = 1$ and $\beta = 1$ the function is linear and consistent with Expected Utility Theory. With $\alpha < 1$ the inverted S-shape becomes stronger as α declines. This leads to the diminishing sensitivity as *p* moves away from 0 and 1 and to probabilistic insensitivity in the intermediate probability region. The probabilistic (in)-sensitivity is stronger the lower α is. The β parameter is affecting the elevation of the function. As β is reduced from 1, the weighting function is elevated and this captures more optimistic preferences, while the opposite is the case as β increases above 1.

For our purpose, it is the α parameter that is the primary suspect contributing to diminishing impatience or hyperbolic discounting (Halevy 2008; Epper et al. 2011). This is because it is assumed that the

[2] This does not prevent our respondents from defining their reference points such that bad outcomes are perceived as losses. We proceed by assuming that this was not the case.

respondents' perceived mortality risk or probability of payment default by the researchers is increasing with time horizon. Respondents can be sensitive to even very small default or mortality risks but this probabilistic sensitivity declines rapidly with higher probability of default due to the diminishing sensitivity of the weighting function as probability of default increases (assuming $\alpha < 1$).

Second, we need a representation of the intertemporal (discounting) preferences. We start from a general hyperbolic function (Loewenstein and Prelec 1992):

(2) $$D(t) = (1+\gamma t)^{-\delta/\gamma}$$

We prefer this model as our data allow us to investigate the existence of general hyperbolicity and not just the existence of present bias. In this formulation it is the γ parameter that captures the degree of hyperbolicity (downward trend in annualized discount rate with extended time horizon *t*). With $\gamma \to 0$, the function moves towards constant discounting with discount rate δ. With $\gamma > 0, \delta > 0$ discount rates decline as the time horizon is extended.

Alternatively, if this tendency of declining discount rates is due to the perceived uncertainty or risk of default, the problem may also be formulated as follows (Halevy 2008):

(3) $$U(c,h) = \sum_{t=0}^{t_n} w\left((1-h)^t\right)\delta^t u(c_t)$$

where *h* is the hazard rate (risk of default). In our experimental study the hazard rate is unobservable and we may only assume that our respondents implicitly transform our intended risk-free MPL time preference experiment to an experiment with variable future uncertainty.

In order to avoid that present bias drives the results, we use time preference PLs where the near future amounts are delayed (by one week) and the far future points in time are 3, 6 and 12 months. We also include three magnitude levels for the future amounts (100, 500 and 1000 ETB) and the respondents adjust the near future amount by identifying a switching point interval containing their point of indifference between the near future and far future amounts. Each prospect *m* of individual *i* may for the point of indifference be defined by the implied annualized discount rate that is a function of the near future and far future points in time and the future amount:

(4) $$D_{im} = D_{im}(t_1, t_2, M_n)$$

We have ten CLs per respondent. Based on these, we estimate individual discount rate elasticities with respect to time horizon and magnitude. A simple functional form representation of this is:

(5) $$D_i\left(t,M\right)=D_{i0}t^{\eta_{it}}M^{\eta_{iM}}$$

Diminishing impatience implies a significant and negative discount rate elasticity with respect to time horizon. Similarly, a magnitude effect, which implies that the level of patience is higher for large than for small amounts, predicts that the discount rate elasticity with respect to magnitude is negative:

(6) $$\eta_{it}=\frac{\partial D_i}{\partial t}\frac{t}{D_i}<0;\ \eta_{iM}=\frac{\partial D_i}{\partial M}\frac{M}{D_i}<0$$

We use alternative models, including a random coefficient model, to estimate these discount rate elasticities and assess the significance of the individual variation in these elasticities.

Based on the proposed hidden uncertainty in our time preference experiments (Halevy 2008; Epper et al. 2011) our first hypothesis is therefore:

H1: *There is a positive correlation between the estimated and predicted individual Prelec 2* α_i *parameter in the atemporal probability weighting function and the estimated individual discount rate elasticity with respect to time,* η_{it} *, in the intertemporal discounting function (4) and (5).*

This hypothesis rests on the assumption that the perceived unobserved default probability increases in time but that this is outweighted due to the non-linear probability weighting (Halevy 2008; Epper et al. 2011). This hypothesis is testable even without data on the perceived risk of default or mortality risk.

The Prelec 2 probability weighting function captures optimism or pessimism through the β parameter. We propose that subjective perceptions (optimism/pessimism) may be associated with the unobservable hazard rate (perceived probability of default or mortality). More specifically, we hypothesize:

H2: *Optimistic preferences associated with the Prelec 2* $\beta<1$ *are associated with higher* η_{it} (*less hyperbolic discount rates or less diminishing impatience*).

The hypothesis rests on the assumption that optimistic respondents have lower perceived hazard rates that may also change less with the length of the time horizon. If diminishing impatience is driven by such pessimistic uncertainty, optimistic beliefs may be associated with less diminishing impatience.

However, this potential uncertainty in the time preference experiments is not atemporal risk but future risk or uncertainty and people may respond differently to future or delayed risk as compared to current risks as demonstrated in some experimental studies. This leads us to another strand of the literature that investigates how delays affect risky decisions (Keren and Roelofsma 1995; Weber and Chapman 2005; Noussair and

Wu 2006; Baucells and Heukamp 2010; Cobble and Lusk 2010). These studies found that risk tolerance increases with delays.

Baucells and Heukamp (2010) used an incentivized experiment with 221 students in business schools in Barcelona and Madrid to investigate the impact of a delay on the choice between two risky prospects. They found the same type of effect of a delay as the common ratio effect from a proportional reduction in the probabilities in a current (atemporal) risk game from high to low probabilities. Based on this finding they concluded that the common ratio effect and the common delay effect are intimately related.

Abdellaoui et al. (2011) investigated how a delay in lotteries affects risk preferences while taking probability weighting into account independently from time preferences. They used and incentivized experiment with 52 undergraduate economics students at Bogazici University in Turkey. The experiment was used to identify future certainty equivalents to future lotteries (at the same future point in time). They compared non-delayed lotteries with lotteries that were six and 12 months delayed. They found higher risk tolerance in delayed lotteries. However, the utility functions appeared not to be affected by the delay of lotteries. The whole effect therefore appeared to materialize through a change in the probability weighting function by an increase in the Prelec 2 alpha parameter (reducing the degree of inverted S-shape) and a reduction in the Prelec 2 beta parameter (less pessimistic responses). This implies that the respondents behaved closer to Expected Utility Theory in delayed lotteries. An implication of this study may be that a probability weighting function derived from a current (atemporal) risk experiment may not be a good representation of the probability weighting function in a temporal discounting experiment with a perceived hazard of payment default for future payments. This gives reason to question the general external validity of the experiment by Epper et al. (2011). It gives us an additional important reason to test the H1 hypothesis with a larger non-student sample under field (non-WEIRD[3]) conditions.

Following from this, if ignorance of risk aversion (utility curvature) is associated with upward bias in discount rates (Andersen et al. 2008), it is also possible that risk aversion is associated with diminishing impatience (less discounting of far future amounts if persons are less risk averse w.r.t. far future risk). We test the hypothesis:

H3: *Risk aversion (utility curvature parameter) is negatively correlated with the discount rate elasticity with respect to time.*

We use a Constant Relative Risk Aversion (CRRA) utility function to capture risk aversion. It is predicted for each respondent based on the structural model.

[3] WEIRD = Western, Educated, Industrialized, Rich and Democratic country setting.

Could there be other factors that explain correlations between risk preferences and time preferences? Dohmen et al. (2010) assessed whether cognitive ability is associated with risk preferences and time preferences using a sample of about 1000 adult Germans. They found that higher cognitive ability is correlated with higher levels of risk tolerance and patience. This may be another reason for correlation between risk aversion and patience through unobserved cognitive ability. A limitation of their experiment for our purpose was that they did not allow identification of diminishing impatience or probability weighting and time and risk experiments were not run for the same individuals. Similarly, Burks et al. (2009) also found that higher cognitive skills were positively related to patience in the short as well as long run, and to risk tolerance. They concluded that cognitive skills affect preferences and choices in ways that favor economic success.

Related to this, there are some studies that have found that measurement error may create bias in estimates of risk aversion (Andersson et al. 2016; Vieider 2018). It is possible that cognitive ability affects responses in complex risk preference elicitation tasks and that this depends on the format of the MCLs. Since we have used such MPLs in the elicitation of both risk preference and discount rate parameters, it is possible that these through measurement errors also could be spuriously correlated and cause measures of risk aversion to be correlated with decreasing impatience. To assess and control for this we use a structural model to explicitly estimate measurement error in the risk preference experiments and use individual measurement error as an indicator of cognitive (in)-ability. We assess how this error is associated with risk aversion and test the following hypotheses:

H4: *Higher measurement error (lower cognitive ability) in the risk experiment is associated with higher estimated risk aversion.*

H5: *Higher measurement error (lower cognitive ability) is negatively related to the Prelec 2 alpha parameter (distorted probability judgments are an indication of limited cognitive ability and weak numeracy skills).*

H6: *Higher measurement error (lower cognitive ability) in the risk experiment is associated with stronger diminishing impatience (more negative discount rate elasticity with respect to time horizon).*

If these our model results support these hypotheses, low cognitive ability contributes to explaining higher estimates of risk aversion and stronger diminishing impatience on the basis of our risk and time preference experiments.

3. Experimental design and sample

3.1. Risk preference experiment

We used Multiple Choice Lists (MCLs) where each CL was designed with a risky prospect that did not vary within the CL. We used the certainty equivalent approach. The risky prospect was compared to varying certain amounts decreasing from the top of the list and down, to identify the certain amount where the respondents preferred to switch between the risky prospect and the certain amount (see Appendix Table A1.1 for an overview of the 12 CLs in the risk preference experiment).

The respondents were informed at the beginning that one of the games would be randomly chosen as real after the game and that their decisions would affect the outcome in the real game. After all the risky prospects were played, one of the CLs was randomly chosen for real payout for one randomly chosen row in that CL. If the respondent had chosen the risky prospect for that row the risky game was played for real. If s/he had chosen the safe amount, the respondent was given the safe amount.

The order of the CLs was randomized, and so was the starting row in each CL. The random order and random starting point were included as variables in the analysis of the risk data to test for order and starting point bias as such bias may be there due to learning, fatigue, anchoring, bias towards the middle or random errors (Andersen et al. 2006; Andersson et al. 2016).

Use of such MCLs may create bias for various reasons as they imply a very large number of binary choices with small differences from row to row in each list. This can make respondents bored and reduce their effort in identifying switch points that reflect their preferences accurately. This could lead to random choices, starting point bias or bias towards the middle (Andersson et al. 2016). Freeman et al. (2019) have also found that such lists with a choice between a risky and a sure option can lead to significantly more risky choices. We used a time saving procedure to reduce the number of questions and reduce the risk of starting point bias and bias towards the middle. We think this procedure also has reduced the tendency towards choice of the risky lottery (Freeman et al. 2019). Our procedure was as follows (see Authors 2019 for the detailed risk analysis):

The MCLs were not shown to the respondents but were the guiding tool for the experimental enumerators. The amount of money for the risky prospect for each CL was put on the table in front of the respondents. A 20-sided die was used to explain the probabilities that varied across CLs. For the initial question in each CL a randomized (in advance by the experimental enumerator) row on the CL was identified as the first binary choice between the row-specific certain amount to be compared with the CL specific risky prospect and the given probability for the good versus the bad outcome for the risky prospect in the CL. The respondent answered whether s/he prefers the risky prospect or the certain amount. If the certain amount is preferred, the instructions to the enumerator were to go to the bottom of the list and ask the preference for the risky prospect versus the lowest certain amount. This is likely to lead to a preference for the risky prospect. Then the enumerator was guided to go to the middle between the randomly chosen first row/certain amount and the lowest amount, and so on to rapidly narrow in towards the switch point. This implied that maximum one switch point was identified in each CL.

Emphasis was given to careful mapping of the probability weighting function in the area with 5-50% probabilities of bad outcome (low probability negative outcomes) because of our focus on livelihood risks that our sample respondents are exposed to, such as climate risks. The risks of drought for example are within this range in this semi-arid area. Other production risks or health risks also fall in this category of low probability bad outcome risks that typically have been associated with risk aversion. This focus also fits with the unobservable hazard rates that are hypothesized to be related to delayed payouts in time preference experiments. The two last series are included to capture the responses to low probability gain opportunities and to map out that part of the weighting function (although a lower precision can be expected there).

3.2. Time preference experiment

A set of 10 CLs with randomized order was used to elicit the time preferences. The future point in time and the future amount were kept constant in each list. Most other studies of time preferences have kept the current or near future amount fixed (e.g. Pender and Kerr 1998; Andersen et al. 2008; Yesuf and Bluffstone 2009). Many of these studies have ended with censoring of the discount rates as they did not offer large enough future amounts to identify an indifference point. Our approach has the advantage of avoiding such censoring and keeps payout expenditures under control. The initial point in time was one week into the future from the time when the experiment took place for nine of the 10 CLs, while one CL offered immediate payout[4].

Like for the risk game, the rapid elicitation approach was used to reduce the number of questions needed to identify the switch point. The starting row in each CL had been randomized in advance. The respondents were asked whether they preferred the future amount or the near future amount at the randomized starting row. Depending on the choice of the respondent, the interviewer goes to the top or the bottom of the list, the direction that is likely to lead to a switch (see example list in the Appendix). If a switch is recorded, the enumerator is instructed to go to the middle row between the first two and continue like that to quickly narrow in the switch point. Like for the risk experiments this approach is used to reduce the number of questions necessary for each CL and also to minimize bias e.g. from starting only from the top or the bottom

[4] This CL was used to get a measure of present bias.

of the list and boredom. This approach is also likely to reduce bias towards the middle. However, the randomly chosen starting point may be associated with some bias if the choice then is erroneous. We test for such potential bias. We also had quite a few cases where the respondent preferred the near future amount even for the bottom row in the list, indicating a very high discount rate. In such cases we created a new row and reduced the near future amount to half of that on the row above. If necessary, this could also be repeated in order to identify/obtain a switch toward the far future amount. This allowed us to identify cases even with extremely high discount rates.

Table A1.2 in the Appendix gives an overview of the CLs with variation in near and far future points in time, and the far future amounts. We see that the future points in time were 3, 6 and 12 months and the amounts were 100, 500 and 1000 ETB. There was a 10% probability of winning in this game[5]. The respondents were informed about this before the start of the game. For delayed payouts a guarantee was given by the local university (Mekelle University) and a reward card was given to the lucky winners of future amounts, stating the time and amount to be paid out. The coauthor who was in charge of the whole fieldwork has also taken the responsibility to arrange all the payouts. Still, it is possible that perceptions of default risk affected the respondents' responses.

3.3. Sample

Our paper is associated with a broader study of resource-poor rural youth in northern Ethiopia that have been given the opportunity to join youth business groups to establish a joint formal business. This business is typically a part-time business established as a primary cooperative based on local cooperative law. Our sample comes from 116 such business groups and we have sampled up to 12 members of each business group. There is no strict upper age limit for group members but the large majority are from 18 to 35 years old. Landlessness or near landlessness is a key criterion for being eligible for the program which aims to create new rural employment opportunities. Two thirds of the members are male. Most groups have been allocated a rehabilitated communal land area that they are responsibility for conserving while they at the same time can invest in a joint business activity on this land.

This study builds on a census of such groups in five districts in Tigray region in 2016. The census covered 742 groups. Out of these, 119 groups were sampled for in-depth survey and field experiments of up to 12 members per group in 2016 (1140 group members). These groups and members were again revisited to carry out risk and time preference experiments in 2017, including some updating of changes since 2016. 116 of the 119 groups were then re-interviewed and involved in the experiments with a total sample of 980

[5] This is the same probability of winning that Andersen et al. (2008) used in their time preference study in Denmark.

respondents. These are the ones that are included in this study. Incomplete data for some variables implied that 941 respondents were included in the final analysis.

4. Estimation methods

4.1. Risk preference estimation

Each choice of the respondent is between a risky and a safe option. The risky option give a high outcome (*x*) with probability *p* and a low outcome (*y*) with probability 1-*p*. We call the safe amount *s*. We place the choice between the risky and safe prospect into a Rank Dependent Utility (RDU) framework (Quiggin 1982). The net utility or value return for a specific risky and a safe option can then be formulated as follows:

(7) $$\Delta RDU = w(p)u(x) + \left[1 - w(p)\right]u(y) - u(s)$$

where *w*(*p*) is the probability weighting function. This model also nests the EU model with linear probability weighting. Since we only allow non-negative outcomes this model is also consistent with Cumulative Prospect Theory (CPT).

We capture the utility function with a Constant Partial Relative Risk Aversion (CPRRA) function which implies limited asset integration and sensitivity to stake levels in the risk experiments (Binswanger 1981; Menezes and Hanson 1970);

(8) $$u(x) = (1-r)^{-1}\left((b+x)^{1-r} - 1\right)$$

where *r* is the constant partial relative risk aversion (CPRRA) coefficient and *b* is a base consumption level set at a daily wage rate rather than wealth. This implies that limited asset integration is assumed and this is in line with empirical evidence (Binswanger 1981; Rabin 2000; Wik et al. 2004) and assumptions made by others (e.g. Anderssen et al. 2008; Vieider et al. 2018).

As our respondents have limited education, they may have problems understanding the games or making correct calculations in the games. We expect errors in their responses, and such errors may imply violations of consistency. Experimental enumerators may also be a source of error and there may be starting point bias or bias associated with the random order of the CLs. The data from these experiments are therefore noisy and such noise needs to be taken into account in the estimation. Each decision between a risky and a sure amount may thus be subject to such errors. We draw on the contextual utility models by Wilcox (2011; 2015) and the decision field theory by Busemeyer and Townsend (1992; 1993). The contextual utility (CU) model of Wilcox (2011) in the case of RDU implies that the probability of the choice of the risky prospect over the safe prospect is:

(9)
$$\Pr\left(Risky\right)=F\left(\frac{\lambda\Delta RDU}{u\left(x\right)-u\left(y\right)}\right)$$

This implies a standardization of the risky prospects to the high and low outcomes and where the safe outcome falls between these through the utility function and probability weighting functions. However, this weighting ignores the probability weighting and the following approach which takes that into account may be preferable.

The decision field theory (DFT) adjustment based on Busemeyer and Townsend (1992; 1993) and Wilcox (2015) brings the probability weighing into the denominator as well as follows:

(10)
$$\Pr\left(Risky\right)=F\left(\frac{\lambda\Delta RDU}{\left[u\left(x\right)-u\left(y\right)\right]\sqrt{w\left(p\right)\left[1-w\left(p\right)\right]}}\right)$$

Both these approaches have the common property that a higher level of risk aversion will lead to a lower probability of choosing the risky prospect. The DFT approach also has the advantage that as *p* approaches 0 or 1 the probability of choosing the stochastically dominating alternative approaches certainty (Wilcox 2015). The use of both approaches serves as a robustness check for our findings but we retain the DFT model as the main model.

We estimate these models by specifying them as probit normal probability density functions for respondents *i* and CL *m* and include a heteroskedastic Fechner error ε_{im} with Wilcox contextual utility (CU):

(11)
$$Probit\left(Risky\right)=\phi\left(\frac{\lambda\Delta RDU_{im}}{\varepsilon_{im}\left[u_{im}\left(x_{im}\right)-u_{im}\left(y_{im}\right)\right]}\right)$$

Or the DFT approach with heteroskedastic Fechner error ξ_{im}:

(12)
$$Probit\left(Risky\right)=\phi\left(\frac{\lambda\Delta RDU_{im}}{\xi_{im}\left[u_{im}\left(x_{im}\right)-u_{im}\left(y_{im}\right)\right]\sqrt{w_{im}\left(p_{im}\right)\left[1-w_{im}\left(p_{im}\right)\right]}}\right)$$

The errors allow for within respondent errors in identification of switching points and thereby the CL-level estimates of weighting function and utility curve parameters. The models are estimated by maximum likelihood for the log likelihood functions for these density functions that are related to the switch point in each CL:

(13)

$$\ln L\left(z_i, m, \alpha_i, \beta_i, r, \xi_{im}\right) = \sum_{im}\left(\left(\ln\Phi\left(\Delta RDU\right) \mid Choice_{im} = 1\right)\right) + \left(\ln\Phi\left(1-\Delta RDU\right) \mid Choice_{ij} = 0\right)$$

Standard errors are clustered at the individual respondent level. We allow linear controls for CL design characteristics in the jointly estimated noise as well as risk preference parameters. Experimental enumerator fixed effects are also included in the noise specification together with respondent education (indicator of cognitive ability). A broader set of respondent characteristics were included for the risk preference parameters. Average predicted individual risk preference and noise parameter estimates are used in the joint analysis of risk and time preferences, see part 4.3.

4.2. Time preference estimation

For time preferences we build on equation (4) and estimate 1-level (equation 14a) and 2-level (equation 14b) Taylor expanded functions for the relationship between inflation corrected annualized discount rates and the time horizon and magnitude levels in each PL. These functions are estimated as follows:

(14a)
$$\log icavdiscr_{im} = \eta_{i0} + \eta_{it} \log timedif_{im} + \eta_{iM} \log icmagn_{im} + \upsilon_{im}$$

(14b)
$$\log icavdiscr_{im} = \begin{bmatrix} \eta'_0 + \eta'_{it} \log timedif_{im} + \eta'_M \log icmagn_{im} + \eta_{t2}\left(\log timedif_{im}\right)^2 \\ +\eta_{M2}\left(\log icmagn_{im}\right)^2 + \eta_{tM} \log timedif_{im} \log icmagn_{im} + \omega_{im} \end{bmatrix}$$

To assess the variation in individual discount rates and their responsiveness to variations in time horizon and magnitude levels of the prospects we used a random coefficient (RC) model as follows:

(15)
$$\log icavdiscr_{im} = \eta_{i0} + \eta_{it} \log timedif_{im} + \eta_{iM} \log icmagn_{im} + \zeta_{im}$$

where the parameter subscript *i* indicates that the parameters are estimated for each respondent.

4.3. Estimation strategy for the relationship between risk preferences and diminishing impatience

Figure 1 provides a model for the relation between the key variables. The risk preferences and the noise variable are first jointly estimated and predicted with a structural model and the dependent diminishing impatience (discount rate elasticity) variable was predicted based on the Random Coefficient variable. Our hypotheses state that all the four predicted variables from the structural risk model are related to the estimated discount rate elasticity with respect to time. Stronger diminishing impatience (more negative discount rate elasticity) is hypothesized to be associated stronger probabilistic insensitivity (lower Prelec 2 alpha) (H1), more pessimistic expectations (higher Prelec2 beta) (H2) and with higher risk aversion (higher CRRA r) (H3).

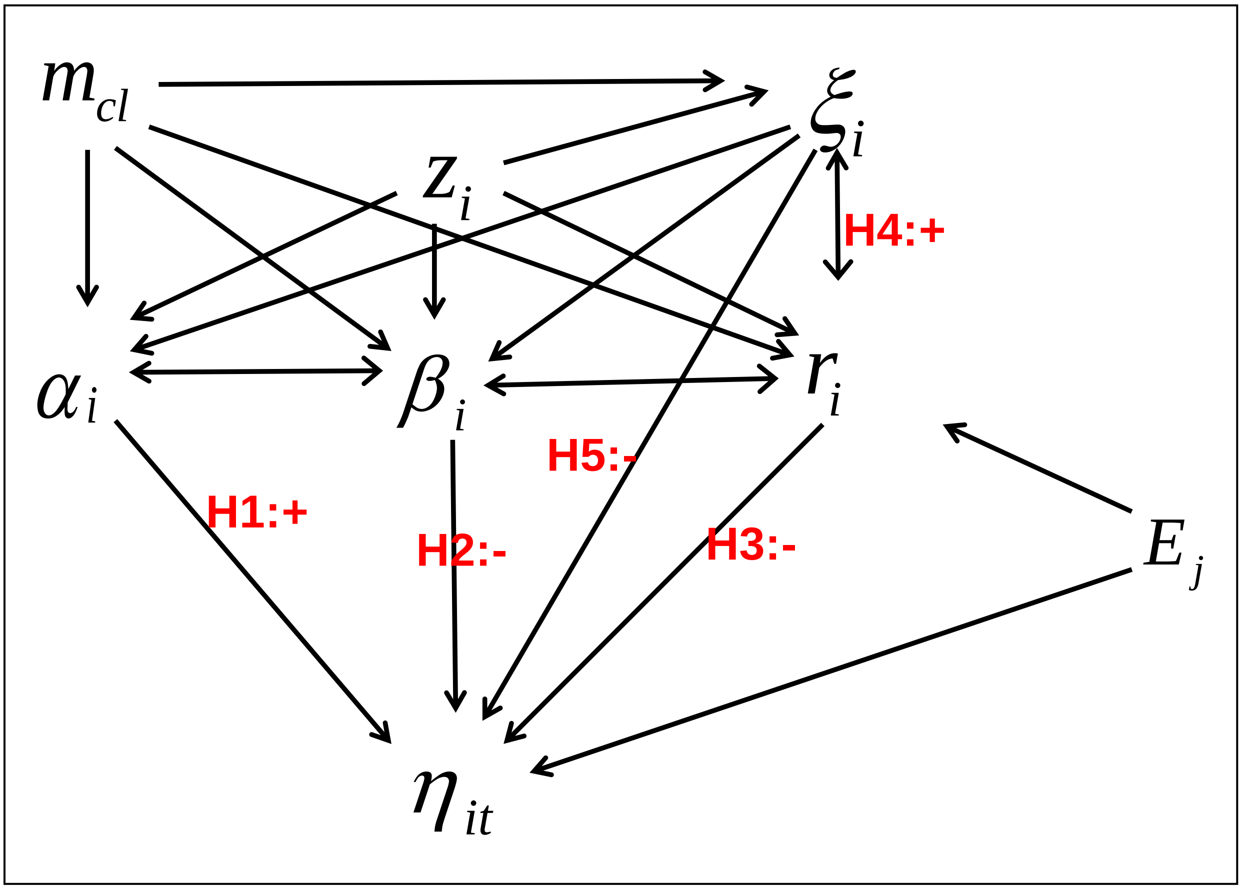

Figure 1. Model relating risk preferences and hyperbolic time preferences, with hypotheses

A set of Choice List characteristics (m_{cl}) were included as controls to reduce design bias. These CL characteristics including the random order and random starting point within CL variables also serve as instruments in the prediction of the risk preference and noise variables. They obviously do not have any direct impact on the time preference variable and therefore satisfy the validity requirement. They need, however, to be strongly related to the risk preference and noise variables to be defined as strong instruments, and thereby eliminate endogeneity bias. We found that the CL characteristics were strongly correlated with all the four predicted variables from the structural risk model, see Appendix Tables A2.1 and A2.2 for the results[6].

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[6] We are unable to measure the strength of instruments with the standard approach, as the predicted variables need to be aggregated to the respondent level for the second stage analysis.

A complicating issue is that the estimated and predicted measurement error (noise) can be correlated with the risk preference parameters as well as with respondent characteristics (z_i) (including unobservable cognitive ability). Earlier studies have shown that cognitive ability may be positively related to risk aversion, while Andersson et al. (2016) indicated that this may be a spurious correlation associated with CL design. We have therefore included hypothesis H4 (higher measurement error (lower cognitive ability) in the risk experiment is associated with higher estimated risk aversion) while controlling for CL design in the estimation of the noise parameter. Based on the finding by Andersson et al. (2016) the position of the risk neutral row in each CL may cause bias due to random errors, we included a variable for the position of the risk neutral row in each CL. This variable also turned out to be highly significant in the estimation.

However, we suspect that there can be spurious negative correlation between measurement error and the Prelec 2 alpha parameter (a sign of weak numerical skills) (hypothesis H5). To inspect the extent of correlation between noise and the risk preference parameters, we ran separate regressions for each risk preference parameter as a first inspection (equations 16a-c). In all regressions we control for another potential source of measurement error, enumerator influence (*Ej*), in the data collection process. Enumerator fixed effects were used in all regressions to control for this. The same enumerator carried out the risk and time preference experiments for each respondent. While they were well trained and monitored closely there is a risk that they introduced systematic bias. Twelve enumerators were used to simultaneously interview a group of up to 12 respondents belonging to the same business group. Since we use predicted variables in these models we use bootstrapping to get corrected standard errors, with 500 replications in each model and by resampling business groups.

$$(16) \qquad \begin{aligned} &(16a) \quad \alpha_i = a_0 + a_1\xi_i + a_{2j}E_{ji} + e_{ai} \\ &(16b) \quad \beta_i = b_0 + b_1\xi_i + b_{2j}E_{ji} + e_{bi} \\ &(16c) \quad r_i = c_0 + c_1\xi_i + c_{2j}E_{ji} + e_{ci} \end{aligned}$$

This is our test of hypotheses H4 and H5 and we included a correlation check for the Prelec 2 beta parameter as well, as a precautious step towards the estimation to test hypothesis H2.

It is possible that the risk preference parameters are correlated. A comprehensive model, where all three risk preference parameters and the noise are included in the same model is therefore run as the final basis for testing hypotheses H1-H3 and H6, equation 17:

$$(17) \qquad \eta_{ti} = \mu_{0e} + \mu_e\alpha_i + \mu_e\beta_i + \mu_e r_i + \mu_j\xi_i + \mu_{ej}E_{ji} + \nu_{ie}$$

The significance and stability of the correlation parameters in the alternative specifications is used as the basis to assess our hypotheses. The analysis is considered as exploratory and recognizes that here are unobserved heterogeneity/endogeneity issues that may cause bias in the estimated parameters even though the chosen instrumentation approach is valid. To our knowledge, this is the most comprehensive assessment of the relationship between diminishing impatience and risk preferences to date.

5. Descriptive statistics

To get appropriate measures of discount rates there is a need to correct for inflation. Consumer prices in Ethiopia increased 10.4 percent year-on-year in August of 2017. The average inflation rate in Ethiopia was 16.4 percent from 2006 until 2017 (Oromia Economist 2019). We make a 10 percent inflation correction (in continuous time) of the future amounts for a 12 months period and proportionally adjust inflation corrected future amounts by the length of time delay for varying time horizons. Deflated continuous time annual discount rates are calculated based on the inflation corrected future amounts with one week delay as the reference base point and the near future point in time, assuming linear utility (Andreoni et al. 2015; Abdellaoui et al. 2019). Table 1 gives an overview of the degree of diminishing impatience in the data, demonstrating strongly hyperbolic discount rates across the sample and that is not caused by present bias.

Table 1. Deflated annual continuous time discount rate distribution by time horizon

Time period months	Deflated mean annual discount rate	Deflated median annual discount rate	Deflated p25 annual discount rate	Deflated p75 annual discount rate	Standard error deflated annual discount rate	Sample size
2.77	53.5	36.6	18.5	64.9	1.4	2934
5.77	34.7	24.0	15.1	35.3	0.8	2934
11.77	23.1	16.7	9.8	25.6	0.4	2934

Note: For series 1-9 with one week delay in initial period, all magnitude levels. The table shows the within and across subject variation in discount rates by varying time horizon.

Table 2 gives an overview of the variation in magnitude effects in the data. We see highly significant magnitude effects.

Table 2. Deflated annual continuous time discount rates by future amount (magnitude)

Far future amount ETB (undeflated)	Deflated mean annual discount rate	Deflated median annual discount rate	Deflated p25 annual discount rate	Deflated p75 annual discount rate	Standard error deflated annual discount rate	Sample size
100	54.3	37.1	24.5	54.2	1.3	2934

500	30.9	18.5	12.1	35.2	0.8	2934
1000	26.1	21.1	10.8	30.6	0.6	2934

Note: For series 1-9 with one week delay in initial period. The table shows the within subject variation in discount rates by future amount (magnitude) levels across time horizons and across the sample.

One CL was used to assess the existence of present bias (Table 3 below). Table 3 inspects the distribution of present bias in the sample based on the choice list with immediate payout compared to the choice list with one week payout, *ceteris paribus.* The diminishing impatience in Table 1 is not due to present bias. Present bias appears from Table 3 to be concentrated in a subsample only as evidenced by the p90 and p95 discount rates.

Table 3. Inflation corrected annual discount rate assessment of present bias, 100 ETB with 12 months horizon

Initial time delay	Mean	Median	p25	p75	p90	p95	St. Error	Sample size
One week	33.3	25.6	16.5	48.7	48.7	91.6	1.0	978
No delay	42.4	25.1	16.2	47.7	89.8	89.8	1.2	978

The table shows the within subject variation in discount rates by varying the front end point in time (effect of present bias). p90 and p95 rates are added to show that present bias is evident for only a sub-sample.

Overall, the tables provide strong evidence of significant diminishing impatience (hyperbolic discount rates), magnitude effects and present bias and that present bias can be ruled out as the main source of hyperbolic discount rates.

6. Results and discussion

6.1. Risk preference results

Figure 2 shows the distribution of the three risk preference parameters from the structural model estimated with the DFT contextual utility models[7]. The figure shows that there is a strong tendency towards over-weighting of small probabilities for the large majority of the sample as the Prelec 2 alpha parameter distribution has its peak around 0.6 and few have an alpha close to or above one. There is a tendency towards optimism as the Prelec 2 beta parameter distribution has its peak below one. The utility curvature parameter distribution (CPRRA-r) shows more variation but the large majority have coefficients that indicate

[7] The distribution is very similar with Wilcox (2011) contextual utility (CU).

substantial risk aversion. This is not surprising for respondents living in a very risk environment with frequent droughts.

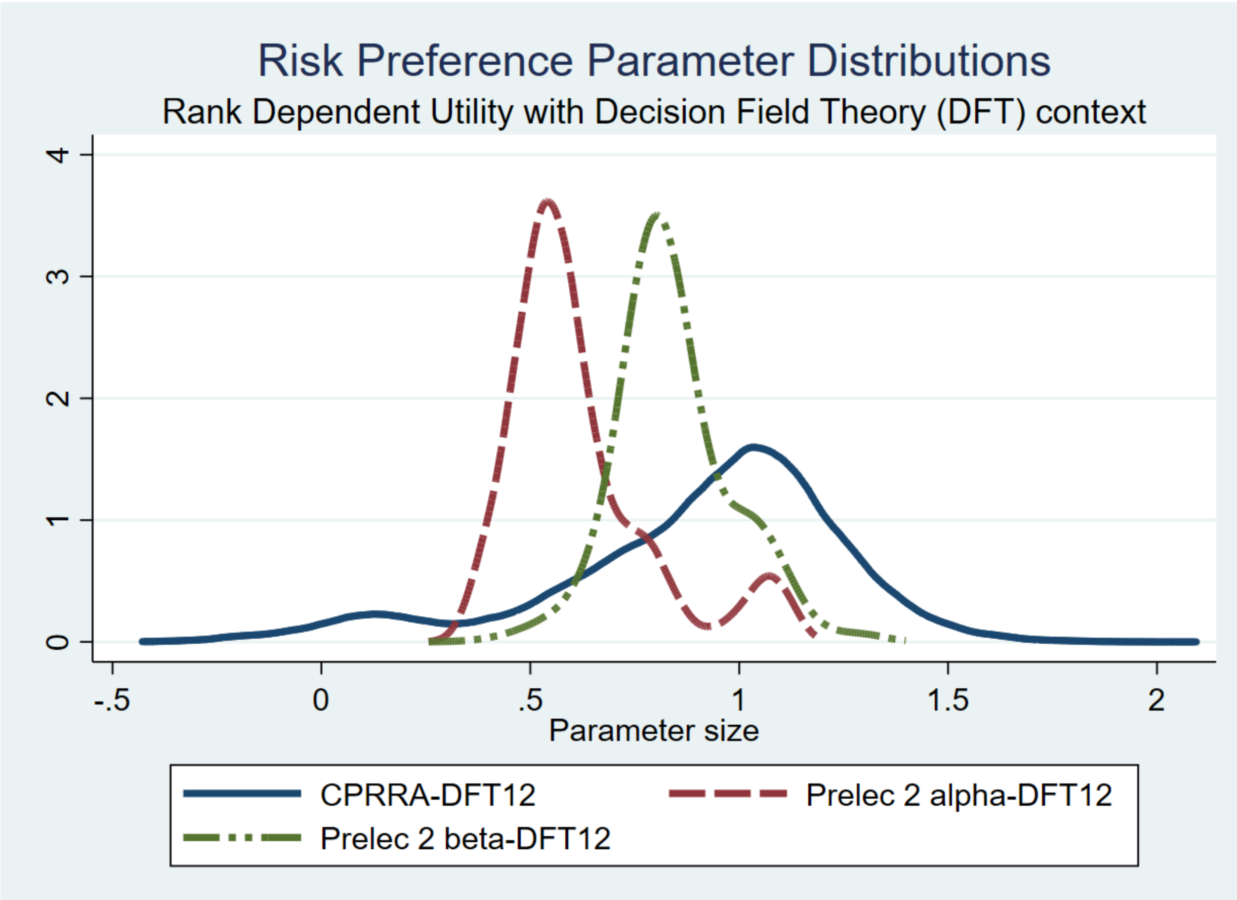


Figure 2. Risk preference parameter distributions, RDU model with Prelec 2 and DFT approach

The detailed estimation results for the structural risk models with DFT and CU specifications are presented in Tables A2.1 and A2.2 in Appendix 2 as they are not our primary interest in this paper. We assess how these estimated parameters are associated with the time preference estimates as well as measurement error that was explicitly estimated when estimating the risk preference parameters in Figure 1.

5.2. Time preference results

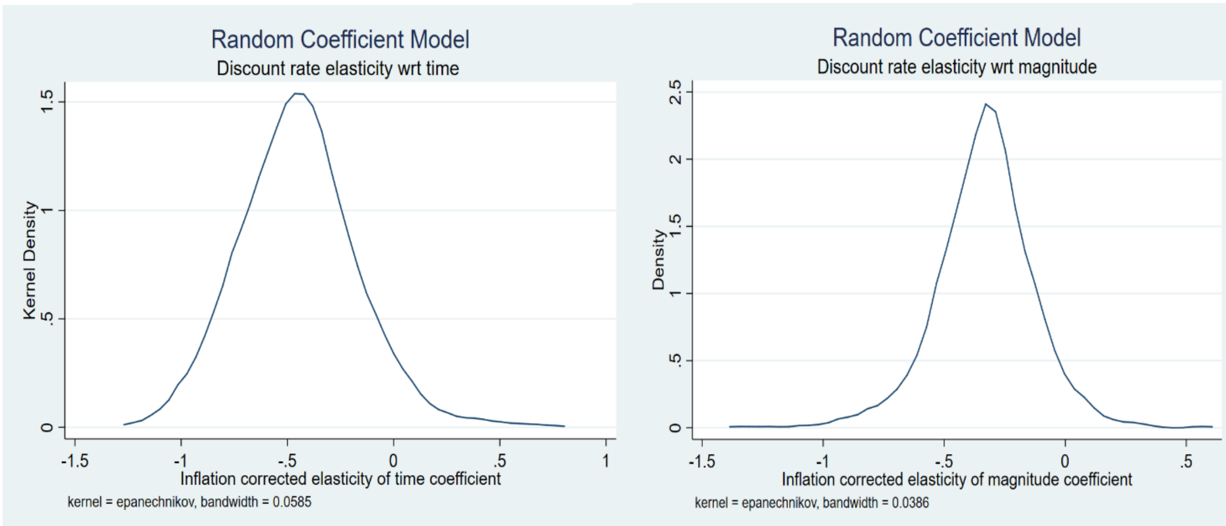
The log-log models estimating inflation corrected discount rate time and magnitude elasticities are presented in Table 4. We see that the time and magnitude elasticities are highly significantly different from zero and negative. We used Taylor expansion models to assess the functional form between discount rates, duration of time horizon and inflation corrected future amounts. The first two models in Table 4 present 1-level Taylor expanded models, which are equivalent to Cobb Douglas models. As controls for the business environment of the respondents, we alternatively used group fixed effects (FE) and group random effects

(RE), recalling that our sample is drawn from 116 business groups that have formed joint businesses. The FE and RE models present almost identical results. Model (3) includes a dummy for the one out of ten CLs

Table 4. Discount rate models in time and magnitude

	(1)	(2)	(3)	(4)	(5)	(6)
	Group FE, 1-lev. T	Group RE, 1-lev. T	Group FE + Present bias	Group RE, 2-lev. T	Group FE, 2-lev. T	RC model, 1-lev. T
Logicffa	-0.336***	-0.336***	-0.310***	-1.056***	-1.056***	-0.332***
	(0.009)	(0.009)	(0.010)	(0.166)	(0.166)	(0.010)
Logtimedif	-0.422***	-0.422***	-0.460***	-0.448***	-0.448***	-0.448***
	(0.013)	(0.013)	(0.013)	(0.094)	(0.094)	(0.015)
Nowdummy			0.250***	0.292***	0.292***	
			(0.020)	(0.021)	(0.021)	
(Logicffa)squared				0.0590***	0.0590***	
				(0.015)	(0.015)	
(Logtimedif)squared				-0.0804***	-0.0804***	
				(0.020)	(0.020)	
Logicffa*logtimedif				0.0461***	0.0461***	
				(0.010)	(0.010)	
Constant	6.509***	6.509***	6.403***	8.475***	8.475***	6.542***
	(0.059)	(0.070)	(0.062)	(0.470)	(0.470)	(0.077)
N	9780	9780	9780	9780	9780	9780
R-square	0.300		0.309		0.312	
Wald chi2		2206.08		3004.74		
F-value	1103.04		911.68		500.79	
P-value	0.0000	0.0000	0.000	0.0000	0.0000	

Note: Business group random effects (RE) and fixed effects (FE) were used for models (1)-(5). 1-lev. T=1-level Taylor expansion, 2-lev. T=2-level Taylor expansion, Logicffa=log of inflation corrected far future amount in Ethiopian Birr (test for Magnitude effect), Logtimedif=log of time difference in months (test for Hyperbolic effect). Nowdummy=1 for CL with immediate near future point in time (test for Present bias). * p<0.05, ** p<0.01, *** p<0.001. Test for parameter constancy in RC (Random Coefficient) model: chi2(2931) = 3.6e+06, Prob > chi2 = 0.0000.



Figures 3a and 3b. Random coefficient discount rate model: Discount rate elasticities with respect to time horizon (3a) and magnitude (3b) distributions.

with present versus future amounts while all the other series had one week delay in near future point in time for potential payout. The results indicate a 25% markup in the discount rate due to present bias for small amounts (100 ETB) and a one year time horizon. However, we see that the negative elasticities for time horizon were not reduced after controlling for present bias. This confirms that there is a strong general hyperbolic pattern in the data that cannot be explained by present bias.

As a robustness assessment of the suitability of the 1-level Taylor expanded model we ran 2-level Taylor expanded models, models (4) and (5) in Table 4. We see that the squared and interacted time and magnitude variables were significant but the overall R-square of the model did not increase much (from 0.309 to 0.312). This indicates that the 1-level Taylor expanded models are good representations of the data. This gives us confidence in using Random Coefficient (RC) 1-level Taylor expanded models to assess the variation in the time and magnitude elasticities within our sample, based on the ten observations per respondent.

Model (6) gives the overall results for the RC model. These overall results of this model are close to the FE and RE models (1) and (2). A test for parameter constancy in the RC models was rejected at an extremely high level of significance (see the footnote in Table 4 for the test result). Based on this finding we computed the linear predictions of the individual discount rate time and magnitude elasticities. Figures 3a and 3b show the distributions of these. The graphs illustrate that there are large individual variations in the discount rate time and magnitude elasticities.

5.3. Relating risk preferences, noise and diminishing impatience

Based on Halevy (2008) and Epper et al. (2011) we assess whether hyperbolic time preferences could be explained by implicit risk and uncertainty regarding future payouts and probabilistic sensitivity to small probability (hazard rate) changes with varying time horizons. Our experiments provided a strong guarantee for future payouts for the 10% who were expected to get a real payout and among these those who preferred a far future payout to a near future payout for the randomly chosen CL and task for real payout. We cannot rule out varying degree of uncertainty about the reliability of delayed payouts.

As a cautious approach to assessing this, our estimation strategy was to first inspect whether there are correlations between the noise parameter and the risk preference parameters, see details in Appendix Table A2.3 with explanations below the table. The final models with all three risk preference parameters included at the same time in models based alternatively on the CU and DFT specifications of the risk preference structural models and without and with the noise parameters from each specification are presented in Table 5. We assess the hypotheses in chronological order based on the results in Tables 5 and A2.3.

Our H1 hypothesis stated that "*there is a positive correlation between the estimated and predicted individual Prelec 2* α_i *parameter in the probability weighting function and the individually estimated discount rate elasticity with respect to time,* η_{it}*, in the intertemporal discounting function*". We assess this in the models in Table 5 where the dependent variable is the deflated discount rate elasticity with respect to time horizon. The Prelec 2 alpha parameters which were strongly correlated with the noise parameters (see Table A2.3) became insignificant when the noise parameter is included but retained positive signs. This implies that the evidence in support of hypothesis H1 is very weak.

Hypothesis H2 stated that "*Optimistic preferences associated with a Prelec 2* $\beta < 1$ *are associated with higher* η_{ti} *(less hyperbolic discount rates or less diminishing impatience)*". The Prelec 2 beta parameter is significant at 0.1% level and with a negative sign in all four models in Table 5, lending strong support to hypothesis H2. "Pessimism/optimism bias" can therefore "explain" part of the hyperbolic time preferences in line with hypothesis H2.

Hypothesis H3 stated that "*Risk aversion (utility curvature parameter) is negatively correlated with the discount rate elasticity with respect to time".* The CPRRA-r parameter was significant at 1% level in three of four models and significant at 0.1% level in the fourth model and with a negative sign in all models, lending strong support to hypothesis H3.

Overall, the three risk preference-related parameters explain only about 4% of the variation in the discount rate elasticity with respect to time horizon.

Table 5. Risk preferences and diminishing impatience, CU and DFT models

CU-Models	(1) η_{ti}	(2) η_{ti}	DFT-Models	(3) η_{ti}	(4) η_{ti}
Prelec 2 alpha CU	0.535***	0.219	Prelec 2 alpha DFT	0.379*	0.085
	(0.186)	(0.224)		(0.206)	(0.210)
Prelec 2 beta CU	-0.768****	-0.843****	Prelec 2 beta DFT	-0.743****	-0.848****
	(0.207)	(0.230)		(0.204)	(0.208)
CPRRA r CU	-0.431***	-0.465***	CPRRA r DFT	-0.333***	-0.368****
	(0.143)	(0.151)		(0.103)	(0.108)
Noise CU		1.597***	Noise DFT		6.172****
		(0.529)			(1.777)
Constant	0.263	-0.065		0.231	-0.295
	(0.373)	(0.409)		(0.336)	(0.366)
N	941	941		941	941
R-sq. within	0.043	0.051		0.040	0.053

Note: All models with Enumerator fixed effects. Bootstrapped standard errors, based on 500 replications and resampling youth groups. * p<0.10, ** p<0.05, *** p<0.01, **** p<0.001.

Are we able to judge whether low cognitive ability causes a bias in the estimated relationship between risk preferences and time preferences based on these models? Our assumption was that cognitive ability was associated with fewer errors and less noise in the risk preference models. As we had no direct measurements of cognitive ability we were unable to directly test how it is related to diminishing impatience. Education may be correlated with cognitive ability and we found a negative correlation between education and noise (significant at 5% level in both models) in line with our basic assumption (Appendix Table A2.1) and we take this as evidence that cognitive ability is negatively related with measurement error.

Table A2.3 in the Appendix assesses whether measurement error in the risk model, as a measure of low cognitive ability, is related to the estimated risk aversion (CPRRA-r) as proposed by Andersson et al. (2016). However, such correlation is weak in our data and does not have a strong effect on the estimated relation between CPRRA-r and the impatience elasticity. We therefore reject hypothesis H4 that *higher measurement error (lower cognitive ability) in the risk experiment is associated with higher estimated risk aversion.*

There was instead a strong correlation between the noise parameters and the Prelec 2 alpha parameters. Hypothesis H5 stated that *higher measurement error (lower cognitive ability) is negatively related to the Prelec 2 alpha parameter (distorted probability judgments are an indication of limited cognitive ability and weak numeracy skills).* This hypothesis has to be rejected as the sign of the relationship between noise and this parameter is positive and significant at 0.1% level in models 1 and 4 in Appendix Table A2.3. Probabilistic insensitivity is not explained by random errors associated with low cognitive ability.

The next issue we assess is whether limited cognitive ability as captured by the noise parameter in the structural risk model is correlated with the estimated discount rate elasticity with respect to time. We find a strong positive correlation (significant at 1 and 0.1% levels) in models 2 and 4 in Table 5. This result points in opposite direction of hypothesis H6. Diminishing impatience cannot be explained by more noisy responses, rather the opposite. Low cognitive ability seems therefore not to explain the diminishing impatience. Based on these findings we therefore conclude that hypothesis H6 that *higher measurement error (lower cognitive ability) in the risk experiment is associated with stronger diminishing impatience (more negative discount rate elasticity with respect to time horizon)* is rejected. This indicates that hyperbolism may not be a result of cognitive limitations that cause more noisy responses.

How do we then explain the strong diminishing impatience in the data, which appears to a limited extent to be due to implicit risks related to uncertainty about future payouts or due to limited cognitive ability leading to measurement errors? One of the potential problems may be that the up-front atemporal risk preference experiments do not provide good estimates of the probability weighting functions for future uncertainty related to the time preference experiments. A number of studies have demonstrated that risk preference experiments with delay in payouts cause a change in risk preference parameters. For example, Noussair and Wu (2006) found higher levels of risk tolerance for future risky payments with three months delay than current payments. Baucells and Heukamp (2010) found a similar effect from delay. Their finding is consistent with the findings of Abdellaoui et al. (2011) who assessed whether the change towards more risk tolerant responses in delayed risk games came through a change in the utility function or the probability weighting function. Abdellaoui et al. (2011) found that the entire effect came through the probability weighting function using risk experiments with six and 12 months delay. Their estimated Prelec 2 alpha parameter increased from 0.63 with no delay, to 0.72 with six months delay and to 0.80 with 12 months delay. They also found a significant reduction in the Prelec 2 beta coefficient, indicating that respondents were more optimistic about the outcomes in future games than current games. These findings indicate a lower probabilistic sensitivity for future risk such as in time preference experiments with delayed payouts that may be perceived as more uncertain. However, their study also relied on a relatively small student sample. If probabilistic insensitivity is weaker in relation to future uncertainty, this makes it more questionable whether such probabilistic uncertainty is driving the diminishing impatience. Further research is needed to more convincingly establish the causal mechanisms.

Holden and Quiggin (2017) proposed that hyperbolism and magnitude effects in time preference experiments are due to partial and variable asset integration which varies systematically with time horizon and magnitude levels. They implemented incentivized risk and time preference experiments in a sample of 350 smallholder farmers from Malawi. They showed that the data are consistent with their proposed theory. They controlled for individual utility curve variation in the same way as Andersen et al. (2008) and found strong hyperbolic and magnitude effects in their data. They did not investigate the degree of variation in asset integration in their data or how or whether it is correlated with limited or variable asset integration in risk experiments. This may be another fruitful area for further research.

There are few experimental studies that estimated discount rates with time horizons longer than one year. Grijalva et al. (2014; 2018) are exceptions. Grijalva et al. (2018) used a CTB approach on a sample of 62 university students from Weber State University. They varied the time horizons from one to 20 years. The experiments were incentivized with a 5/62 chance of winning where the payments could be up to 20 years into the future. They found annual discount rates in the range of 1.9-5.5% and evidence of a hyperbolic pattern and that this pattern was correlated with the confidence in receiving future payments. The fact that their discount rates are lower than those typically found in studies with shorter time horizons also points towards a hyperbolic pattern that we also see in our study when horizons are shortened from one year to six and three months.

6. Conclusions

We contribute to the literature that investigates the relationship between risk preferences and time preferences by combining incentivized double MCL experiments in a field experiment with a sample of 980 non-student youth and young adults that run joint businesses in groups organized as primary cooperatives in Ethiopia. Risk preferences and time preferences are of high importance for their risky natural resource based businesses that face substantial climate and market risks and that require long-terms investments to become sustainable. We used three, six and 12 months horizons in the time preference experiments and three magnitude levels for future amounts. We find strong evidence of diminishing impatience and magnitude effects in the data. While we also found evidence of present bias, nine out of 10 of our time preference series compared two future points in time and still revealed a very strong hyperbolic pattern. Median deflated discount rates increased from 16.7% with 12 months horizon and to 24.0 and 36.6% with horizons shortened to six and three months. With a random coefficient model we show that there is large and highly significant individual variation in the degree of diminishing impatience which we estimate as discount rate elasticities with respect to time horizon.

We assess how risk aversion and probabilistic sensitivity derived from the risk experiments are associated with their time preferences and particularly their degree on diminishing impatience (hyperbolicity) associated with varying time horizons in the time preference experiments. In particular, we assess whether implicit uncertainty associated with delayed payouts in the time preference experiments in combination with probabilistic sensitivity can explain diminishing impatience as suggested by Halevy (2008) and Epper (2011). We find only weak evidence of such an effect. More pessimistic and more risk averse respondents had more hyperbolic time preferences and these results were not sensitive to measurement error.

Overall, risk aversion, probability weighting and measurement error (cognitive ability) could only explain a very small share of the large variation in diminishing impatience in our data. The main implications of our findings are that present bias and uncertainty about future payouts do not provide universal explanations for hyperbolism. More research is needed to better understand general hyperbolism and individual variation in such hyperbolism.

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Appendix 1. Overview of MCLs and Experimental Protocol

Table A1.1. Overview of risky prospects in risk game

Series	Prob(bad outcome)	Bad outcome	Good outcome
1	1/20	0	100
2	1/10	0	100
3	2/10	0	100
4	3/10	0	100
5	5/10	0	100
6	1/20	20	100
7	1/10	20	100
8	2/10	20	100
9	3/10	20	100
10	5/10	20	100
11	15/20	20	300
12	19/20	20	1500

Table A1.2. Overview of time preference PLs

Series	Initial point in time, weeks	Future point in time, months	Future amount, ETB	Task Row 10 Amount, ETB
1	1	3	100	5
2	1	6	100	5
3	1	12	100	5
4	1	3	100	25
5	1	6	500	25
6	1	12	1000	25
7	1	3	100	50
8	1	6	500	50
9	1	12	1000	50
10	0	12	100	5

An overview of the switch point distribution in the 10 time preference CLs is presented in Figure A1 with reference to the overview of the CLs in Table A1.2 with information about future amounts, length of time horizon, minimum amount at task row 10 in each CL, and whether the near future point in time was one week into the future or at present (one CL only, CL 10). Interestingly it is this CL 10 that get the latest switch point with only about 50% having switched at task row number 10 (accepting 5 ETB now to 100 ETB one year from now). This CL can most appropriately be compared with CL 3 which only differs in terms of one week delay and indicates the effect of present bias.

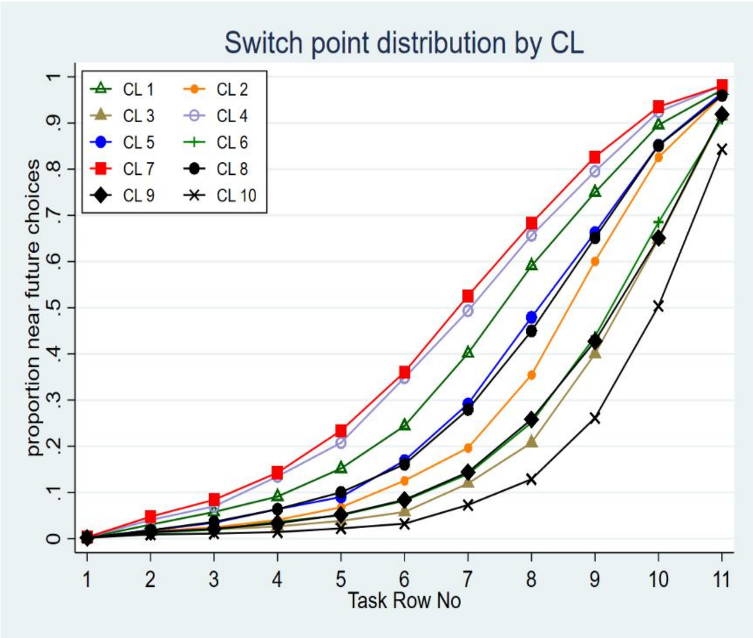

Figure A1. Switch point distribution in time preference CLs.

Time preference elicitation:

All instructions for respondents were translated to the local language Tigrinya.

Instructions to experimental enumerators:

- **a.** In these experiments there is no risk.
- **b.** The choices are between amounts of money to be received with certainty at different points in the future.
- **c.** In each case the respondent chooses between two options and indicates the one he/she prefers.
- **d.** You tick the preferred choice in each task.
- **e.** You will introduce several series of choices between more distant future and more near future money options (in ETB).
- **f.** In each series, we keep the future amount constant while we vary the more near future (or current) amount till we identify the switch point for the respondents.
- **g.** We expect only one switch point per series for responses to be consistent in that specific series.
- **h.** Make sure that you in each series make it very clear to the respondents when the two points in time are as compared to the date of the interview.

i. Remind the respondent about this as you move down each series till you identify the switch point.
j. They should make choices that are most preferred given their current living conditions and need for money at the different points in time that are indicated in each series.

Starting point bias. There may be a problem of starting point bias and respondents to continue to give the same answer as you move through a series stepwise from one end. To minimize the risk of starting point bias you should:

a) Randomize the starting point in each series (pull a playing card for yourself).
b) Afterwards move to the corner where you expect a switch compared to the first response to the random starting point.
c) When (if) you get a switch select the task in the middle between the two earlier responses that resulted in a switch.
d) And continue like that till you have identified the switch point.
e) If the near future amount is preferred when you are at the bottom row in a series, add a line and reduce the near future amount to half of that on the bottom line to see if that leads to a switch point. If not, repeat the same on another line till you get a switch (some may have extremely high discount rates).
f) You should then also explore the reasons for such extreme discount rates and note these down on the experimental protocol.

Instructions to respondents:

a. You will be asked to respond to a series of money payment options at different points in time in the future.
b. The distance into the future as well as the amounts will vary from task to task and you shall always in each case indicate which of the two options you prefer, given your current situation and future anticipated needs.
c. Make sure you make careful decisions as you do not know which of these may become subject to real payout after you have answered all the questions.
d. This will be determined through a lottery afterwards. Lucky winners will get payout at the time they have chosen for the series and task that was picked in the lottery and your choice in that series and task.
e. Mekelle University (Dr. NN) takes responsibility for the payouts.
f. The lucky winners will get a **Reward ticket** as a guarantee of the future payment.
g. By presenting the Reward ticket to Mekelle University at the time of payment you will get the cash amount stated on the ticket. Dr. NN will transfer the money to you through Dedebit Microfinance, call you to inform that the money is transferred, and then you can collect the money from your nearest Dedebit Microfinance office by showing your ID and telling the officer the amount and the name of the sender(Dr. NN).
h. There is a 10% chance of winning in this lottery.

The order of the 5 pages with time preference experiments were randomized to reduce bias

Example of MPL for time preference estimation:

		Time preference series 8				
Time pref. Series no.	Start point	Task no.	Receive at far future period: **6 months from now, ETB**	Choice	Receive at near future period: **1 week from now, ETB**	Choice
8		1	1000		1000	
8		2	1000		900	
8		3	1000		800	
8		4	1000		700	
8		5	1000		600	
8		6	1000		500	
8		7	1000		400	
8		8	1000		300	
8		9	1000		200	
8		10	1000		100	
8		11	1000		50	

Risk preference Experiments

Instructions to experimental enumerators:

Explanation for risk experiments with money:

Risk of starting point bias: Do as with the time preference series:

a. Randomize the task you start with within each series (throw the die).
b. This should be part of the pre-making of the questionnaires before you start.
c. Next, you move towards the end point in the direction you expect a switch to check whether you get it.
d. Narrow in quickly on the switch point by going to the middle task between the last two tasks that was assessed and within which the switch point is located (if consistent preferences are observed).

With real money and varying probabilities of low and high outcomes

a. The probability of low (bad) outcome for the risky prospect varies from game to game.
b. You will identify the certain outcome that makes the respondent switch (switch point) between preferring the risky prospect to preferring the certain outcome.

Instructions to respondents:

1. You have the choice between a risky prospect which has a high (good) or a low (bad) outcome.
2. There is in each game a certain probability (chance) of low (bad) outcome for the risky prospect.

3. One of the gambles gives you ETB 100 if you are lucky and ETB 0 if you are unlucky and a chance/probability, say one out of ten (10% chance) of low (bad) outcome.
4. You have the choice between this and a certain amount.
5. We vary the certain amount till you switch from preferring one or the other.
6. To determine whether you are lucky we will use a 20-sided die.

Random sampling for payout:

a. One of the experiments below will be randomly sampled for real payout.
b. Your choice in the randomly sampled task in that game will be your payout.
c. Your choices will there affect the outcome.
d. Therefore, think carefully about your preferred choices.

The order of the 5 pages with risk preference experiments was randomized to reduce bias

Example of MPL for risk preference elicitation:

				Risk preference series 6				
S. no.	Start point	Task no.	Prob-bability of bad outcome	Low outcome, **ETB**	High outcome, **ETB**	Choice	Certain amount**,** **ETB**	Choice
6		1	2/10	20	100		100	
6		2	2/10	20	100		95	
6		3	2/10	20	100		90	
6		4	2/10	20	100		85	
6		5	2/10	20	100		80	
6		6	2/10	20	100		75	
6		7	2/10	20	100		70	
6		8	2/10	20	100		65	
6		9	2/10	20	100		60	
6		10	2/10	20	100		50	

Identification whether there will be a real payout in one of the time preference experiments:

a. Use 20-sided die.
b. Put the die under the cup on top of the plastic on the table and shake it once: The respondent has won if the die has landed on 1 or 11, otherwise not (10% chance of winning).
c. If they win, use the die again to randomly identify which of the 10 time series that they played to be used for payout (die number 1 and 11 for series 1, die numbers 2 and 12 for series 2 etc.).

d. Use the die a third time to identify the Task number within the series (1-11).
e. Use the die more than once only if it gives a number above 11 (or higher if extra rows were added).
f. Their choice within that Task is their amount won.
g. Their choice in that task determines their payout and the timing of the payout.

The household **1=Won / 0 = Did not Win**

Series selected if they Won:_____________

Task chosen if they Won:_____________

Payout amount:_______________

Time (delay time) when payout will take place:__________________________________

Name (upto grand father) of the youth group member _____________________________

NB! The project needs to arrange such that payouts are granted at the appropriate time!

The winning persons should be given a Reward ticket stating their name, youth group id, youth group member id, amount to be paid, date of reward ticket given and time of payment. These Reward tickets should be collected when the payout takes place as documentation that it has taken place.

Signature for receiving a Reward Ticket if the household Won:

Date: ______________Signature:_____________________________

Supervisors shall have a separate notebook which will be a registry for payments to youth group members and handing out of Reward tickets.

Payment for Risk preference games:

a. Use 20-sided die (in cup with cartoon) to identify which of the 10 risk series that will be used for payout (die numbers 1 and 11 for risk series 1, die numbers 2 and 12 for risk series 2, etc.), and similarly for the choice of Task (row) in the risk series identified.
b. This should be done for each at the end of all games, while they are sitting at their place. Nobody should move from their spot till all have completed (no spectators allowed for each).
c. Ensure privacy during the whole process.

d. If some complete before others, they should not come close to or interact with those who have not yet completed.
e. You use the Prospect they have chosen for that task, the risky prospect or the certain amount depending on their choice in that specific task.
f. If they have chosen the risky prospect you identify the probability of Good (High) and Bad (Low) outcomes and assign die numbers to each, e.g. 30% probability of Good outcome in Risk series 3 game implies that you assign die numbers 1, 2, 3, 11, 12, and 13 to the low payout and the remaining die numbers to high (good) payout.
g. The die has to be shaken under the cup only once to determine the number and identify whether they lost or won.
h. If they for the randomly identified task chose the certain amount, you give them that certain amount.

Payment in risk preference experiments:

1. Risk series randomly assigned for payout:_________________
2. Task row randomly assigned for payout:_________________
3. Identify whether the Respondent had chosen the Risky Prospect (=1) or the Certain Amount (=2) for that Task: Prospect chosen (circle):___ 1______2_
4. If the certain amount was chosen, write the amount below as amount recived.
   Amount recieved: _____________________

5. If the risky prospect was chosen, assign die numbers to low and high payouts based on the probabilities in the identified risk series.

   Die number outcome:_____

   Implication (circle): 1=High outcome, 0=Low outcome

   Amount:___________

Signature for amount received:_________________

Appendix 2. Supplementary findings

Risk preference model results

Table A2.1 presents the error component of the structural model and Table A2.2 presents the risk preference parameter estimates from the structural model.

Table A2.1. Model error and error sources in CU and DFT models

Noise	DFT12	CU12
Page number	-0.0067**	-0.0038***
	(0.002)	(0.001)
Startp. Taskno	0.0091***	0.0029***
	(0.001)	(0.000)
Risk neutral Taskno	-0.0882***	-0.0268***
	(0.006)	(0.002)
Risk neutral Taskno, squared	0.0092***	0.0030***
	(0.001)	(0.000)
Prob. Bad outcome	0.268***	0.0451***
	(0.018)	(0.008)
Education, years	-0.0036*	-0.0012*
	(0.001)	(0.000)
Enumerator FE	Yes	Yes
Constant	0.470***	0.170***
	(0.028)	(0.010)
N	112606	112606

Note: Standard errors in parentheses, corrected for clustering at respondent level. * p<0.05, ** p<0.01, *** p<0.001.

Table A2.2. Risk preference models with CU and DFT specifications

CPRRA	Prelec 2 alpha DFT12	Prelec 2 alpha CU12	Prelec 2 beta DFT12	Prelec 2 beta CU12	CPRRA DFT12	CPRRA CU12
Page number	0.0094*	0.0077**	0.009	-0.008	0.019	0.0564*
	(0.004)	(0.003)	(0.013)	(0.009)	(0.026)	(0.022)
Startp. Taskno	-0.003	0.000	-0.0264***	-0.0159***	0.0388**	0.0222*
	(0.002)	(0.001)	(0.005)	(0.003)	(0.012)	(0.009)
Risk neutral Taskno	0.0877***	0.0727***	0.0449***	0.0375***	-0.170***	-0.173***
	(0.004)	(0.005)	(0.008)	(0.007)	(0.026)	(0.021)
Age, years	-0.0027**	-0.0026***	-0.004	-0.004	0.005	0.005
	(0.001)	(0.001)	(0.003)	(0.003)	(0.006)	(0.005)
Male, dummy	0.010	0.022	-0.004	0.045	-0.013	-0.117
	(0.016)	(0.013)	(0.059)	(0.040)	(0.104)	(0.081)
Education, years	-0.004	-0.003	-0.016	-0.015	0.021	0.020
	(0.003)	(0.002)	(0.013)	(0.008)	(0.024)	(0.016)
Birth rank	-0.006	-0.005	-0.015	-0.013	0.026	0.024
	(0.004)	(0.003)	(0.012)	(0.010)	(0.022)	(0.021)
Number of brothers	-0.002	-0.002	-0.019	-0.0286*	0.034	0.0600*
	(0.005)	(0.005)	(0.015)	(0.013)	(0.026)	(0.027)
District Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.470***	0.488***	0.889***	0.967***	1.123***	0.763**
	(0.047)	(0.040)	(0.165)	(0.124)	(0.296)	(0.271)

Note: Standard errors in parentheses, corrected for clustering at respondent level. * p<0.05, ** p<0.01, *** p<0.001.

Number of observations are the same as in Table A2.1 (jointly estimated).

Table A2.3. Correlations between noise and risk preference parameters, CU and DFT models.

	(1) Prelec 2 alpha CU	(2) Prelec 2 beta CU	(3) CPRRA-r CU	(4) Prelec 2 alpha DFT	(5) Prelec 2 beta DFT	(6) CPRRA-r DFT
Noise	3.073****	0.706	-2.991	1.520****	-0.335	-0.289
	(0.435)	(2.341)	(4.273)	(0.149)	(0.609)	(0.884)
Constant	0.183***	0.756**	1.215**	0.023	0.950****	1.060***
	(0.058)	(0.318)	(0.582)	(0.058)	(0.240)	(0.350)
N	946	946	946	946	946	946
R-sq., within	0.099	0.000	0.002	0.263	0.003	0.001

Note: All models with Enumerator fixed effects. Bootstrapped standard errors, based on 500 replications and clustering at individual enumerator level. * p<0.10, ** p<0.05, *** p<0.01, **** p<0.001.

Table A2.3 presents the results from the correlations between the noise parameter and the risk preference parameter with the CU and DFT specifications, while controlling for enumerator fixed effects. These models also served to assess our hypotheses H4 and H5 about possible connections between cognitive ability, which may influence noise and thereby indirectly the risk preference parameters.

Table A2.3 shows that the correlation between noise and the CPRRA-r parameter is insignificant and the sign is opposite to what was stated in hypothesis H4. There is therefore no support for it in our data. Hypothesis H5 stated that probabilistic insensitivity could be due to low cognitive ability and thereby the Prelec 2 alpha parameter should be negatively correlated with noise if higher noise is caused by lower cognitive ability and a low Prelec 2 alpha parameter is a sign of limited numeracy skills. The surprising result is that noise is strongly positively correlated (significant at 0.1% level in both models) with the Prelec 2 alpha parameter in both the CU and DFT models. This also implies that hypothesis H5 has no support in the data. Also the Prelec 2 beta parameter was uncorrelated with model noise. Optimism/pessimism seems therefore unrelated to noise in the models.