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Abstract

We use a field experiment and a within-subject design based on multiple Choice Lists (CLs) that integrate time and risk. Diminishing impatience with extended time horizons is studied by varying time horizons from one week to two years. Time-dated risky prospects are constant within CLs and are always compared with time-dated certain amounts to identify time-dated Certainty Equivalents. Non-linear probability weighting is modeled with a 2-parameter Prelec function. First, we identify a strong diminishing impatience associated with longer time delay between prospects. Second, we test whether non-linear probability weighting can explain and reduce the observed diminishing impatience by replacing linear probability weighting with an estimated inverted S-shaped Prelec function. We find that this does not reduce the observed degree of diminishing impatience. We conclude that the observed diminishing impatience is neither explained by the combination of present bias and certainty bias nor by non-linear weighting of risk in future prospects.

Keywords: Time preferences, Diminishing impatience, Risky preferences, Probability weighting, Field experiment, Within-subject design.
JEL Classifications C93 . D91

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1. Introduction

Time and risk preferences are fundamentally important for individuals' savings and investment decisions. Yet, there is no consensus on how best to measure and estimate these preferences or how they are related (Abdellaoui et al., 2013; Andersen et al., 2008; Andreoni and Sprenger, 2012a, 2015; Cheung, 2019; Miao and Zhong, 2012; Halevy, 2008; Epper et al., 2011). On time discounting many studies have frequently found behavioral deviations from Samuelson's Discounted Utility model (SDU) (Samuelson, 1937) such as present bias and diminishing impatience and many economists have modeled these as quasi-hyperbolic (QH) discounting, e.g. (Laibson, 1997; Cohen et al., 2020; Harrison et al., 2022). However, there are also studies that have identified general hyperbolic discounting but they are less well founded in terms of the theoretical explanation and have been less well documented with incentivized experiments (Frederick et al., 2002; Hepburn et al., 2010), until recently (Grijalva et al., 2014, 2018; Holden and Quiggin, 2017). This new evidence points towards general hyperbolic discounting or diminishing impatience as the time horizon is extended. Figure 1 illustrates the distinction between these.

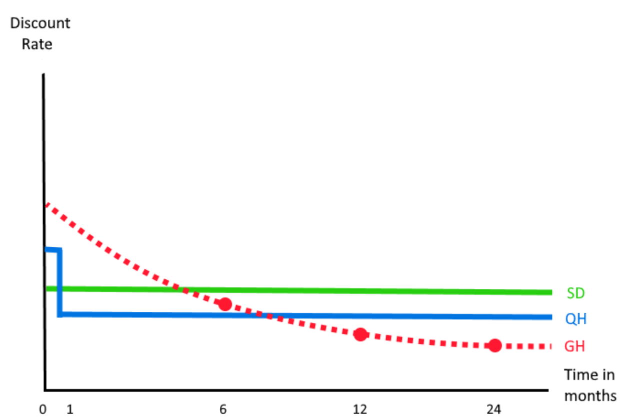

Figure 1: Alternative discounting models

The seminal contribution that has stimulated a lot of research on the relationship between risk and time preferences is Andersen et al. (2008). They used separate Choice Lists (CLs) for risk and time to jointly estimate risk and time preferences. They argued that time preference estimation that ignores the concavity of the utility function leads to upward bias in the estimated discount rates. They estimated the utility curvature with the risk experiment within an Expected Utility framework and demonstrated a substantial upward bias in the discount rate unless utility curvature is controlled for, based on a large scale field experiment in Denmark. Their work has later been contested on several grounds. On theoretical assumptions and their realism many experimental studies have revealed behavior in response to risk that deviates from Expected Utility theory (EU) and that is more consistent with non-linear probability weighting as in Rank Dependent Utility (RDU) theory (Quiggin, 1982). The concavity of the utility function may become substantially reduced with RDU as compared with EU. More fundamentally, others have suggested that utility in time is different from utility in risk and have found that these two forms of concavity even may not be correlated (Abdellaoui et al., 2013; Cheung, 2016, 2019).

Should one then go back to ignoring behavior under risk when studying time preferences? This may not be the case. Halevy (2008) linked diminishing impatience in time and probability weighting by contrasting the certainty of the present and the uncertainty associated with all future prospects. Epper et al. (2011) also explained diminishing impatience as a combination of uncertainty about future payoffs and subjective probability weighting related to such delayed payoffs. In this paper we assess the presence of general hyperbolic (GH) discounting that implies that diminishing impatience is not only explained by present bias (quasi-hyperbolic discounting) but is associated more generally with extended time horizons. It implies that δ(annualized discount rate)/δ(length of time horizon)< 0 also when the starting point for the time horizon is into the future and thereby eliminating present bias. Note that GH nests the constant discounting and the quasi-hyperbolic models. In this study we investigate whether or not or to what extent non-linear probability weighting in risky prospects may explain diminishing impatience by jointly estimating risk and time preferences based on original data from a field experiment with time-dated risky and certain amounts in a within-subject design.

To stay away from the complicating portfolio and inter-temporal diversification issues (Andersen et al., 2018b; Harrison et al., 2022), we only introduce risk in one of the time-dated prospects. Our field experiment is in a developing country context with a large sample of rural young business group members in Ethiopia. Their on average low and variable level of education re-enforced the need to have simple elicitation tools and we used variants of CLs with binary choices where safe amounts in the near (far) future were compared to far (near) future safe (risky) amounts. For the risky prospects, unlike in the standard Holt and Laury (2002) approach, we keep the probabilities for high and low outcomes constant within each CL. Only the time-dated certain amounts vary within each CL and allow the identification of a time-dated Certainty Equivalent within an interval of certain amounts bordering the switch point in the CL. Each subject responded to a total of 14 CLs of which eight CLs contain risky and safe outcomes at different points in time and the remaining six CLs contain only certain time-dated amounts. Time delays vary from one week to six, 12, and 24 months. Subjects had a 10% probability of one of the 14 CLs to be randomly drawn as a real game. Confidence in future payouts among the respondents was ensured through giving them reward tickets that can be cashed out at the local credit and savings institution (DECSI) at the appropriate time.

This allows us to further investigate the theory of Epper et al. (2011); Epper and Fehr-Duda (2015); Halevy (2008) that an RDU model can explain diminishing impatience in inter-temporal choice. We utilize variation in the time-dated amounts in our CLs to elicit utility curvature and to separate it from probability weighting. We test the Expected Value (EV), the Rank-Dependent Expected Value (RDEV) (Yaari, 1987) and the RDU (Quiggin, 1982) models for risky prospects versus Samuelson's constant discounting (SD), quasi-hyperbolic (QH) discounting, and general hyperbolic (GH) discounting. We test for and identify diminishing impatience in future risky prospects with longer time horizons. We utilize this to investigate our primary research question that non-linear probability weighting can explain this diminishing impatience. We evaluate it by assessing the parameter sizes of the time horizon dummy variables in the GH models without and with non-linear probability weighting and the overall performance of the GH models versus the SD and QH models.

Second, our study allows us also to assess whether we find the same near linear utility in time as found in a number of recent studies (Andreoni et al., 2015; Abdellaoui et al., 2013; Cheung, 2019). We regard near-zero discount rates as a lower bound and thereby impose a restriction on the concavity of the time-dated utility function.

The results demonstrate strongly diminishing impatience with future time horizons expanding from 6 to 12 and 24 months when the reference point was one week into the future, showing that this is not explained by present bias. The introduction of non-linear probability weighting through endogenous or constrained Prelec α and β parameters to answer our key research question, did not reduce the diminishing impatience in our data (Prelec, 1998). The answer to our key research question is therefore that the strong diminishing impatience in our data cannot be explained by probability weighting in time-dated risky prospects.

The paper proceeds as follows. Section 2 presents our experimental design, section 3 gives an overview of the sampling and data. Section 4 presents the theoretical framework and hypotheses and section 5 the estimation strategy. The results are presented in section 6 and these are discussed in relation to some of the most relevant literature in section 7 before we conclude.

2. Experimental design

We used a multiple Choice List (CL) approach with a within-subject design to elicit time preferences with safe and risky prospects. An overview of the full set of 14 Choice Lists (CLs) is presented in Table 1. The first six CLs are without risk and each CL includes choices between a fixed far future amount and a fixed time horizon while the near future amounts decline systematically from the top row to the bottom row of the CL (see Appendix 1 for an example CL). The far future points in time are 6, 12 and 24 months into the future. The near future point in time is one week into the future to avoid present bias, while the varying time horizons can detect diminishing impatience with longer time horizon that is not explained by present bias. The future amounts are 300 ETB or 1500 ETB to assess the importance of magnitude effects (utility curvature).[1]

CLs 7-14 include one risky and one safe outcome. For these eight CLs we included one risk and one safe prospect[2]. Two of these CLs contained a risky near future outcome (CL 9 and 11) while the rest contained a risky

[1]Due to significant inflation in the study region, future amounts are deflated before they are used in the analysis. For simplification of exposition, we use nominal future amounts in tables but we should remember that e.g. 1500 ETB 6 months from now is a larger amount than 1500 ETB 24 months from now.

[2]We avoided CLs with two risky prospects due to the complexity of analyzing such prospects (Andersen et al., 2018b).

far future outcome. A 20-sided die was used to illustrate the probabilities for the risky prospects. The outcomes for the risky prospects are always a given probability of a positive outcome or nothing and this prospect is kept constant within the CL while the dated safe amount varies across rows to identify the dated certainty equivalent of the risky dated prospect. Three of the prospects have very short horizons (CLs 10, 12 and 14) where the choice is between risky amounts one week into the future and sure amounts today. The remaining three CLs (7, 8 and 13) include far future risky prospects and sure near future (one week) amounts.

Each CL has 11 rows (see Appendix for full view of all series). If no switch point were found when reaching the bottom row, additional rows were added until a switch point was reached. A similar approach was not used at the top of the lists.

The order of the CLs was randomized to avoid confounding of order effects with CL design. Within each CL the starting row was randomized and a rapid elicitation method was used to find the switch point. This method avoided multiple switch points in each CL. However, it could result in no switch point in a CL. The design allows us to control for possible bias associated with random order and random starting point in each CL in the estimation.

We used the random lottery method to provide monetary incentives in our experiments. The respondents were informed that there was a 10% probability of winning in the experiment and that the lucky winners will be randomly drawn just after the completion of the experiment. Our approach therefore eliminates the possibility of future uncertainty being confounded with the timing of the payments (Epper and Fehr-Duda, 2015). A 20-sided die was used both to illustrate probabilities in the risky prospects and to randomly draw winners and CLs for payout in the games. For the randomly identified CL for payout for the winning respondents, a new random draw was made to identify the winning row in the CL. The choice of the respondent was then used to identify the payout and the timing of the payout. If this choice was a risky prospect, this risk was immediately resolved by using the 20-sided die once more. The winners were then given a reward ticket that could be cashed in at the appropriate date at the local credit and savings organization's office (DECSI) and had a guarantee from Mekelle University. As we have a project that has done research related to the business groups the respondents belonged to for more than three years, they had experienced that the researchers were reliable and returned. They were also informed that we had a project that would go on for four more years[3]. These facts also created trust and credibility of the experiment among our respondents who could consider future payments as certain.

Table 1: Time and risk preference choice list overview

CL No.	P(good) FFT	FFT months	FFA ETB	P(good) NFT	NFT months	NFA ETB
1	1	24	300	1	0.25	15-300
2	1	6	300	1	0.25	15-300
3	1	12	300	1	0.25	15-300
4	1	24	1500	1	0.25	75-1500
5	1	6	1500	1	0.25	75-1500
6	1	12	1500	1	0.25	75-1500
7	0.05	12	1500	1	0.25	5-100
8	0.05	6	1500	1	0.25	5-100
9	1	12	15-300	0.05	0.25	1500
10	0.05	0.25	1500	1	0	5-100
11	1	12	15-300	0.15	0.25	500
12	0.15	0.25	500	1	0	5-100
13	0.9	12	100	1	0.25	30-100
14	0.9	0.25	100	1	0	5-100

Note: FFT=far future time, FFA=far future amount, NFT=near future time, NFA=near future amount, P(good)=probability of good outcome for risky prospects.

3. Data

3.1. Sampling

The samples consists of rural youth that are members of youth business groups that are formalized and organized as primary cooperatives in northern Ethiopia. Resource-poor youth are found eligible to join such youth business groups that are provided an area of rehabilitated communal land for establishment of a sustainable business. They live in a risky semiarid environment

[3]At the time of our experiments nobody expected the civil war that suddenly started in November 2020.

and their production activities[4] are therefore risky. The business groups are required to manage their land resource in a sustainable way in order to retain the right to use it. Our sample comes from four districts (*woredas*) in Tigray Region and consists of up to 12 group members from each business group. For estimation purposes we split the sample in two to retain one sample for initial estimation and the second sample for assessment of the within-CL stability of the cumulative switch point distributions. Each sample consists of approximately 400 respondents and both samples were drawn from the same pool of business groups in the four districts.

3.2. Cumulative switch point distributions

We see varying degree of right censoring across CLs for CLs 1-6 and 13. The rows that were added in such cases are not shown in the figures but they implied that switch points and discount rate ranges were also identified for these right censored CLs and respondents.

We see left censoring for a number of the CLs with risky prospects. The largest sample share (40-45%) with left censored observations is observed for CLs 9 and 11 where the respondents were asked about the preference for a low probability high outcome far future prospect versus a sure near future prospect. We return to the issue of how we handled the censored CLs and respondents in the estimation strategy.

CLs 7, 8, 10 and 12 also have 15-20% left censoring. In these CLs it was the near future prospect that was risky (low probability of winning). The last two CLs (13 and 14) contain risky prospects with high probability of winning with long (12 months) and short (one week) horizons.

4. Theory and Estimation Strategy

4.1. Theoretical model integrating time and risk preferences

We begin with an additive time-separable inter-temporal utility function with exponential discounting as the benchmark model. We assume that respondents have a linear time-dated utility function within given time periods (Andreoni and Sprenger, 2012a; Vieider et al., 2019). We focus exclusively on "gains only" situations so that we can ignore "gain-loss" asymmetries.

[4]Their production activities included livestock, forestry, horticulture, and irrigation agriculture, which all are sensitive to the stochastic rainfall pattern.

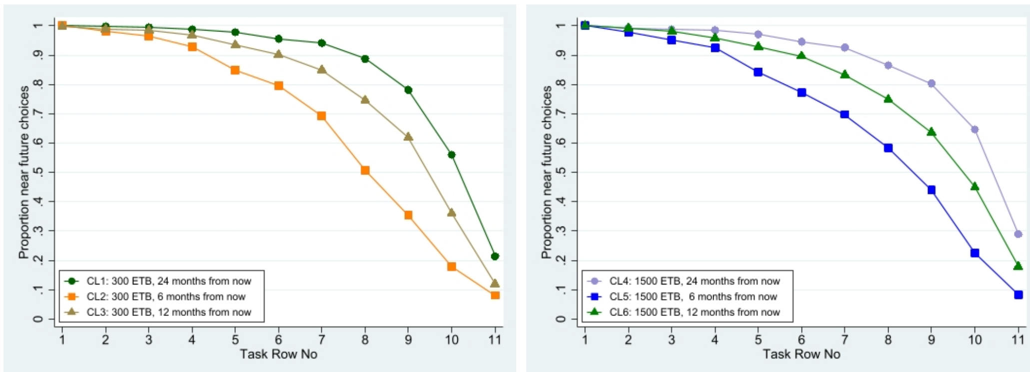

Figure 2: Risk-free time-dated prospects, 300 and 1500 ETB future amounts and 6, 12 and 24 months time horizons

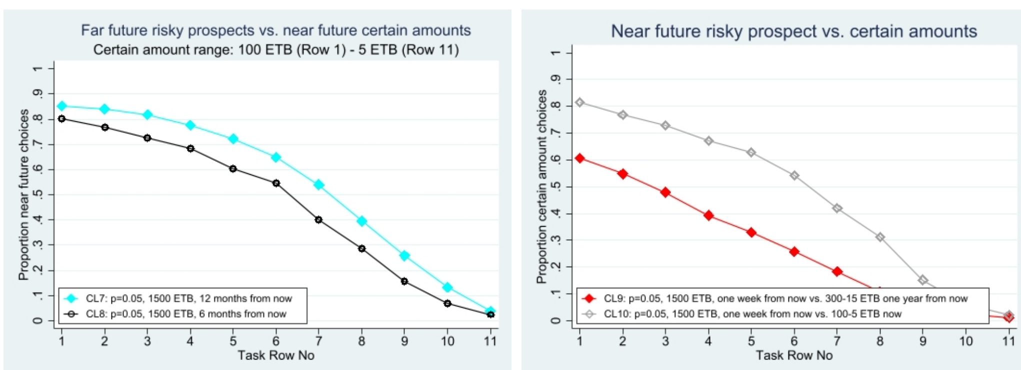

Figure 3: Risky far future and near future prospects versus time-dated certain amounts

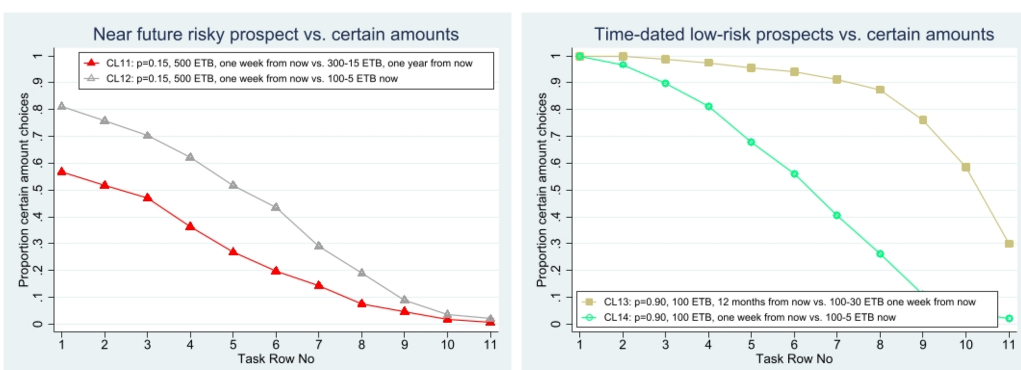

Figure 4: High- and low-risk prospects and alternative time horizons

The hyperbolic and magnitude anomalies that we seek to explore are evident in experiments with gains only and therefore are not a direct effect of gain-loss asymmetries (Holden and Quiggin, 2017). Respondents are given the choice between two prospects, M_A at time t_1 and M_B at time t_2, where $t_2 > t_1 > t_0 = 0$. Decision-makers must choose between U_A and U_B. In the dated utility it is assumed that the prospects are integrated with a basic background consumption b at that point in time.[5] The inter-temporal binary choice between the two time-dated prospects can then be formulated as follows:

$$\begin{aligned} U_A &= e^{-\delta(t_1-t_0)}u(b+M_A) + e^{-\delta(t_2-t_0)}u(b) \\ U_B &= e^{-\delta(t_1-t_0)}u(b) + e^{-\delta(t_2-t_0)}u(b+M_B) \end{aligned} \tag{1}$$

where δ is the exponential continuous time discount rate.

Alternatively, the far future prospect (M_B) or the near future prospect (M_A) can be made risky. A risky prospect has a probability $p < 1$ of a positive outcome, and 1-p probability of zero outcome. We allow subjective probability weighting for the risky prospects, giving weighted probability $w(p)$ of winning and weighted probability $[1 - w(p)]$ of not winning. The binary choice between a risky far future prospect and a certain near future prospect is modeled as follows:

$$\begin{aligned} U_A &= e^{-\delta(t_1-t_0)}u(b+M_A) + e^{-\delta(t_2-t_0)}u(b) \\ U_B &= e^{-\delta(t_1-t_0)}u(b) + e^{-\delta(t_2-t_0)}(w(p)u(b+M_B) + [1-w(p)]u(b)) \end{aligned} \tag{2}$$

In the other case with the near future prospect (M_A) being risky, we may model the binary choice as follows;

$$\begin{aligned} U_A &= e^{-\delta(t_1-t_0)}(w(p)u(b+M_A) + [1-w(p)]u(b)) + e^{-\delta(t_2-t_0)}u(b) \\ U_B &= e^{-\delta(t_1-t_0)}u(b) + e^{-\delta(t_2-t_0)}u(b+M_B) \end{aligned} \tag{3}$$

[5] This base consumption is representing the degree of asset integration that is assumed. The lower the base consumption, the lower the degree of asset integration. With zero asset integration ($b = 0$), the prospects are judged in total isolation (narrow framing or bracketing). With full asset integration b is the total wealth of the respondents. In risk preference experiments it has been found that the degree of asset integration is very limited (Binswanger, 1981; Andersen et al., 2018a). We have chosen to set it at th local daily wage, following Andersen et al. (2008).

A general formulation allows both prospects to be risky or safe as $w(1) = 1$ and $w(0) = 0$.

Each choice by the respondent in CLs 7-14 is between a risky and a safe option. The risky option gives 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 present (discounted) utility or value return for a specific risky and a safe option can then be formulated as follows:

$$\Delta RDU = e^{-\delta(t_r - t_0)}(w(p)u(b+x) + [1 - w(p)]u(b+y)) - e^{-\delta(t_s - t_0)}u(b+s) \quad (4)$$

with t_r giving the time date of the risky prospect and t_s giving the time date of the safe prospect, thus generalizing equations (2) and (3) above in equation (4). $w(p)$ is the probability weighting function.

The model nests EU when $w(p) = p$ and EV when utility is linear. We compare models based on EV vs. RDEV vs. RDU (concave vs. linear utility and linear vs. non-linear probability weighting). We assess how well these models fit with alternative constant (SD), quasi-hyperbolic (QH) and general hyperbolic (GH) discounting functions. The possible (degree of) diminishing impatience is captured by the size of the parameters on the time horizon dummy variables in the GH specification.

The probability weighting function is modeled with a Prelec (1998) 2-parameter weighting function:

$$w(p) = e^{-\beta(-\ln p)^{\alpha}}, \alpha > 0, \beta > 0 \quad (5)$$

where α captures the degree of (inverse) s-shape of the weighting function with $\alpha > (<)1$, and the β captures the elevation of the function, with $\beta < 1$ giving more elevated (optimistic) and $\beta < 1$ giving less elevated (pessimistic) weighting of prospects. The function is strictly increasing and continuous within the interval $[0, 1]$[6].

Non-linear utility is allowed for with a Constant Elasticity of Marginal Utility (CEMU) function[7]:

[6] Alternative linear and non-linear models can be run by imposing constraints on the α and β parameters as for EU $\alpha = \beta = 1$

[7] This is also often called a Constant Relative Risk Aversion utility function but in our case risk aversion is (partially) captured through the probability weighting function.

$$u(x) = (1-\theta)^{-1}((b+x)^{1-\theta} - 1) \tag{6}$$

where θ captures the constant elasticity of marginal utility. The utility function is linear for $\theta = 0$.

Rank-dependent utility theory and cumulative prospect theory introduce probability weighting and the most common empirical finding is that respondents overweight low probabilities and underweight high probabilities. We may call this "probabilistic risk preferences". The inverted S-shape implies that respondents are probabilistic risk lovers for low probability risks and probabilistic risk averse for high probability risks.

4.2. Estimation Strategy

The estimation based on the binary choice data is using the maximum likelihood estimation approach with the Luce error specification ((Holt and Laury, 2002)). The Luce error specification allows respondents to make errors in their choices. The error probability is captured by the parameter μ in the Luce specification.

$$\nabla U = \frac{U_A^{\frac{1}{\mu}}}{U_A^{\frac{1}{\mu}} + U_B^{\frac{1}{\mu}}} \tag{7}$$

Equation (7) nests the discounted risky and certain prospects based on the alternative linear (EV, RDEV)) and non-linear (RDU) utility, probability weighting, and discounting functions as special cases.

This give rise to the following likelihood function:

$$\begin{aligned} &\ln L(\delta_t, \mu, \alpha, \beta, \theta; Choice_{CL_{p,t,m}}, Z_i, X_j) = \\ &\sum_i((ln(\Phi(\nabla U)|Choice_{t,m} = 1) + (ln(\Phi(1-\nabla U)|Choice_{t,m} = 0)) \end{aligned} \tag{8}$$

where $Choice_{ij} = 1(0)$ denotes the choice of alternatively U_A or U_B for each row in each CL.

Three different specifications for δ_t are allowed, including constant (SD), quasi-hyperbolic (QH) and general hyperbolic[8] (GH) specifications:

[8] With limited variation in time horizons the use of horizon-specific dummy variables gives more flexibility than imposing a specific hyperbolic functional form. Our approach is thereby more flexible and agnostic about the functional form.

$$
\begin{aligned}
SD :& \delta_t = \delta \\
QH :& \delta_t = \delta_{tf} + \delta_{t0} CL_{t0} \\
GH :& \delta_t = \delta_{t24} CL_{t24} + \delta_{t12} CL_{t12} + \delta_{t6} CL_{t6} + \delta_{t0} CL_{t0}
\end{aligned} \tag{9}
$$

The quasi-hyperbolic (QH) specification includes a dummy for the three CLs that compare current prospects with near future (1 week) prospects while the δ_{tf} estimates the average discount rate for all the other CLs with longer time horizons and near future equal to one week. This parameter (δ_{t0}) may be high due to a combination of present bias and a short horizon effect. The full hyperbolic model contains dummies for each time horizon length in addition to the current vs. one week prospects. With diminishing impatience the longest horizon (24 months) should give the lowest discount rate (δ_{t24}) and the incremental dummy variable parameters for shorter horizons should give positive mark-up values as the discount rates are measured in deflated annualized rates. No diminishing impatience except that caused by present bias should imply $\delta_{t12} = \delta_{t6} = 0$. If ignorance of non-linear probability weighting is the reason for observed diminishing impatience, implying $\delta_{t6} > \delta_{t12} > 0$, the introduction of the RD-specifications should reduce the size of these parameters and make them insignificantly different from zero.

The Luce error (μ) is allowed to vary with the order of the CLs, with random starting row in the CL, and with enumerators running the experiments for each subject (enumerator FE). We run representative agent models. We impose the relevant constraints to assess sequentially models based on the alternative theoretical assumptions and to assess their relative performance, see Table 2.

To assess whether probability weighting can explain diminishing impatience, we examine in the models above how the introduction of the RDEV and RDU models influence the discount rates and the degree of variation in discount rates by time horizon. If non-linear probability weighting explains apparent non-linear discounting, the RDEV-SD and RDEV-QH as well as RDU-SD and RDU-QH models should perform as well as the RDEV-GH and RDU-GH representative agent models. However, if the time horizon dummy discount rate parameters in the GH models are large and significant for shorter time horizons after the introduction of the RDEV- or RDU-specifications, probability weighting may not explain the observed diminishing impatience associated with extended time horizon in the data.

Table 2: Model specifications

		Discounting model	
Models	Samuelson (Constant)	Quasi-hyperbolic	General hyperbolic
	SD	QH	FH
EV	EV-SD	EV-QH	EV-GH
RDEV	RDEV-SD	RDEV-QH	RDEV-GH
RDU	RDU-SD	RDU-QH	RDU-GH

EV: Linear utility and linear probability weighing, RDEV: Linear utility and non-linear probability weighting, RDU: Non-linear utility and non-linear probability weighting.

As additional robustness checks we complement and combine the nine specifications above with some additional parameter restrictions due to the following; a) Some models with linear utility failed to converge and were replaced by models with almost linear but concave utility functions; b) Fully flexible probability weighting parameters combined with a fully flexible elasticity of marginal utility (CEMU-θ) parameter resulted in implausible negative discount rates, very concave utility (very large CEMU-θ), and large Prelec β. We therefore imposed restrictions on the CEMU-θ and did a sensitivity analysis for the range of the CEMU-θ that gave non-negative discount rates for all time horizons; c) As the experiment contains limited variation in probabilities with only high and low p and no intermediate values, the Prelec parameters may not be very robustly estimated. As a complement we therefore draw on another risk experiment for the same sample population which included much more variation in p but that did not have any time delayed prospects. As our focus is on representative agents, we use population-averaged Prelec parameters and in one specification also the risk based utility curvature estimate, CRRA-r [9] as constrained parameters in the analysis of our experimental data that combines time-dated utility and risk.

[9]It is more questionable whether CRRA-r from that experiment can be substituted for CEMU-θ in our experiment

5. Results

5.1. EV (linear utility and linear probability weighting) discounting models

The results for the EV models with the three alternative discounting approaches are presented in Table 2. The model with constant discounting (SD) gave an average discount rate of 48.6% across all treatments[10]. The quasi-hyperbolic model which allowed a separation of the discount rate for the short-term/ current vs. longer-term prospects, gave an average discount rate of 318.0% for the short-term/current CLs vs. an average discount rate of 40.9% for the longer-term prospects for the same subjects with our within-subject design. The third model allows for further differentiation of the discount rates for six, 12 and 24 months horizons. The average discount rate is 22.4% for the 24 months horizon, 38.5% for the 12 months horizon, and 93.2% for the 6 months horizon, and 320.5% for the present vs. one week horizon CLs[11]. These results provide strong evidence of diminishing impatience in these models with linear utility and linear probability weighting as the time horizon dummies are highly significant and we see a strong decline in the discount rates as the time horizon is extended.

5.2. Non-linear probability weighting with linear utility (RDEV) discounting models

We present models with 1-parameter and 2-parameter Prelec probability weighting functions in Tables 3 and 4. This is a first test of whether non-linear probability weighting can explain (part of) the strong diminishing impatience we saw in Table 2[12].

The models with the 1-parameter Prelec functions generate the 1-parameter Prelec α that varies from 0.907 to 1.02 in Table 3 and that therefore is close to 1 and this means the probability weighting function remains close to linear. The implication of this is that also the discount rate (time horizon) parameters in Table 3 are close to those in the EV-models in Table 2.

Table 4 presents RDEV models with the the 2-parameter Prelec function that allows for more flexible probability weighting. We see that the

[10]This model failed to generate a Wald chi2 statistic and p-value for the model. This was also the case for the later models with the SD specification.

[11]Note that the intercept in this model represents the 24 months time horizon CLs.

[12]The 1-parameter (Prelec α) probability weighting function only allows for (inverted) S-shape of the function, while the 2-parameter (Prelec α and Prelec β) function also allows for optimism/pessimism.

Table 3:
Integrated time and risk preference models: EV-models

EQUATION	VARIABLES	(1) EV-SD	(2) EV-QH	(3) EV-GH
Discount rate	Present bias		2.771***	2.981***
Time horizon	and 1 week		(0.064)	(0.061)
	6 months			0.708***
				(0.024)
	12 months			0.161***
				(0.022)
	24 months			0.224***
				(0.024)
	Constant	0.486***	0.409***	
		(0.041)	(0.034)	
Luce error	CL order FE	Yes	Yes	Yes
	Enumerator FE	Yes	Yes	Yes
	Start row FE	Yes	Yes	Yes
	Constant	0.481***	0.479***	0.375***
		(0.034)	(0.034)	(0.026)
	Observations	62,862	62,862	62,862
	Log likelihood	-29161	-28358	-27460
	N_clusters	404	404	404
	p		0.000	0.000
	Wald chi2		1883	2650

Discount rates measured in 100% annualized deflated units. EV: Linear utility, SD: Samuelson Constant Discounting, QH: Quasi-hyperbolic, GH: General hyperbolic. Cluster-corrected standard errors, clustering on subjects. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4:
Integrated time and risk preference models: 1-parameter Prelec function

EQUATION	VARIABLES	(1) RDEV-SD	(2) RDEV-QH	(3) RDEV-GH
Discount rate	Present bias		2.882***	3.177***
Time horizon	and 1 week		(0.046)	(0.043)
	6 months			0.717***
				(0.022)
	12 months			0.095***
				(0.022)
	24 months			0.222***
				(0.025)
	Constant	0.490***	0.394***	
		(0.041)	(0.035)	
CEMU-θ	Constant	0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)
Prelec α	Constant	1.020***	0.955***	0.907***
		(0.018)	(0.016)	(0.018)
Luce error	CL order FE	Yes	Yes	Yes
	Enumerator FE	Yes	Yes	Yes
	Start row FE	Yes	Yes	Yes
	Constant	0.482***	0.476***	0.375***
		(0.034)	(0.033)	(0.025)
	Observations	62,862	62,862	62,862
	Log likelihood	-29149	-28290	-27238
	N_clust	404	404	404
	p		0.000	0.000
	Wald chi2		3928	6629

Discount rates measured in 100% annualized deflated units.
RDEV=Rank Dependent Expected Value, SD=Samuelson Constant Discounting, QH=Quasi-hyperbolic, GH=General hyperbolic. Cluster-corrected standard errors, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

SD (constant discounting) model gives a Prelec $\alpha = 0.568$ and a Prelec $\beta = 1.593$ which indicates a strongly inverted S-shaped and pessimistic probability weighting and an average discount rate of 50.2%. This changes dramatically when we open for present bias/short horizon effects in the discounting as can be seen in model (2) in Table 4. This RDEV-QH model gives again a close to linear probability weighting function, like in Table 3. The average discount rate for delayed prospects is 39.9% and 324.9% for the present/short horizon (1 week) prospects. However, with the introduction of the more flexible time horizon (RDEV-GH) specification, an even stronger inverse-S and pessimistic function than in the SD model is estimated. The RDEV-GH model with the highly non-linear probability weighting function again identifies strong diminishing impatience with increasing time horizon albeit it failed to estimate the present bias/short-term discount rate properly. With this strongly inverted-S shaped probability weighting function the discount rate is 22.6% for the 24 months horizon, 49.2% for the 12 months horizon, and 96.3% for the 6 months horizon which even implies a stronger diminishing impatience across these time horizons than in the model with linear probability weighting in Table 2. We further scrutinize these results in the next section where we open for non-linear utility as the failure to properly identify the present bias/short horizon effect in the RDEV-GH model in Table 4 may affect the other parameters in this model.

5.3. Rank dependent utility (RDU) discounting models

5.3.1. RDU models with endogenous Prelec α and β and constrained CEMU-θ

As a bridge towards the previous models we introduced models with weakly concave utility functions. When the CEMU-θ was raised to 0.08 the model also identified the present bias/short horizon parameter in the RDU-GH specification that failed in the RDEV-GH specification in Table 4, see Table 5[13].

There are two important changes to observe when comparing the RDEV models in Table 4 and the RDU models in Table 5. First, we see that the discount rates are reduced on average as would be expected with a concave versus a linear utility function. Second, the strongly non-linear prob-

[13]For CEMU-θ in the range 0-0.07 we obtained only large and implausible negative numbers for this parameter.

Table 5:
Integrated time and risk preference models: With unconstrained 2-parameter Prelec function, CEMU-$\theta = 0$

EQUATION	VARIABLES	(1) RDEV-SD	(2) RDEV-QH	(3) RDEV-GH
Discount rate	Present bias		2.850***	-99.625
Time horizon	and 1 week		(0.057)	(0.000)
	6 months			0.737***
				(0.022)
	12 months			0.266***
				(0.019)
	24 months			0.226***
				(0.025)
	Constant	0.502***	0.399***	
		(0.037)	(0.036)	
Prelec α	Constant	0.568***	0.914***	0.523***
		(0.030)	(0.042)	(0.028)
Prelec β	Constant	1.593***	1.047***	1.635***
		(0.059)	(0.055)	(0.055)
Luce error	CL order FE	Yes	Yes	Yes
	Enumerator FE	Yes	Yes	Yes
	Start row FE	Yes	Yes	Yes
	Constant	0.482***	0.476***	0.373***
		(0.034)	(0.033)	(0.025)
	Observations	62,862	62,862	62,862
	Log likelihood	-28805	-28288	-27959
	N_clusters	404	404	404
	p		0.000	0.000
	Wald chi2		2507	1248

Discount rates measured in 100% annualized deflated units.
RDEV=Rank Dependent Expected Value, SD=Samuelson Constant Discounting, QH=Quasi-hyperbolic, GH=General hyperbolic. Cluster-corrected standard errors, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

ability weighting function is corrected in the RDU-GH model compared to the RDEV-GH model. The RDU-FH model in Table 5 that also used a 2-parameter Prelec function produces a close to linear probability weighting function and discounting parameters that imply strongly diminishing impatience with extended time horizon. The RDU-GH model generates probability weighting parameters that are close to those in the RDU-QH in Table 5 and the RDEV-QH specifications in Tables 3 and 4. The RDU-GH model generates an average discount rate of 16.6% for the 24 months horizon, 26.4% for the 12 months horizon, 88.3% for the 6 months horizon, and 336.1% for the present/one week horizon CLs.

As a next step we adjusted the constrained CEMU-θ up until the longest horizon discount rate in the RDU-FH model is approximately zero. This occurred for a CEMU-θ = 0.3[14]. When we compare the results in Tables 5 and 6 we see that the discount rate declined from 44.9% to 29.2% in the RDU-SD models as the result of increasing the CEMU-θ from 0.08 to 0.3. For the RDU-QH models the average discount rate for future prospects declined even more, from 43.2 to 19.5%, while it increased slightly, from 286.0 to 289.5%, for the present/one week horizon CLs.

For the RDU-GH models in Table 6 the reduction of the discount rate is from 16.6 to 0% for the 24 months horizon, from 26.4 to 11.2% for the 12 months horizon, and from 88.2 to 71.5% for 6 months horizon, and from 336.1 to 323.4% for the present/one week horizon CLs. These changes are accompanied with a slightly more non-linear and optimistic probability weighting function as the endogenously determined parameter values for Prelec α declined from 0.905 to 0.858 and the Prelec β declined from 0.948 to 0.848. A more concave utility function is therefore leading to a more inversely S-shaped and optimistic probability weighting function. However, the degree of diminishing sensitivity has not been affected much and remains strong and highly significant.

5.3.2. RDU models with constrained Prelec α and β parameters

The models above attempt to estimate the Prelec α and β parameters but may not provide accurate estimates as they are based on a limited number of CLs with high and low values of p. We benefit from having access to estimates

[14]Models with CEMU-θ equal to 0.1 and 0.2 are included in the Appendix and give intermediate results between those in Tables 5 and 6.

Table 6:
Integrated time and risk preference models: With unconstrained 2-parameter Prelec function, and constrained CEMU-$\theta = 0.08$

EQUATION	VARIABLES	(1) RDU+SD	(2) RDU+QH	(3) RDU+GH
Discount rate	Present bias		2.860***	3.195***
Time horizon	and 1 week		(0.057)	(0.047)
	6 months			0.716***
				(0.022)
	12 months			0.098***
				(0.021)
	24 months			0.166***
				(0.025)
	Constant	0.449***	0.346***	
		(0.037)	(0.036)	
CEMU-θ	Constant	0.080	0.080	0.080
		(0.000)	(0.000)	(0.000)
Prelec α	Constant	0.556***	0.899***	0.905***
		(0.029)	(0.042)	(0.040)
Prelec β	Constant	1.526***	1.006***	0.948***
		(0.055)	(0.052)	(0.047)
Luce error	CL order FE	Yes	Yes	Yes
	Enumerator FE	Yes	Yes	Yes
	Start row FE	Yes	Yes	Yes
	Constant	0.439***	0.432***	0.342***
		(0.031)	(0.030)	(0.022)
	Observations	62,862	62,862	62,862
	Log likelihood	-28698	-28180	-27137
	N_clusters	404	404	404
	p		0.000	0.000
	Wald chi2		2530	6290

Discount rates measured in 100% annualized deflated units.
RDU=Rank Dependent Utility, SD=Samuelson Constant Discounting, QH=Quasi-hyperbolic, GH=General hyperbolic. Cluster-corrected standard errors, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 7:
Integrated time and risk preference models: With unconstrained 2-parameter Prelec function, CEMU-$\theta = 0.3$

EQUATION	VARIABLES	(1) RDU-SD	(2) RDU-QH	(3) RDU-GH
Discount rate	Present bias		2.895***	3.234***
Time horizon	and 1 week		(0.057)	(0.047)
	6 months			0.712***
				(0.021)
	12 months			0.112***
				(0.019)
	24 months			0.001
				(0.026)
	Constant	0.292***	0.195***	
		(0.035)	(0.034)	
CEMU-θ	Constant	0.300	0.300	0.300
		(0.000)	(0.000)	(0.000)
Prelec α	Constant	0.520***	0.852***	0.858***
		(0.026)	(0.042)	(0.040)
Prelec β	Constant	1.346***	0.898***	0.848***
		(0.045)	(0.046)	(0.041)
Luce error	CL order FE	Yes	Yes	Yes
	Enumerator FE	Yes	Yes	Yes
	Start row FE	Yes	Yes	Yes
	Constant	0.323***	0.316***	0.254***
		(0.022)	(0.022)	(0.016)
	Observations	62,862	62,862	62,862
	Log likelihood	-28377	-27854	-26849
	N_clusters	404	404	404
	p		0.000	0.000
	Wald chi2		2608	6249

Discount rates measured in 100% annualized deflated units.
RDU=Rank Dependent Utility, SD=Samuelson Constant Discounting, QH=Quasi-hyperbolic, GH=General hyperbolic. Cluster-corrected standard errors, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

of these parameters from a large sample from the same population where more comprehensive atemporal risk preference experiments were used to estimate these parameters more accurately (Holden and Tilahun, 2021b). This study found an average Prelec $\alpha = 0.62$ and an average Prelec $\beta = 0.9$[15]. In Table 7 we present the results for the three types of discounting models with these as constrained Prelec parameters and a near-linear utility function (CEMU-$\theta = 0.03$). Table 7 shows that the average discount rate in the RDU-SD model increases to 82.9%, to 72.1% for the future prospects in the RDU-QH model and retains strong diminishing impatience in the RDU-GH model. There are therefore no indications that the stronger degree of non-linear probability weighting can explain the diminishing impatience associated with longer time horizons in our data.

A further robustness check for a CEMU-$\theta = 0.3$ is presented in Table 8, with overall lower discount rates as would be expected but without any substantial reduction in the degree of diminishing impatience.

Table 9 presents models where the CEMU-θ is set equal to the average CRRA-r estimated by Holden and Tilahun (2021b). We see that this leads to close to zero discount rate in the SD-model and for longer time horizons in the QH-model and to strongly negative discount rates for the 24 months horizon in the GH-model. This is consistent with the findings in other studies that question the use of risk-based utility in the estimation of time-dated utility curvature.

The key discount rate estimates are summarized in Figure 6 with the insights about our main research question; whether probability weighting can explain diminishing impatience associated with longer time horizons in our data. To answer definitely yes to this question, the models that incorporate non-linear probability weighting based on observed responses in our experiments should eliminate all signs of diminishing impatience and make the time horizon dummies in the models with rank dependent probability

[15]Holden and Tilahun (2021b) found these parameters to be affected by recent shocks and also studied the individual variation but we utilize only the population averages for these parameters in our representative agent analysis in this study. Their study also estimated the utility curvature simultaneously based on 12 CLs. However, the recent literature has questioned whether the utility curvature estimated in an atemporal risk experiment applies to time-dated utility such as in our experiment (Cheung, 2016, 2019). Estimates of utility curvatures in such risk experiments tend to be higher than those found in inter-temporal time-dated experiments.

Table 8:
Integrated time and risk preference models: With constrained 2-parameter Prelec function, Prelec $\alpha = 0.62$, Prelec $\beta = 0.9$, CEMU-$\theta = 0.03$

		(1)	(2)	(3)
EQUATION	VARIABLES	RDU-SD	RDU-QH	RDU-GH
Discount rate	Present bias		3.249***	3.740***
Time horizon	and 1 week		(0.058)	(0.049)
	6 months			0.902***
				(0.020)
	12 months			0.310***
				(0.017)
	24 months			0.228***
				(0.026)
	Constant	0.829***	0.721***	
		(0.062)	(0.055)	
CEMU-θ	Constant	0.030	0.030	0.030
		(0.000)	(0.000)	(0.000)
Prelec α	Constant	0.620	0.620	0.620
		(0.000)	(0.000)	(0.000)
Prelec β	Constant	0.900	0.900	0.900
		(0.000)	(0.000)	(0.000)
Luce error	CL order FE	Yes	Yes	Yes
	Enumerator FE	Yes	Yes	Yes
	Start row FE	Yes	Yes	Yes
	Constant	0.457***	0.437***	0.335***
		(0.042)	(0.040)	(0.029)
	Observations	62,862	62,862	62,862
	Log likelihood	-31155	-30158	-28646
	N_clusters	404	404	404
	p		0.000	0.000
	Wald chi2		3159	6281

Discount rates measured in 100% annualized deflated units.
RDU=Rank Dependent Utility, SD=Samuelson Constant Discounting, QH=Quasi-hyperbolic, GH=General hyperbolic. Cluster-corrected standard errors, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 9:
Integrated time and risk preference models: With constrained 2-parameter Prelec function, Prelec $\alpha = 0.62$, Prelec $\beta = 0.9$, CEMU-$\theta = 0.3$

		(1)	(2)	(3)
EQUATION	VARIABLES	RDU-SD	RDU-QH	RDU-GH
Discount rate	Present bias		3.189***	3.513***
Time horizon	and 1 week		(0.052)	(0.049)
	6 months			0.814***
				(0.022)
	12 months			0.176***
				(0.018)
	24 months			0.010
				(0.026)
	Constant	0.443***	0.330***	
		(0.052)	(0.042)	
CEMU-θ	Constant	0.300	0.300	0.300
		(0.000)	(0.000)	(0.000)
Prelec α	Constant	0.620	0.620	0.620
		(0.000)	(0.000)	(0.000)
Prelec β	Constant	0.900	0.900	0.900
		(0.000)	(0.000)	(0.000)
Luce error	CL order FE	Yes	Yes	Yes
	Enumerator FE	Yes	Yes	Yes
	Start row FE	Yes	Yes	Yes
	Constant	0.313***	0.305***	0.245***
		(0.026)	(0.024)	(0.017)
	Observations	62,862	62,862	62,862
	Log likelihood	-30019	-28891	-27474
	N_clusters	404	404	404
	p		0.000	0.000
	Wald chi2		3813	5258

Discount rates measured in 100% annualized deflated units.
RDU=Rank Dependent Utility, SD=Samuelson Constant Discounting, QH=Quasi-hyperbolic, GH=General hyperbolic. Cluster-corrected standard errors, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 10:
Integrated time and risk preference models: With constrained 2-parameter Prelec function, Prelec $\alpha = 0.62$, Prelec $\beta = 0.9$, CEMU-θ=CRRA-r=0.9

		(1)	(2)	(3)
EQUATION	VARIABLES	RDU-SD	RDU-QH	RDU-GH
Discount rate	Present bias		1.718***	2.168***
Time horizon	and 1 week		(0.209)	(0.211)
	6 months			0.665***
				(0.023)
	12 months			0.464***
				(0.021)
	24 months			-0.458***
				(0.027)
	Constant	-0.016	-0.019	
		(0.028)	(0.028)	
CEMU-θ	Constant	0.900	0.900	0.900
		(0.000)	(0.000)	(0.000)
Prelec α	Constant	0.620	0.620	0.620
		(0.000)	(0.000)	(0.000)
Prelec β	Constant	0.900	0.900	0.900
		(0.000)	(0.000)	(0.000)
Luce error	CL order FE	Yes	Yes	Yes
	Enumerator FE	Yes	Yes	Yes
	Start row FE	Yes	Yes	Yes
	Constant	0.098***	0.098***	0.077***
		(0.008)	(0.008)	(0.006)
	Observations	62,862	62,862	62,862
	Log likelihood	-28729	-28676	-28031
	N_clusters	404	404	404
	p		0.000	0.000
	Wald chi2		67.48	1072

Discount rates measured in 100% annualized deflated units.
RDU=Rank Dependent Utility, SD=Samuelson Constant Discounting, QH=Quasi-hyperbolic, GH=General hyperbolic. Cluster-corrected standard errors, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

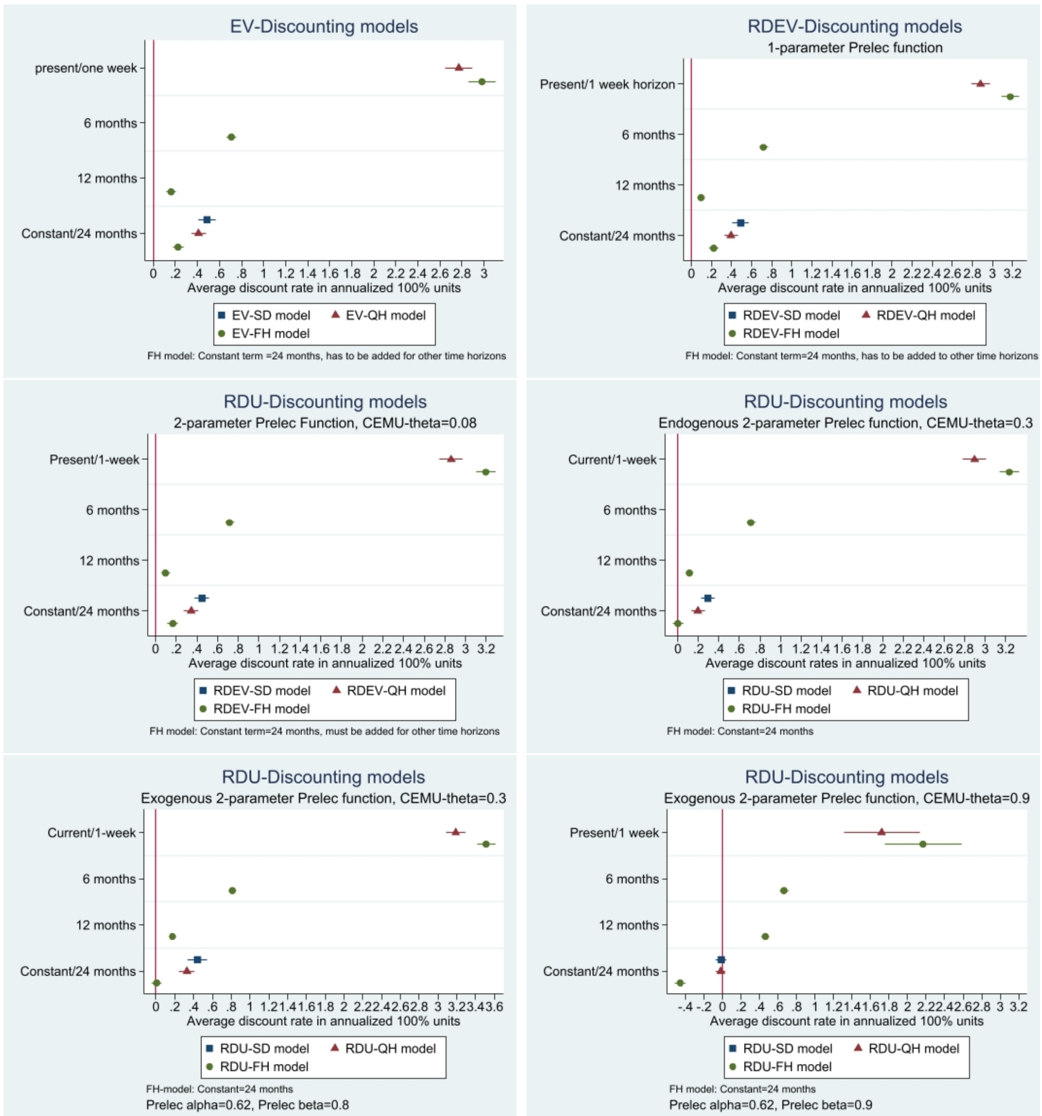

Figure 5: Discount rate estimates for 6x3 different model specifications

weights, insignificant. Or, if probability weighting partially can explain diminishing impatience, the models that take such probability weighting into account should reduce the size of the time horizon parameters compared to models with linear probability weighting.

Figure 6 shows that the time horizon dummy parameters in the RDEV-FH and RDU-FH models are also highly significant and no smaller than those in the EV models. The answer to the main research question is therefore a clear No. Our data and models based on different assumptions about probability weighting and utility curvatures provide evidence of strongly diminishing impatience with extended time horizon. The FH models perform much better than the QH models and indicate that there is more to this diminishing impatience than present bias although the very high discount rates estimated for present versus one week delayed prospects also revealed the importance of taking present bias into account although we are unable, with our design, to separate the effect of present bias and the very short horizon of one week.

As a further robustness check of the data and distribution of the switch points in each CL, the cumulative distributions of switch points are compared in two separate random samples drawn from the same population. These cumulative distributions are presented in Appendix, Figures A.5 and A.6. The distributions look strikingly similar for the training sample and the validation sample and is a further indication that the data are robust.

6. Discussion

Our paper's main attributes and contributions are that we a) include more time horizon variation than most other studies that jointly study risk and time (one week to two years), b) we vary the timing of risky prospects and the timing of certain prospects, c) in each CL the risky prospect is constant and compared to varying time-dated certain amounts to minimize certainty bias, d) we carry out substantial robustness checks for alternative functional forms for the probability weighting function and the utility function to assess how these influence the discount rates, e) we used a fairly large scale field experiment with 404 business group members in a developing country setting and a within-subject design and f) we assess the stability of the switch point distributions for two random samples from the same population.

We will now discuss our findings and compare them with other related studies to highlight how our study adds to the literature on time and risk preferences. In the introduction we showed how we depart from recent much cited and influential studies on time and risk preferences. We built on two major findings in this literature; 1) that utility in time is different from utility in risk and is close to linear; and 2) present bias is best controlled for by comparing time-dated future prospects.

Other studies than those we already have discussed that jointly assess time and risk preferences include Coble and Lusk (2010) who combined the Holt and Laury (2002) risk experimental design with a time preference design within a discounted expected utility (DEU) framework. This allowed them to estimate the inter-temporal elasticity of substitution as well as a simple discount factor. Their time preference CLs built on Harrison et al. (2002). An important difference in this design compared to ours is that they fixed the near future amount and varied the far future amount. In a developing country setting where respondents often can have very high discount rates their approach would lead to a lot of top censoring of the discount rates (Pender, 1996; Holden et al., 1998). We avoided this by fixing the far future amount and varied the near future amount and if necessary added rows at the bottom for even smaller near future amounts for respondents with extremely high discount rates. This at the same time allowed us also to have an upper limit for future payouts in the game.

A complicating issue related to time-dated risky prospects is whether risks are correlated or uncorrelated over time and whether respondents may make decisions to pool such risks and diversify their portfolio (Andersen et al., 2018b). Andreoni and Sprenger (2012b) find evidence of such risk-pooling behavior and inter-temporal diversification that resulted in a much smaller share of corner solutions in their CTB lists with risk than lists without risk. Epper and Fehr-Duda (2015) show that an RDU model can be fitted to the data used by Andreoni and Sprenger (2012b). They show that the data exhibit sub-proportionality in probability weights in line with an inverted S-shaped probability weighting function. They conclude that an RDU model provides a unified explanation of all the key findings in Andreoni and Sprenger (2012b). RDU is not only suitable in atemporal but also inter-temporal situations (Epper and Fehr-Duda, 2015).

Andreoni and Sprenger (2012a) used a Convex Time Budget (CTB) approach for the estimation of time preferences. This approach allows respondents to combine varying levels of near future and far future amounts rather than just corner solutions of either near future or far future amounts and may be used to study inter-temporal substitutability or trade between near-future and more far-future selves. They also estimated the concavity of the utility function with their approach and found it to be close to linear. They argued that using a risk experiment to elicit utility curvature in a riskless setting is questionable. Abdellaoui et al. (2013), Miao and Zhong (2012), and Cheung (2019) provide further evidence that utility under risk and over time are different and that utility over time is close to linear. Cheung (2019) used an innovative design based on Holt and Laury (2002) to include time-dated outcomes and was able to jointly estimate utility under risk and over time. His design gave much stronger concavity under risk than over time and the two measures were uncorrelated at the individual level. The finding of significant but weak concavity of utility in time resulted in a very small bias in estimated discount rates compared to a linear utility over time assumption.

We need to discuss the certainty effect as we in our CLs with risk compare certain and a risky prospects that occur at different points in time. The certainty effect goes back to Keren and Roelofsam (1995) who found that present bias disappears when risk in terms of 90% chance of getting current versus future amounts replaces certain payments. Halevy (2008) associates diminishing impatience and certainty bias to the certainty of the present and the uncertainty of the future. We combine two design characteristics to avoid this confound as the explanation for diminishing impatience. First, we compare near future and more far future prospects[16]. Second, all our CLs were risky in the sense that they did not guarantee a payout, only a 10% probability of payout for participants and each of the 14 CLs had the same likelihood of payout for the winners. Still, there may be a certainty framing effect in prospects that compare risky and safe amounts within CLs. Vieider (2018) has demonstrated that such an apparent effect may depend on the specific design of the CLs. By a slight change of a design that creates a certainty effect, he demonstrates a bias in opposite direction. He attributes this so-called certainty effect to the relative salience of the risky and certain prospects and reference dependent utility. Such reference dependence is also demonstrated by Holden and Tilahun (2021a) using the risky investment game of Gneezy and Potters (1997). They find preference for a more risky portfolio when the reference point is a risky prospect than when it is a safe prospect. In all our CLs with risk the risky prospect is the reference point in the CL and is compared with alternative safe amounts.

[16]The exceptions are CLs 10, 12 and 14 that include current and near future prospects.

A recent study that compares utility of risk and time is Cheung (2019). He uses a transformation of the Holt and Laury (2002) design with payouts at different points in time to measure utility over time. He suggests that his design overcomes weaknesses in earlier designs such as the confounding of marginal utilities, estimation methods and experimental design by using one unifying design and estimation framework (binary choice). The study uses six CLs which vary the future time in each list while payouts at near future and far future points in time stay constant in the two prospects in each CL. The curvature of utility over time can then be studied by observing how the switch point changes across the six CLs. In addition, a single standard HL choice list is used to get a measure of utility under risk. The study uses a standard one week delay as the near future time horizon and could therefore identify one exponential discount rate, a utility in time parameter and a utility in risk parameter. Based on a student sample from University of Sidney, models based on EU and RDU are used to estimate representative agent models. A discounted utility model based on the six CLs give near linear utility and a fairly high discount rate. Joint estimation with the risk CL under EU, forcing time and risk utilities to be the same, gives substantial utility curvature and a much lower discount rate. With a Prelec I function to capture probability weighting, a joint estimation of time and risk CLs still gives substantial utility curvature and an inverted S-shaped probability weighting function. With only one risky CL per respondent it is not possible to make a clear separation of utility in risk curvature and probability weighting for a representative agent from a heterogeneous sample of respondents. The study also estimates a discounted incremental utility model based on Blavatskyy (2016) and this model finds an intermediate utility curvature and discount rate. An interesting finding is that the individual estimates of utility curvature in time and in risk are very different and are very weakly correlated. Our estimates in this study are consistent with these findings and indicate that time-dated utility is weakly concave while utility in risk can be substantially more concave. Such utility curvature estimates should therefore not be used as substitutes.

An important difference between our model and the models estimated by Cheung (2019) is that we allow partial asset integration, that is we assume that the experimental payouts are combined with a short term basic income (daily wage rate) in the time-dated utility function at each point in time. Cheung, on the other hand, estimates a discounted incremental utility model which assumes that payouts over time in the game are integrated. However, we find it implausible, at least in our case, that it is more appropriate to integrate payouts over time than to integrate time-dated background income with payouts at the time of payout when payout points in time are six to 24 months apart. The discounted incremental utility model makes more sense when payouts are not very far apart. However, partial asset integration with background income also makes sense when comparing time-dated utilities over shorter time horizons. In this study we have relied on a constant partial asset integration (with a daily wage rate) in time-dated utility and have demonstrated that diminishing impatience with longer time horizons cannot be attributed to non-linear probability weighting associated with risky future prospects. Another possible explanation for diminishing impatience has been provided by Holden and Quiggin (2017). Their study did, however, not attempt to jointly estimate risk and time preferences based on CLs that combined risk and time. Instead they rely on a strongly concave utility function based on risk estimated utility in the same study area. We suggest that future work should use CLs that combine risk and time horizon variation and that, like Holden and Quiggin (2017), investigate how varying assumptions about asset integration influence the degree of diminishing impatience. Is behavior in time and risk better explained by a combination of non-linear probability weighting and variable asset integration than by non-linear utility? We think this is an interesting area for future research. Variable asset integration may not only explain diminishing impatience but also magnitude effects in inter-temporal choice (Holden and Quiggin, 2017; Sun and Potters, 2021).

The trend has been towards joint estimation of risk and time preferences because of the theoretical links from utility function curvature and non-linear probability weighting. However, our study provides empirical evidence that none of these two links had a strong influence on subjects' discount rates and diminishing impatience. Does this imply that we may go back to simpler ways of estimating discount rates that can be done without at the same time eliciting risk or uncertainty preferences? We have not explicitly included uncertainty preferences in our study. One question is how closely risk preferences and uncertainty preferences are correlated in the probability weighting dimension. If such preferences are quite strongly positively correlated, our findings may also carry over to the world of uncertainty. Another issue is how the variation in time horizon affects unobservable uncertainty. We will not draw any conclusions on these issues as we think further studies are needed before conclusions can be drawn.

7. Conclusion

We have used a field experiment that used time-dated and risky prospects to assess whether non-linear probability weighting can explain diminishing impatience associated with longer time horizons based on a within-subject design. First, our data provides strong evidence of falling discount rates from very high rates for very short horizons of one week to horizons of six, 12 and 24 months. The dominant theory within economics to explain diminishing impatience has been present bias and an associated certainty bias and a related uncertainty necessarily associated with all future events. We avoided such a certainty bias by comparing future prospects that necessarily all exhibit an element of uncertainty on top of the varying risk that we explicitly imposed on the different treatments in our experiment. Even our treatments with potential immediate payout were risky and therefore only gave a probabilistic likelihood of payout. The risky prospects with high and low payout probabilities revealed an invested S-shaped probability weighting function in line with many other studies. Our main research question was whether such probability weighting could explain the diminishing impatience associated with longer time horizons in our data as proposed by Halevy (2008) and Epper et al. (2011). After careful testing of a range of functional forms for utility and probability weighting we conclude that the pattern of diminishing impatience is not explained by the non-linear probability weighting derived from our experiments with risky future prospects. Our study therefore provides strong empirical experimental evidence that diminishing impatience is not a behavioral attribute that can be solely explained by present bias and certainty bias and therefore be fully captured through quasi-hyperbolic discounting and non-linear weighting of risky future prospects.

Declarations

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- Conflict of interest/Competing interests

  The authors declare no conflicts of interest.

- Ethics approval

  Funding was approved based on an independent assessment and approval of ethical standards being met by the project by a scientific committee.

- Consent to participate

  All subjects participating in the project participated on a voluntary basis and were always asked up-front about their willingness to participate after having received information about what participation implied and that the project adhered to strict confidentiality and anonymity of individual information (informed concent).

- Consent for publication

  The article will be published as an open access article as required by the funding institution.

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Appendix A. Additional robustness checks: Models and Figures

Table A.11:
Integrated time and risk preference models: With unconstrained 2-parameter Prelec function, CEMU-$\theta = 0.1$

		(1)	(2)	(3)
EQUATION	VARIABLES	RDU-SD	RDU-QH	RDU-GH
Discount rate	Present bias		2.863***	3.198***
Time horizon	and 1 week		(0.057)	(0.047)
	6 months			0.716***
				(0.022)
	12 months			0.099***
				(0.021)
	24 months			0.151***
				(0.025)
	Constant	0.435***	0.333***	
		(0.037)	(0.036)	
CEMU-θ	Constant	0.100	0.100	0.100
		(0.000)	(0.000)	(0.000)
Prelec α	Constant	0.553***	0.895***	0.901***
		(0.029)	(0.042)	(0.040)
Prelec β	Constant	1.509***	0.996***	0.939***
		(0.054)	(0.052)	(0.046)
Luce error	CL order FE	Yes	Yes	Yes
	Enumerator FE	Yes	Yes	Yes
	Start row FE	Yes	Yes	Yes
	Constant	0.428***	0.421***	0.334***
		(0.030)	(0.029)	(0.022)
	Observations	62,862	62,862	62,862
	Log likelihood	-28671	-28152	-27112
	N_clusters	404	404	404
	p		0.000	0.000
	Wald chi2		2537	6289

Discount rates measured in 100% annualized deflated units.
RDU=Rank Dependent Utility, SD=Samuelson Constant Discounting, QH=Quasi-hyperbolic, GH=General hyperbolic. Cluster-corrected standard errors, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.12:
Integrated time and risk preference models: With unconstrained 2-parameter Prelec function, CEMU-$\theta = 0.2$

EQUATION	VARIABLES	(1) RDU-SD	(2) RDU-QH	(3) RDU-GH
Discount rate	Present bias		2.878***	3.215***
Time horizon	and 1 week		(0.057)	(0.047)
	6 months			0.714***
				(0.022)
	12 months			0.105***
				(0.020)
	24 months			0.077***
				(0.025)
	Constant	0.365***	0.265***	
		(0.036)	(0.035)	
CEMU-θ	Constant	0.200	0.200	0.200
		(0.000)	(0.000)	(0.000)
Prelec α	Constant	0.537***	0.874***	0.881***
		(0.027)	(0.042)	(0.040)
Prelec β	Constant	1.426***	0.946***	0.893***
		(0.049)	(0.049)	(0.044)
Luce error	CL order FE	Yes	Yes	Yes
	Enumerator FE	Yes	Yes	Yes
	Start row FE	Yes	Yes	Yes
	Constant	0.375***	0.368***	0.293***
		(0.026)	(0.025)	(0.019)
	Observations	62,862	62,862	62,862
	Log likelihood	-28527	-28007	-26981
	N_clusters	404	404	404
	p		0.000	0.000
	Wald chi2		2570	6276

Discount rates measured in 100% annualized deflated units.
RDU=Rank Dependent Utility, SD=Samuelson Constant Discounting, QH=Quasi-hyperbolic, GH=General hyperbolic. Cluster-corrected standard errors, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

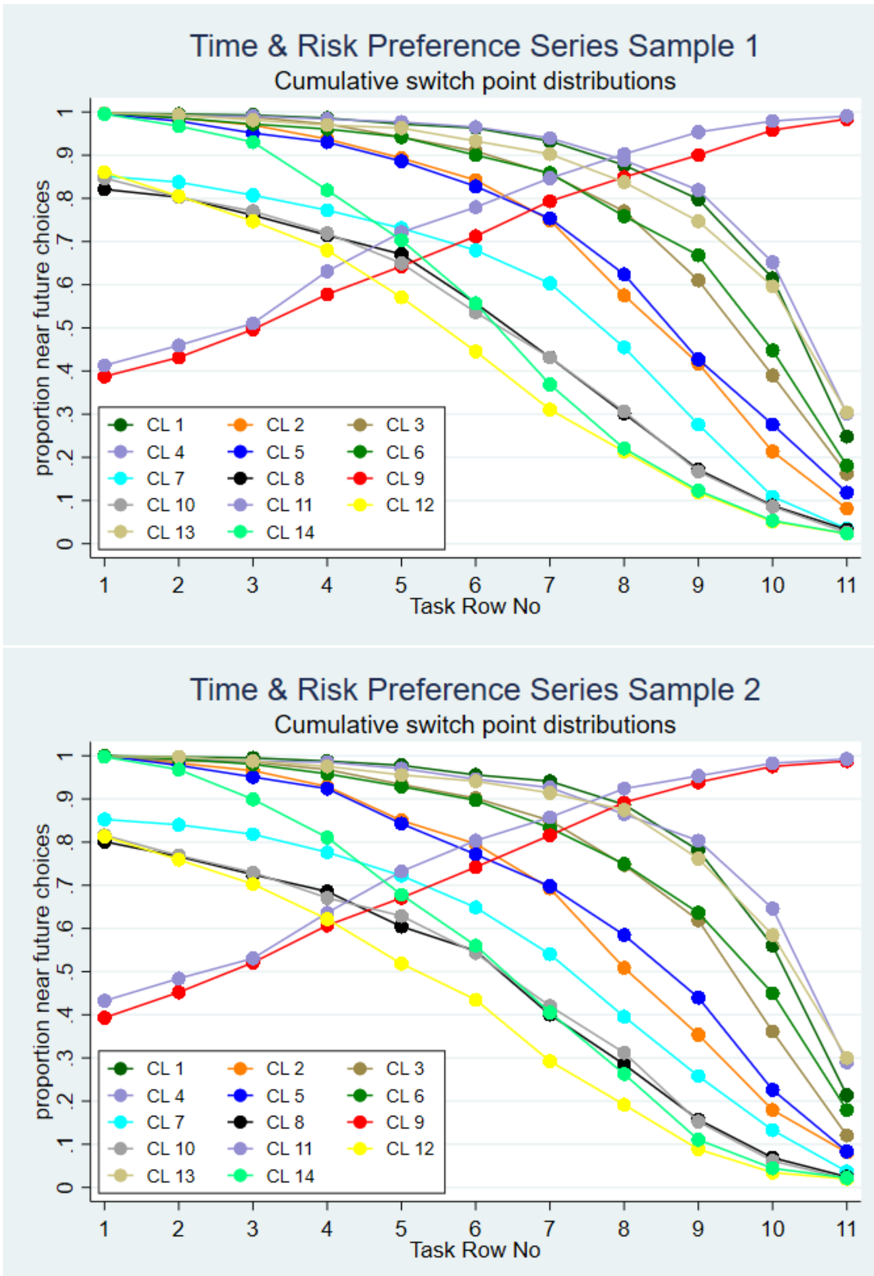

Figure A.6: a. Sample 1 vs. b. Sample 2 Cumulative distributions