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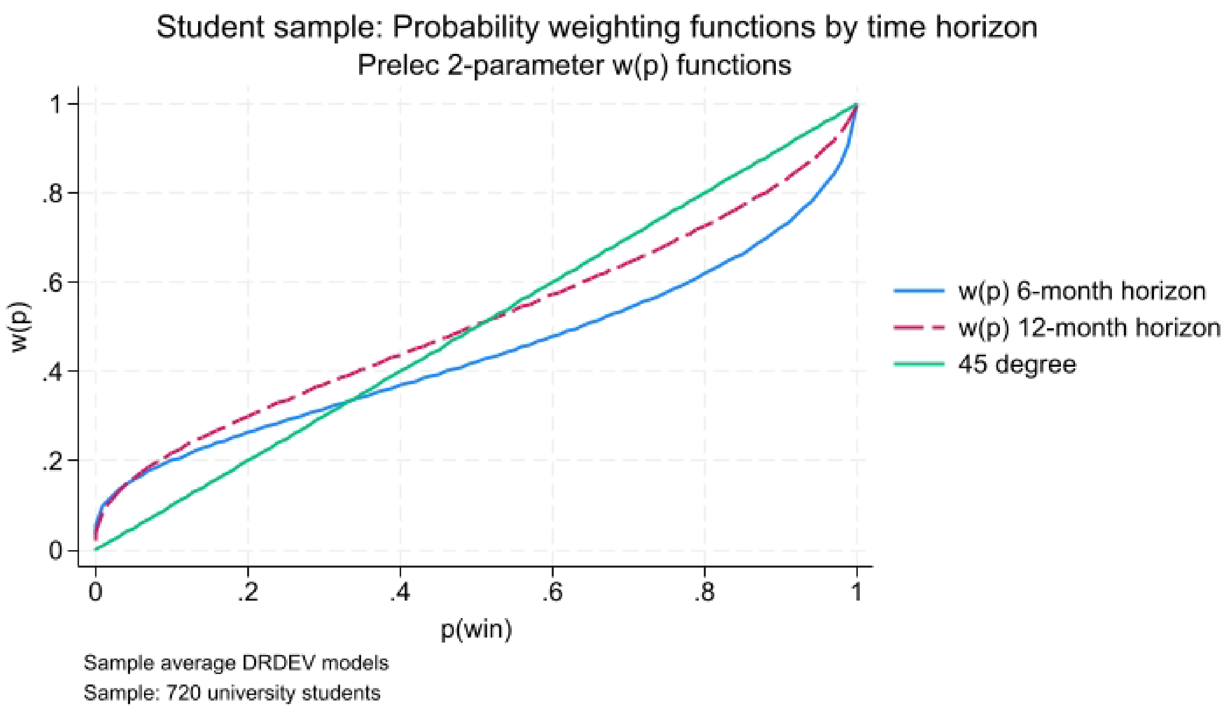

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Are decision errors explaining hyperbolic discounting and non-linear probability weighting?

Stein T. Holden[1*], Sarah Tione[2], Mesfin Tilahun[1,3], Samson Katengeza[2]

[1*]School of Economics and Business, Norwegian University of Life Sciences, P. O. Box 5003, Ås, 1432, Akershus, Norway.
[2]Department of Agricultural and Applied Economics, Lilongwe University of Agriculture and Natural Resources, Bunda Campus, Lilongwe, Malawi.
[3]Department of Economics, Mekelle University, Adi Haki Campus, Mekelle, Tigray, Ethiopia.

*Corresponding author(s). E-mail(s): stein.holden@nmbu.no[‡];
Contributing authors: sarahtione@gmail.com; mesfin.tilahun.gelaye@nmbu.no; samkatengeza@gmail.com;

Abstract

We study risky inter-temporal choice in a large random student sample (n=721) and a large rural sample (n=835) in Malawi. All respondents were exposed to the same 20 Multiple Choice Lists with a rapid elicitation method that facilitated the identification of near-future Certainty Equivalents of future risky prospects placed 6, 12, and 24 months into the future. The probabilities of winning in the risky future prospects varied and facilitated the estimation of probability weighting functions for the risky prospects placed 6 and 12 months into the future. The experiment is used to test whether decision errors can explain or be highly correlated with hyperbolic discounting and non-linear (inverse-S-shaped) probability weighting. We find evidence that decision errors are strongly correlated with hyperbolic discounting but do not find that decision errors are correlated with the strong inverse-S-shaped probability weighting (w(p)) patterns in our two samples. We find stronger S-shaped and more pessimistic w(p) functions for 6-month horizon risky prospects than for 12-month horizon risky prospects in both samples. Both patience and optimism bias contribute to subjects taking

[‡]ORCID=0000-0001-7502-2392

higher risks related to more risky distant future prospects. This can lead to the postponement of climate action.

Keywords: Decision errors, discounting, risky inter-temporal choice, probability weighting, Malawi.

JEL Classification: C91 , C93 , D81 , D84 , D91.

1 Introduction

The psychology of probability weighting and hyperbolic discounting has until recently been poorly understood (Enke & Graeber, 2023; Enke, Graeber, & Oprea, 2023; O'Donoghue & Somerville, 2018). Hyperbolic discounting has frequently been associated with present bias driven by immediate pleasure, addiction, or procrastination and has often been modeled with a quasi-hyperbolic model. However, much evidence shows that hyperbolic discounting persists after the removal of or control for such present biases. Hyperbolic discounting functions have been used to describe but not explain such increasing patience associated with extended time horizons. The other phenomenon, non-linear probability weighting, most commonly associated with over-weighting small and underweighting large probabilities, has been included in Rank-Dependent utility theory (RDU) and Cumulative Prospect theory (CPT). These theories are also mainly descriptive and do not provide any deeper explanations for this behavioral phenomenon. However, the theory has been conveniently used to "explain" why the same people may buy insurance and lottery tickets and, therefore, are risk-averse in one context and risk-lovers in another.

The role of risk and time preferences as important elements to explain decision-making under risk/uncertainty and over time has been acknowledged and subject to much research. Much of this research chose to study one of the phenomena at the time to keep complexity manageable. However, more recently, research has increasingly focused on jointly assessing decisions under risk and over time. Fundamentally, risk and uncertainty are about future outcomes that have not yet been revealed. The distance into the future when the outcomes are revealed and how the delayed outcomes are weighted against the known or unknown subjective probabilities matter for the anticipated state-contingent decisions. Expected utility theory (EUT) links risk preferences to the curvature of the utility function. Risk experiments have, therefore, been proposed as the basis for estimating the curvature of the utility function, which is needed to estimate time preferences. However, the assumptions of EUT are violated in many behavioral studies in favor of other non-expected utility theories, such as rank-dependent utility (RDU) and cumulative prospect theory (CPT) (Quiggin, 1982; Tversky & Kahneman, 1992). In particular, non-linear probability weighting with an inverse-S-shaped probability weighting function is a common, widespread empirical characteristic (l'Haridon & Vieider, 2019; Vieider, Martinsson, Nam, & Truong, 2019). Non-linear probability weighting also implies that the utility curvature will differ from the EUT case with linear probability weighting. Furthermore, recent literature indicates that it may be questionable whether utility under risk and over time can be assumed to be the same in curvature and has also found that utility in time may be close to linear (Cheung, 2019).

Another strand of the literature on risk and time has demonstrated that decision errors may cause biases in parameter estimates and low prediction power (Enke & Graeber, 2023; Enke et al., 2023). They argue that making such inter-temporal decisions is difficult, and subjects may, therefore, resort to simplifying heuristics that can be inaccurate and lead to systematic errors. It is, therefore, important to use experimental designs and estimation approaches that reduce or minimize and account for and possibly control for such possible decision errors. Enke and Graeber (2023) have introduced a model of cognitive uncertainty and measure such uncertainty as an indicator of the noisiness and possible heuristic nature of people's decisions. After an experiment, they asked directly how certain subjects were about their decisions. These perceived levels of uncertainty and awareness of one's own limited cognitive abilities and knowledge were then correlated with behavior in several experiments. They found that cognitive uncertainty was associated with a more inverse-S-shaped probability weighting function. A follow-up paper by Enke et al. (2023) shows that choice inconsistency and cognitive uncertainty may explain hyperbolicity in inter-temporal decision-making.

In this paper, we investigate whether decision errors may explain or correlate with the non-linear (inverse-S-shaped) probability weighting and the hyperbolic discounting phenomena based on an integrated risk and time experiment implemented in two large samples in the African context. To get important variation in cognitive skills, one of the samples consists of university students in a nationally representative university in Malawi (high education sample), and the other consists of rural respondents covering smallholder households in six districts of the country (limited education sample). We combine the money sooner or later approach (Cohen, Ericson, Laibson, & White, 2020) with later risky prospects, thereby integrating decisions over time and under risk in multiple Choice Lists (CLs).

We take a different approach to Enke and Graeber (2023); Enke et al. (2023) to investigate their theory that decision errors can drive the phenomena we study. More specifically, we use experiments that simultaneously require an integration of decisions under risk and over time. This allows us to simultaneously assess whether non-linear probability weighting and hyperbolic discounting correlate with the frequency of choice inconsistencies across many binary experimental decisions and CLs. One advantage of our approach is that, unlike Enke and Graeber (2023), we do not rely on the subjects' own awareness and statement about their uncertainty and limitations.

We measure cognitive imprecision as the extent of consistency violations based on the identified switch points between risky prospects and sure amounts based on binary decisions in paired CLs that differ only in one parameter, the time horizon or the probability of winning in the risky prospect. The switch point in a CL represents a proxy interval ($[CE_{min}, CE_{max}]$) for the true underlying near-future certainty equivalent (CE) of the more distant-future risky prospect in each CL. We investigate how time delay (6 and 12 months) affects probability weighting and discounting.

Time delay may be associated with increasing cognitive uncertainty. This should have several predictable effects based on the theory of Enke and Graeber (2023); Enke et al. (2023). Based on 20 CLs, each used to obtain a near-future CE estimate of a future risky or safe prospect, we carry out six paired CL consistency checks in time and six paired CL consistency checks in probability at the subject level. The number of consistency violations in time and probability are used as measures of subject-level cognitive imprecision. We propose that this cognitive imprecision is a sign of cognitive uncertainty. Based on Enke et al. (2023), we test the hypotheses that: a) stronger hyperbolic discounting is associated with higher cognitive imprecision (more consistency violations) in paired time prospects; b) stronger non-linear probability weighting (over-weighting of low probabilities and under-weighting of large probabilities) is associated with higher cognitive imprecision in paired probability prospects. We also assess the correlation between our two cognitive imprecision measures and add them to assess their combined effect or correlation with hyperbolic discounting and non-linear probability weighting.

The main contributions of our paper are: a) We are the first to test whether the subject-level number of paired-CL consistency violations can explain hyperbolic discounting and non-linear (inverse-S-shaped) probability weighting based on a within-subject multiple Choice List design that integrates decisions under risk and over time; b) To our knowledge, we are the first to estimate probability weighting functions for risky prospects placed 6 and 12 months into the future and compare how they differ in a large (n=721) nationally representative university student (high education) sample and a large (n=835) representative rural (low education) sample in a developing country. Earlier studies on how delay affects risk tolerance have relied on relatively small (student) samples and have not controlled for probability weighting (Noussair & Wu, 2006) or variation in decision errors (Abdellaoui, Diecidue, & Öncüler, 2011; Kemel & Paraschiv, 2023).

Both the student and the rural samples provide strong evidence of hyperbolic discounting and inverse-S-shaped probability weighting ($w(p)$) functions. The $w(p)$ functions differ significantly between the 6-month and 12-month horizons in both samples, with the $w(p)$ functions being less non-linear and more elevated in the 12-month horizon than in the 6-month horizon, consistent with findings in earlier studies in small student samples (Abdellaoui, Diecidue, Kemel, & Onculer, 2022; Abdellaoui et al., 2011; Kemel & Paraschiv, 2023; Noussair & Wu, 2006). We find strong evidence that the within-subject decision errors (number of consistency violations) correlate with the discount rates and can explain a substantial share of the strong hyperbolic discounting patterns observed in both samples. On the other hand, the decision errors were not strongly correlated with the degree of inverse-S-shaped probability weighting functions in our samples. Separate models for the shares of the two samples that committed no probability-related decision errors reveal even stronger inverse-S-shaped (and more pessimistic) $w(p)$ functions in the 6-month time horizon than the full sample. These results reveal substantial risk aversion in a large share of the probability region ($p > 0.2$; see Figures 3 and 6). In the 12-month horizon, the degree of risk aversion is much lower, showing that both student and rural subjects are more optimistic and, therefore, more risk-tolerant when the time horizon is extended from 6 to

12 months. They are also more patient (have substantially lower discount rates) in the 12-month than the 6-month horizon, indicating that decision errors could not explain all of the hyperbolic patterns. We show, however, that a survival constraint or limited trust in future payments can explain a share of the remaining hyperbolic pattern in line with the models of Halevy (2008) and T. Epper, Fehr-Duda, and Bruhin (2011); T.F. Epper and Fehr-Duda (2024).

The rest of the paper is organized as follows. Part 2 explains the experimental design and elicitation procedure. Part 3 explains sampling, data, and ethics. Part 4 outlines the theoretical basis and estimation strategy. The main results are presented in Part 5 before we discuss and conclude in Part 6.

2 Experimental design

2.1 Overview and design of Choice Lists

An overview of the Time and Risk (TR) Multiple Choice Lists (MCLs) is given in Table 1. The order of the CLs was randomized with the first six CLs (in random order) for the elicitation of time preferences (simple design), presented first, then followed by the remaining 14 CLs (in random order) that include both risk and time afterward. An example of one of these 14 CLs is presented in Table 2.[1] The respondents face an overall risk. They are informed that each of them has a 10% chance of winning in the games they will play, and each game out of 20 games (CLs) has an equal chance of being selected as the real game for the lucky winners. They were informed that their decisions could affect their payouts and that they, therefore, should be careful when making their decisions. For the lucky winners, one random CL and one random row in the CL were selected for real payout. Their choice on that row determined whether they received the near-future safe amount or had to play the risky prospect with a delayed payout if they were lucky enough to win. The experiment was, therefore, incentive-compatible. Late payments were arranged through mobile banking for the students and rural samples. One of the co-authors was in charge of this. There were budgetary and logistical reasons for limiting the probability of winning in these games while at the same time including an ambitious set of treatments in terms of variation in time horizons, probabilities, and magnitude levels in the large student and rural samples.

CLs 1-6 assess the effect of time horizon (6, 12, and 24 months) and the effect of five doubling (5x) the future amounts (from MKw 3000 to 15000). These CLs are constructed such that the list of near-future amounts is constant across time horizons in lists 1-3 and 4-6, and the amounts in CLs 4-6 are everywhere 5x larger than for lists 1-3 to facilitate careful comparison of switch points across lists for stochastic dominance assessment, the assessment of within-subject consistency of decisions by pairing CLs by changing time horizon, and for assessment of utility curvature (diminishing utility) associated with large future amounts.

A similar approach was used to facilitate a careful pair-wise comparison of decisions for alternative time horizons in CLs 7-12 choices for p(win)=0.1 and 0.25 future

[1] An example experimental protocol in English is presented in Appendix A. The protocols were translated into the local language *chichewa* used in the interviews.

prospects and for CLs 13-18 for p(win)=0.75-0.9. These can also be paired with CLs 4-6 for p(win)=1 for consistency checks.

CLs 19 and 20 obey the same rule, with CL 20 having all five times (5x) the amounts in CL 19. In expected returns in the risky prospects, these two CLs are also equivalent to CLs 3 and 6, allowing the assessment of whether another layer of probabilities makes a difference. CLs 11 and 12 also have special properties with risky and safe prospects having the same time horizon, one week into the future. These two CLs can also reveal the extent of risk-loving behavior in these low p(win) near-future prospects. In other words, the whole set of CLs facilitates many pairwise comparison tests that can give useful insights through aggregate and subject-level consistency checks. We return to how we do this after we have explained the rapid elicitation procedure used to identify the switch points in each CL.

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	3000	1	0.23	100-3000
2	1	6	3000	1	0.23	100-3000
3	1	12	3000	1	0.23	100-3000
4	1	24	15000	1	0.23	500-15000
5	1	6	15000	1	0.23	500-15000
6	1	12	15000	1	0.23	500-15000
7	0.1	12	15000	1	0.23	50-5000
8	0.25	12	15000	1	0.23	50-5000
9	0.1	6	15000	1	0.23	50-5000
10	0.25	6	15000	1	0.23	50-5000
11	0.1	0.23	15000	1	0.23	50-5000
12	0.25	0.23	15000	1	0.23	50-5000
13	0.9	24	15000	1	0.23	500-15000
14	0.75	24	15000	1	0.23	500-15000
15	0.9	6	15000	1	0.23	500-15000
16	0.75	6	15000	1	0.23	500-15000
17	0.9	12	15000	1	0.23	500-15000
18	0.75	12	15000	1	0.23	500-15000
19	0.5	12	6000	0.5	0.23	200-6000
20	0.5	12	30000	0.5	0.23	1000-30000

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.

2.2 The rapid elicitation procedure

We used a rapid elicitation procedure from a random starting point to elicit the switch points in each CL. The rapid elicitation procedure has several purposes. It can help avoid bias towards the middle and can help to control for potential starting point bias. It reduces the number of binary questions presented to the respondents and is time-saving. It simplifies the respondents' decisions by presenting them with only two

Table 2 Example of TR Choice List

CL no.	Start point	Task no.	Prob. win	Receive FFT= 12 months, MKw	Choice	Prob. win	Receive NFT= 1 week, MKw	Choice
8		1	0.25	15000		1	5000	
8		2	0.25	15000		1	4000	
8		3	0.25	15000		1	3000	
8		4	0.25	15000		1	2000	
8		5	0.25	15000		1	1500	
8		6	0.25	15000		1	1200	
8		7	0.25	15000		1	900	
8		8	0.25	15000		1	600	
8		9	0.25	15000		1	300	
8		10	0.25	15000		1	150	
8		11	0.25	15000		1	50	

options at the time: a risky prospect (kept constant within the CL) and a safe amount. It is a paper-and-pencil procedure handled by experimental enumerators who fill in the respondents' decisions in the experimental protocol in both the student and rural samples.[2]

The enumerators present each CL in the form of the risky prospect with the amount that can be won (money on the table), the probability of winning (illustrated with a 20-sided die), and the future point in time (months into the future) for potential payout versus the safe amount for payout one week into the future. The enumerator has identified (pre-filled) a randomized starting row (and thereby a safe amount) in each CL. Therefore, the full CL with all the rows is not presented to the subject but is used by the enumerator who fills the experimental protocol. The subject is asked for her/his preference between the near future safe amount and the risky prospect. If the subject prefers the risky amount, the enumerator has to go to the top of the CL and offer the largest safe amount there versus the risky prospect as the second binary choice offered. If the subject then prefers the safe amount, the enumerator offers an intermediate safe amount in the middle row between the first random row (amount) and the second maximum amount. The third decision helps narrow the range and finally identify a switch point in the CL. If the subject in the first decision prefers the safe amount, the enumerator goes to the bottom of the CL and offers the smallest safe amount there versus the risky prospect. With a switch to a preference for the risky prospect, the enumerator goes to the middle row between the bottom row and the initial random starting row. Again, the narrowing goes on till the switch-point rows are identified, and thereby, a Certainty Equivalent (CE) interval is identified for the risky prospect. If the subjects prefer the risky prospect at the top of the CL, there is no interior switch point in the CL, and the CE of the risky prospect is higher than the safe amount at the top of the CL. At the bottom of the CL, if the respondent

[2]While the student sample could have responded to a computerized approach, the rural sample did not have the skills to do this.

prefers the safe amount, the CE is below this small amount. Here, we instructed the enumerators to add a row to the CL by offering an amount half the size of the safe amount at the initial bottom row in the CL. Further rows could be added to identify a switch point and, thereby, a CE interval for the risky prospect.

3 Sampling, Data, and Ethics

3.1 Sampling

3.1.1 Student sample

This study used a student and a rural sample from a developing country, Malawi. The student sample is from Lilongwe University of Agriculture and Natural Resources (LUANAR). The sample is a stratified random sample of 721 students from 46 classes with up to 16 students per class. The sample was stratified by study year and program to cover a range of subject specializations. The student sample is nationally representative because students come from all parts of the country. Most students are BSc students, but a small share (0.028) are MSc students. About 30% of the students study economics or business. The sessions took place during the coronavirus pandemic. This necessitated strict corona-safety measures before, during, and after each session to prevent the spreading of the virus.

3.1.2 Rural sample

The rural sample consisted of a stratified random sample of 835 subjects from 64 villages in two districts in the Central Region and four in the Southern Region of Malawi. These two regions contain 89% of the population in the country, and our sample should be a good representation of the large rural population dominated by poor smallholder farming households in the country. Up to four family members per household, all above 16 years of age, were included in our experiments. The sampling strategy secured a larger variation in the age distribution than in the student sample and a fairly large share of young individuals compared to a sample of household heads only.

3.2 Data management

The data from the two samples have been managed and analyzed separately. Researchers at LUANAR have taken responsibility for the data collection, cleaning, anonymizing, and safe data storage. The data are intended for collaborative research for the NMBU and LUANAR researchers involved in the project and for providing opportunities for MSc and Ph.D. students in the two universities and possibly students from elsewhere to learn and write papers and theses.

3.3 Ethical issues

1. Approval: Our experiments included only standard incentivized games that are part of the toolkit of behavioral and experimental economists. As the two universities involved in this research did not have their own Institutional Review Boards

for ethical approval of the experiments or the survey instruments at the time of the project fieldwork, our project relied on the high standard used by Norwegian researchers when implementing this kind of research. These guidelines are available here:

https://www.forskningsetikk.no/en/guidelines/social-sciences-humanities-law-and-theology/guidelines-for-research-ethics-in-the-social-sciences-humanities-law-and-theology/

Norwegian researchers are required to follow these guidelines and the project has followed these guidelines strictly. One challenge was that the project started during the coronavirus pandemic. It necessitated very strict rules during the implementation of surveys and experiments to prevent the spreading of the virus and ensuring that all coronavirus regulations were strictly followed through disinfecting all equipment (such as tablets used for the data collection) and hands, use of face masks, and appropriate distancing.

The project is a capacity-building and research collaboration project funded under NORHED II by the Norwegian Agency for International Development (NORAD). Funding is based on ethical approval by the NORAD staff in charge of these projects.

2. Accordance: All the experiments were carried out following the relevant guidelines and regulations.
3. Informed consent: Prior informed consent was obtained from all the students and rural subjects after being introduced to the project, survey, and experiments.
4. Anonymity: All the subjects are granted anonymity. Personal identifiers are kept separately from the data by the responsible data manager.
5. Conflicts of interest: The authors declare no conflicts of interest.

4 Theory: Cognitive limitations, decision-making, and decision errors

We used incentivized experiments, and the theoretical idea is that the respondents aim to make decisions that maximize their utility based on their information and how it is interpreted. Respondents may make errors for many reasons, creating randomness in their decisions. Even the best football players make many mistakes, although they know the rules of their game very well.

Our starting point is that our brains have difficulties making quick and precise mathematical judgments of numeric information. The numeracy skills and ability to make correct calculations and judgments vary substantially across individuals. Such skills are trainable, and subjects who have been through a longer formal education and screening and selection into higher education institutions, such as universities, are expected to be able to make more precise judgments and calculations for numerical alternatives. When subjects are asked to make many binary choices between preferred alternatives, we expect subjects with lower numeracy skills, those who are more uncertain about their underlying preferences, and those who are less focused and motivated for the tasks to make more errors. Therefore, the frequency of such errors at the subject level may indicate the cognitive imprecision of their decisions. In our experimental data, we investigate whether such errors due to cognitive imprecision can explain hyperbolic discounting and non-linear probability weighting.

Our experiments were designed to make it simple for decision-makers to make optimal decisions. They were further designed to help identify inconsistent choices within subjects through simple paired tests in time and risk dimensions as indicators of the degree of cognitive (im-)precision of their decisions. We have followed a strict, standardized procedure (bisection and rapid elicitation), where each binary decision relies on risk and/or time tradeoffs. Other studies have shown that the presentation of such simple binary alternatives is more easily comprehended by subjects with limited numeracy skills than more complex formats such as full Choice Lists, e.g., based on the Holt and Laury (2002) design (Charness, Eckel, Gneezy, & Kajackaite, 2018; Charness & Viceisza, 2016).

The standard approaches to deal with this kind of decision error have been to use a random utility model or variants of models with Luce error and Fechner error specifications (Fechner, 1860; Luce, 1959; McFadden, 1974). Such models have typically separated the error component from the deterministic structural component of the model. Such models may have allowed for contextual errors that can vary systematically with experimental design elements, other contextual factors, and subject characteristics. This can be one way of controlling for variation in the within-subject tendency to make inconsistent decisions across many choice tasks.

However, such an approach does not guarantee that decision errors are independent of the structural model parameters. Risk and time preferences are determined in the deterministic part of such models based on the assumption that these preferences are uncorrelated with the factors affecting the decision errors. In this study, we relax this assumption and allow decision errors to be correlated with the structural variables in our models to investigate whether such errors may correlate with and possibly contribute to explaining hyperbolism and non-linear probability weighting that do not have a good or solid theoretical explanation. Our exploratory study builds on the recent literature investigating whether decision errors and cognitive uncertainty can explain these phenomena. Recent literature tries to explain these phenomena as outcomes of decision errors associated with imprecise perceptions and cognitive uncertainty, building on psychophysics in psychology (Woodford, 2020). For example, Khaw, Li, and Woodford (2021) suggest that decision errors associated with cognitive imprecision may explain small-stakes risk aversion or the so-called Rabin paradox (Rabin, 2000). Khaw et al. (2021) find that subjects making more random choices exhibit greater small-stakes risk aversion based on a sample of 20 students at the University of Columbia who responded to several 100 trials, all with a fixed p(win)=0.58 and varying amounts in the games in a random order. Based on a similar approach, Frydman and Jin (2022) study how risky choice is influenced by noisy lottery payoffs due to information processing constraints in the brain. In two experiments, they first show that more frequent decisions are associated with stronger responses to payoff incentives and more rapid and precise responses. They associate decision errors with the functional forms of the value function in Prospect Theory.

These recent studies assume that decision errors are due to imperfect perceptions and not limited optimization skills. Unlike these recent studies, we do not assume decision-makers have perfect optimization skills but imperfect perceptions. We also consider the optimization skills and decision abilities to vary. We, therefore, do not assume that decision-makers apply the Bayes rule based on their prior beliefs to compute their posterior distributions of the payoffs in their choice sets. Rather, we allow their heuristics to remain a black box. We acknowledge that we do not know the prior beliefs of each subject, e.g., about their expected luck in the game. However, our cognitive limitations framework allows for framing elements in the game to influence the decisions. We, therefore, allow for such priors in our structural models and test whether they influence their decisions. We argue broadly that decision errors due to imperfect perceptions, fuzzy preferences, or simple heuristics that lead to systematic errors may jointly or to varying degrees explain the hyperbolic discounting and non-linear probability weighting phenomena.

We hope to gain insights by combining two samples with large differences in the level of education but coming from the same cultural background to help us assess how differences in educational level influence decision errors and possibly are associated with hyperbolic discounting and non-linear probability weighting. University students should have stronger numeracy skills and be able to make more consistent choices than our less well-educated rural sample.

Decision errors could be caused by cognitive limitations related to knowing one's preferences (fuzzy preferences) and the ability to make comparisons of simple choice alternatives in the confrontation with complex reality in the near and more distant risky and uncertain future where there are many unknowns. Uncertainty about amounts alternatively received at different future points may also influence risk perceptions through the probabilities we illustrated with a 20-sided die. We aim to test the following hypotheses:

H1. Students commit fewer decision errors than the rural (low education) subjects.

H2a. The rural sample exhibits stronger hyperbolic discounting than the student sample.

H2b. The rural sample exhibits a stronger inverse-S-shaped probability weighting ($w(p)$) function than the student sample.

H3a. More time-related decision errors are associated with stronger hyperbolic discounting in both samples.

H3b. More probability-related decision errors are associated with stronger inverse-S-shaped $w(p)$ functions in both samples.

We rely on structural econometric models to test these hypotheses. We use non-parametric stochastic dominance tests to identify the subject-level consistency errors of decisions across CLs. We outline these tests in the next section before we present the structural econometric models.

4.1 Assessment of within-subject (in-)consistency across CLs in the TR experiment

The subjects make a large number of binary decisions where the choice options are between a future (risky) prospect $R(X, t_2, p)$ and a near future safe amount $(C, t_1, p = 1)$, where the risky prospect is drawn from a list of 20 CLs, and the first safe amount is randomly drawn from a list of 11 safe amounts in the CL. A strictly standardized rapid elicitation (bisection) method is used to move from the random starting safe amount in the CL to a final switch point, identifying the interval for the near future Certainty Equivalent (CE) for the future risky prospect. Correctly identifying the CE for the risky prospect relies on subjects having stable and clear perceptions, stable preferences, and sufficient numeracy skills to avoid committing any decision errors in the sequence of binary choices from the random starting row to the switch point in the CL. Given their unobservable preferences, we cannot verify whether each CL decision is correct or wrong. However, by comparing their identified near future CEs for the 20 CLs, we can assess their across-CL CEs for consistency based on two simple rationality requirements. These are positive discount rates and probability weighting functions that are non-decreasing in the probability of winning. We have only included the assessment of consistency violations at the subject level in this study as these are our primary focus.[3]

From a theoretical perspective, we may expect that intertemporal decisions with a longer time horizon lead to more fuzzy preferences and less consistent decisions. Longer time horizons also introduce uncertainty that comes on top of the specified probabilities in future risky prospects. We assume that this potential uncertainty increases with time delay and should not change the ranking of paired CLs for consistency assessment.

The investigation of (in-)consistency in choices is made for pairs of CLs as follows. We utilize the determined switch points in the two CLs. These represent the elicited near-future CEs for the two associated risky prospects in the two CLs. We characterize the risky prospect R by the amount that can be won (X), the probability of winning (p), and the time horizon for the payout of the risky amount that can be won (t). For the CL-pair to be compared, two characteristics are the same, while the third is different. E.g., if we compare two CLs with different time horizons, one with a 6-month horizon and one with a 12-month horizon, we expect $CE(R(X, p, t = 6)) > CE(R(A, p, t = 12))$. This is based on the assumption that discount rates are non-negative. A delay in the payout for a risky prospect will, therefore, always reduce its near-future CE. Likewise, for two CLs that differ only in the probability of winning (p): e.g., we expect $CE(R(X, p = 0.9, t = t_2)) > CE(R(X, p = 0.75, t = t_2))$. The near-future CE of a risky prospect with a higher p, should be higher than for a risky prospect with a lower p, *ceteris paribus*. This is based on the assumption that the non-linear probability weighting function is non-decreasing in the p-interval $[0, 1]$.[4]

The fact that the CEs are identified as intervals (CE_{min}, CE_{max}) may imply that the true CE for the two paired CLs may fall within the same interval and/or the elicited switch points fall between the same rows in the two CLs. We do not consider such cases to represent inconsistent choices. Inconsistent choices for the pairs are represented by cases where the CE interval is stated as higher, whereas it should be considered lower by the nature of the risky prospects.

[3]Graphs assessing the sample-level stochastic dominance are available from the authors upon request.

[4]Decision errors may also be more likely if the $w(p)$ function is flatter (intermediate probability levels) and for subjects that are more probabilistically insensitive in this region. Such subjects should be less likely to make errors in the near zero and near one range of probabilities, where they should be more probabilistically sensitive. We tested for such inconsistencies in the probability range 0.1-0.9. We acknowledge that such correlations make establishing causality between decision errors and inverse-S-shaped $w(p)$ function difficult. Nevertheless, subjects without such consistency errors should not have an inverse-S-shaped $w(p)$ function driven by such errors.

Based on six paired CLs that differ only in the time horizon and six paired CLs that differ only in the probability of winning, we identify two subject-level consistency violation count variables (indices), *viol*6*t* and *viol*6*p*. We assess whether the two types of violation counts by subjects are correlated with the discount rates and the non-linear probability weighting parameters. More specifically, we use the *viol*6*t* (time-related) errors to test the hypotheses about the hyperbolic discounting pattern and the *viol*6*p* (probability-related) errors to test the hypotheses about stronger inverse-S-shaped probability weighting function.

We cannot rule out that subjects with more violations also have systematically different risk and time preferences, which cannot be fully identified for such subjects. On the other hand, we can assess whether the number of violations is a sign of cognitive limitations that lead to higher errors and systematic correlations with the structural discounting and risk response parameters. The size and direction of the correlations with the structural model parameters facilitate the testing of our hypotheses. Controlling for the number of violations may help reduce bias in the estimated underlying latent variables. We are confident that subjects who do not commit such decision errors should reveal less biased estimates of their preference parameters, given that the structural models are correctly specified. However, the models with these consistent decision-makers may also mask internal heterogeneity, which may be revealed by including additional variables.

There are many possible reasons for consistency violations. Using structural models with contextual Luce errors allows us to partially separate the error sources and the random and non-random components. The different sources include: a) subjects may not know the near and far-future utilities that well, b) their precision in the judgment and making of such decisions may be low, c) their numeracy skills may be limited, making it hard to judge trade-offs in time (discounting) and risk (probability of winning), d) they may be overwhelmed with many binary choices to make (they may get bored or ignorant in their decisions and make random choices), e) they may be affected by the initial random starting certain amount in each CL (starting point bias), f) there may be interviewer bias, g) distant future prospects may be harder to judge than near-future prospects as the inherent future uncertainty on top of the stated future probability risks may become more dominant and blur the difference between prospects.

We did not attempt to study or inquire about their specific decision heuristics. However, some subjects gave some comments related to their decisions. Quite a few responded that the distant future prospect was too far away and may indicate difficulties in judging and valuing such prospects.

4.2 Econometric structural model integrating time and risk decisions: Estimation strategy

We assume that the decision-makers aim to maximize the discounted probability-weighted expected utility of the two binary options presented to them in each choice. For simplicity and consistency with Cumulative Prospect Theory (CPT), we assume no integration of the decisions with background wealth.[5] We construct structural models with separate contextual Luce errors that are allowed to vary with CL characteristics.

The inter-temporal binary choice between the two time-dated prospects can then be formulated as follows:

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

where δ is the exponential continuous time discount rate.[6]

Alternatively, the far-future prospect ($M_B = X$) can be risky, while the near-future prospect is a safe amount ($M_A = s$). A risky prospect has a probability $p < 1$ of a positive outcome and a 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 in net present utility (NPU) terms:

$$\begin{aligned} NPU_A &= e^{-\delta(t_1-t_0)}u(s) \\ NPU_B &= e^{-\delta(t_2-t_0)}(w(p)u(X)) \end{aligned} \tag{2}$$

We are interested in the type of hyperbolic discounting that is not driven by present bias. We eliminate potential present bias by avoiding present-time valuation by offering the choices between:

$$\begin{aligned} NFU_A &= u(s) \\ NFU_B &= e^{-\delta(t_2-t_1)}(w(p)u(X)) \end{aligned} \tag{3}$$

The sizes of the discount rates for the longer time horizons (6, 12, and 24-month horizons) that are of particular interest to us in this study capture the possible (degree of) diminishing impatience.

By offering alternative amounts s till a switch point is reached between $u(s)$ and $e^{-\delta(t_2-t_1)}(w(p)u(X))$, we obtain a near-future Certainty Equivalent (CE) interval for the far-future risky prospect captured by the near-future amounts s on the rows just above and below the switch point in the CL.

While the RDU theory is typically framed in an atemporal setting, we apply it in an intertemporal setting. We call the model a Discounted Rank Dependent Utility (DRDU) model, acknowledging that we are not estimating a full CPT model as we do not have CLs in the loss domain. The model nests DEU when $w(p) = p$ and DEV

[5]This assumption may be relaxed but would require additional assumptions about the degree of asset integration.

[6]For simplicity, we assume there is a single discount rate for each prospect. However, we will allow this discount rate to be determined freely for each time horizon length. This means we strictly do not impose any specific functional form assumption on the discounting function. By inspecting the discount rates for the different prospects with alternative time horizons, we can assess, e.g., the pattern of increasing patience (lower discount rates) with extended time horizons.

when $w(p) = p$ and utility is linear. We compare models based on discounted expected value (DEV) vs. discounted rank-dependent expected value (DRDEV) vs. discounted rank-dependent utility (DRDU) (linear vs. non-linear probability weighting and linear vs. non-linear utility).

A unique element of our model is that we allow the $w(p)$ to vary with time horizon [7] and the $w^t(p)$ function is modeled with a Prelec (1998) 2-parameter weighting function:

$$w_t(p) = exp(-\beta_t(-\ln p)^{\alpha_t}), \alpha_t > 0, \beta_t > 0 \tag{4}$$

where α_t captures the time-horizon specific degree of (inverse) S-shape of the weighting function with $\alpha_t > (<)1$, and the β_t captures the time-horizon specific elevation of the function, with $\beta_t < 1$ giving more elevated (optimistic) and $\beta_t > 1$ giving less elevated (pessimistic) weighting of prospects. The function is strictly increasing and continuous within the interval $[0, 1]$[8].

For sensitivity and robustness analyses, we open for a potential non-linear utility function in the form of a Constant Elasticity of Marginal Utility (CEMU) function[9]:

$$u(x) = (1-\theta)^{-1}((b+X)^{1-\theta} - 1) \tag{5}$$

where θ captures the constant elasticity of marginal utility, b captures eventual asset integration but we assume $b = 0$ in line with CPT. The utility function is linear for $\theta = 0$.[10] As our primary focus is on discounting and probability weighting, we, for simplicity, assume linear utility in our base models. As we included CLs with substantial variation in the future amounts, we were able to do pair-wise non-parametric tests for such non-linearity, see Appendix A. The linear utility assumption was preferable in the student sample.[11] In the rural sample, we found indications of weak concave utility, see Appendix A. We ran models with CEMU-$\theta = 0.2$ for the rural sample as a robustness test. These models gave discount rates closer to those in the student models with linear utility, see Table A3.

The RDU model with linear utility has also been called the Yaari (1987)-dual model. Here, we apply a discounted version of this model. We call it the Discounted Rank Dependent Expected Value model (DRDEV). It is well suited for investigating how discounting and probability weighting of future prospects are associated with the time horizon and probability of winning. Our data allow us to estimate the $w_t(p)$ function and the discount rates separately for t=6 and t=12 months and to measure the hyperbolic effect as the gap in the discount rates in the 6- and 12-month models while controlling for a change in the $w(p)$ function. Usually, $w(p)$ functions have been estimated in the gains or loss domain. One of our contributions is to estimate it separately for risky prospects placed 6 and 12 months into the future.

To test our hypotheses, we investigate how the three estimated parameters (discount rate, Prelec α, and Prelec β) correlate with the number of consistency violations

[7] We have sufficient CLs to estimate the $w_t(p)$ function separately for the 6- and 12-month horizons based on our within-subject 20 CL design.

[8] Alternative linear and non-linear models can be run by imposing constraints on the α and β parameters as for DEU or DEV models with $\alpha = \beta = 1$

[9] 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.

[10] A recent literature has found that utility in time is close to linear (Cheung, 2019).

[11] We tested parametric models with concave utility for our student sample, but these models produced implausible negative discount rates for the longest time horizon (24 months).

in time- and probability-paired CLs and compare the results in the student and rural samples. In particular, we investigate how the inconsistent CEs across time-paired CLs are associated with hyperbolic discounting (widening gap between the 6-month and 12-month discount rates as the number of violations increases). Second, we assess whether the number of probability-paired CL consistency violations is associated with a lower Prelec α (more inverse S-shaped $w(p)$ function) (the degree of probabilistic insensitivity). We also assess whether the number of consistency violations is associated with the Prelec β parameter in terms of pessimism or optimism bias, but we do not have any hypothesis related to this.

Testing our hypotheses relies on framing our models into a stochastic choice framework. There are alternative approaches to doing this. Luce error and Fechner error specifications are the most commonly used. We tested both approaches with contextual error specifications to allow for heteroskedasticity. We found the models with contextual Luce errors to perform the best with our experimental data.[12] We, therefore, proceed by estimating our binary choice data with the maximum likelihood estimation approach with the contextual Luce error specification (Holt & Laury, 2002). We return to the details of the contextual error specification below.

We constructed and estimated structural maximum likelihood models for the binary choice data with the Luce error specification (Holt & Laury, 2002). The Luce error specification allows respondents to make errors in their choices. The parameter μ in the Luce specification captures the error probability.

$$\nabla DRDU = \frac{NFU_A^{\frac{1}{\mu}}}{NFU_A^{\frac{1}{\mu}} + NFU_B^{\frac{1}{\mu}}} \tag{6}$$

Equation (6) nests the discounted risky and certain prospects based on the alternative linear (DEV, DRDEV) and non-linear (DRDU) utility, probability weighting, and discounting functions as special cases.

This gives rise to the following likelihood function where the discount rate (δ_t), the Prelec α_t, the Prelec β_t, and the Luce error (μ_t) are all estimated as time-horizon specific parameters that are allowed to vary with the number of time- and probability-consistency violations (v^t, v^p).

$$\begin{aligned} &\ln L(\delta_t(v^t, v^p), \alpha_t(v^t, v^p), \beta_t(v^t, v^p), \mu_t(v^t, v^p, CL_{p,t,m}, E^d, s^r); Choice_{CL_{p,t,m}}) = \\ &\sum_i((ln(\Phi(\nabla DRDU)|Choice_{t,m} = 1) + (ln(\Phi(1 - \nabla DRDU)|Choice_{t,m} = 0)) \end{aligned} \tag{7}$$

where $Choice_{ij} = 1(0)$ denotes the choice of alternatively M_A (near-future safe amount) or M_B (far-future risky amount) for each row in each CL. We use only the two switch point rows in each CL. The safe amounts in these two rows represent the upper and lower bounds for the near-future CE for this CL's given risky and time-delayed prospect. While estimation could be made directly on this CE interval, we

[12]The contextual Fechner error specifications that have often been recommended resulted in implausible $w(p)$-function parameter estimates, especially for the longer time horizon (12 months). The Prelec α parameter became very large (>2), and the Prelec β parameter was very low (close to 0).

estimate it as a binary choice closer to how the respondents made the binary decisions around the switch point in the experiment.

Although we have a within-subject design, we allow separate estimations of the structural parameters for each time horizon (6- and 12-month). The cognitive ability to compare safe amounts in the near future with riskier amounts in the far future may depend on the time horizon if hyperbolic discounting is associated with such cognitive (in-)ability. To assess this, we allow the discount rate (δ_t) and probability weighting parameters to vary with the subject-level indicators for the cognitive inaccuracy (decision errors) in line with our hypotheses.

The structural parameters are, therefore, allowed to vary linearly with the decision errors as follows:

$$\begin{aligned}
\delta_t &= \delta_{t0} + \delta_{t1} v_i^t + \delta_{t2} v_i^p \\
\alpha_t &= \alpha_{t0} + \alpha_{t1} v_i^t + \alpha_{t2} v_i^p \\
\beta_t &= \beta_{t0} + \beta_{t1} v_i^t + \beta_{t2} v_i^p
\end{aligned} \tag{8}$$

where v^t and v^p represent the subject-level number of consistency violations in time- and probability-paired CLs, and Mem_i represents the student memory index (student sample only).

We allow for contextual heteroskedastic Luce errors and investigate how the Luce error is related to the random order of the CL (CL^r), enumerator dummies (E^d), the consistency violation variables in some specifications, and the student memory variable in some specifications of student models. The randomization of the order of the CLs was used to control for order effects. There may be learning effects that reduce the error in the process, but subjects may also become less focused after exposure to many CLs. With 20 CLs per subject, we assess such possible dynamic effects by including dummies for the CL order. We included dummies for enumerators randomly allocated to subjects in each class/village. Although the enumerators received standardized training and methods for implementing the experiment, there may be some variation in how they executed their responsibilities. We could assess their relative performance by assessing how enumerators possibly influenced errors in the experiment. In this paper, they just represent additional controls in the error specification of the models. In Appendix D, we also included discounted expected value (DEV) models with the $p(win)$ in the risky prospect in the CL (p_{CL}) in the error specification. A CL with a higher probability of winning is assumed to be associated with less uncertainty and, therefore, a lower error.

$$\mu_{tn} = \mu_{t0} + \mu_{t1} v_i^t + \mu_{t2} v_i^p + \mu_{t3} p_{CL} + \mu_{t4} s^r + \mu_{tn5} CL^r + \mu_{tn6} E^d \tag{9}$$

Our within-subject design with 20 CLs per subject allowed us to estimate the probability weighting function parameters for two different time horizons, six and 12 months into the future. We estimated joint and separate models for these two time horizons but found the separate estimation by time horizon preferable as the key parameters of interest differed substantially across the models. Such a splitting by time horizon allowed us to assess the influence or correlation between the inconsistency count variables in time- and probability-paired CLs on the different structural model parameters for each time horizon. This also facilitated testing our hypotheses H2a, H2b, H3a, and H3b.

We estimated the likelihood function with the Newton-Raphson optimization algorithm[13] while clustering errors at the subject level.

5 Results

5.1 Decision errors: Subject-level consistency violations

We made three subject-level paired consistency comparisons based on the identified near-future CEs associated with CLs 1-3 and three subject-level paired consistency comparisons for CLs 4-6.[14] A subject may then make from zero to six such violations for these time-paired CLs. The associated count variable is v^t in the structural model and $viol6t$ in our tables with results.

We included consistency checks for CLs with risky future prospects in the flatter p-domain $(0.1 - 0.9)$, given that we expect an inverse-S-shaped $w(p)$ function. Based on the CL overview in Table 1, such subject-level consistency checks were made for CL pairs 7 and 8, 9 and 10, 11 and 12, 13 and 14, 15 and 16, 17 and 18, giving 6 CL-paired tests. The subject-level count variable for the number of inconsistent choices is v^p in the structural model notation and $viol6p$ in the tables and results.

Table 3 shows the shares of inconsistent responses by CL pair separately in the student and rural samples. The shares of inconsistent responses are slightly higher in the rural sample, as could be expected, but they are also high among students, in the range of 0.168-0.265 and in the range of 0.199-0.323 in the rural sample. These ranges indicate a quite even distribution of errors across the CL pairs. It shows that such low accuracy in these binary decisions is common in both samples.

We assess the correlations between the CL-pair violations (Table 4 for students and Table 5 for the rural subjects). The correlations in these tables demonstrate that the errors tend to be closely correlated across CLs 1-3 and 4-6 in both samples, demonstrating that the same subjects face problems when comparing time-paired CLs. For the probability-paired CLs, the correlation coefficients are much lower.

The cumulative distribution of the $viol6t$ and $viol6p$ variables in the two samples are presented in Figure 1. We see that only about 20-25% of the subjects had no violations, with slightly higher shares for the students than for the rural subjects for both variables. Fairly high shares of the subjects had only one consistency error in both samples and across both types of consistency checks. The differences between the rural and student samples are scrutinized further in the last two graphs in Figure 1, showing the mean number of violations by type of violation and with 95% confidence intervals, and the sample differences are further scrutinized by estimating Cohen's ds for the two errors. The Cohen's ds are fairly small (0.15-0.22) although significantly

[13] We also tested the alternative Broyden-Fletcher-Goldfarb-Shanno optimization algorithm, which gave identical results but sometimes resulted in some convergence problems.

[14] As there is no explicit risk associated with these CLs, these are equivalent to the Net Present Values (NPV) of these future amounts one week into the future. With non-negative discount rates, the NPVs should decline with the time horizon. If not, we consider it a consistency violation.

Table 3 The share of inconsistent responses in paired CL checks

Variable	Student Obs	sample Mean	Rural Obs	sample Mean
Time inconsistencies (violations)				
CL1-CL2D	721	0.168	835	0.199
CL1-CL3D	721	0.265	835	0.281
CL3-CL2D	721	0.264	835	0.313
CL4-CL5D	721	0.179	835	0.217
CL4-CL6D	721	0.250	835	0.259
CL6-CL5D	721	0.257	835	0.301
Probability inconsistencies (violations)				
CL8-CL7D	721	0.251	835	0.297
CL10-CL9D	721	0.247	835	0.291
CL12-CL11D	721	0.243	835	0.225
CL14-CL13D	721	0.227	835	0.271
CL16-CL15D	721	0.227	835	0.299
CL18-CL17D	721	0.218	835	0.286

Table 4 Student sample: Assessment of error correlations across CL pairs

T-violation correlations	CL1-2D	CL1-3D	CL3-2D	CL4-5D	CL4-6D	CL6-5D
CL1-2D	1.000					
CL1-3D	0.336	1.000				
CL3-2D	0.363	-0.174	1.000			
CL4-5D	0.023	0.072	0.066	1.000		
CL4-6D	0.075	0.002	0.070	0.358	1.000	
CL6-5D	-0.034	0.029	-0.034	0.372	-0.148	1.000
P-violation correlations	CL7-8D	CL9-10D	CL11-12D	CL14-13D	CL16-15D	CL18-17D
CL7-8D	1.0000					
CL9-10D	-0.0199	1.0000				
CL11-12D	0.0677	-0.0015	1.0000			
CL14-13D	0.0597	-0.0268	0.1018	1.000		
CL16-15D	0.0674	-0.0114	0.0941	0.029	1.000	
CL18-17D	0.1130	0.0097	0.0540	0.066	0.002	1.000

different at the 5% level for both types of errors. Therefore, higher education has a surprisingly low negative effect on the tendency to commit such inconsistency errors when exposed to this experimental tool.

This subject-level variation in inconsistency counts should provide a good basis for assessing whether such errors can contribute to explaining (correlate with) hyperbolic discounting and non-linear (inverse-S-shaped) $w(p)$ functions. We inspected the correlation coefficients between the $viol6t$ and $viol6p$ variables in our two samples and found them low: 0.10 in the student sample and 0.12 in the rural sample. This

Table 5 Rural sample: Assessment of error correlations across CL pairs

T-violation correlations	CL1-2D	CL1-3D	CL3-2D	CL4-5D	CL4-6D	CL6-5D
CL1-2D	1.000					
CL1-3D	0.302	1.000				
CL3-2D	0.357	-0.232	1.000			
CL4-5D	0.058	-0.013	0.128	1.000		
CL4-6D	0.048	0.007	0.115	0.366	1.000	
CL6-5D	0.073	0.031	0.065	0.340	-0.214	1.000
P-violation correlations	**CL7-8D**	**CL9-10D**	**CL11-12D**	**CL14-13D**	**CL16-15D**	**CL18-17D**
CL7-8D	1.000					
CL9-10D	0.034	1.000				
CL11-12D	0.101	0.027	1.000			
CL14-13D	0.011	0.073	-0.025	1.000		
CL16-15D	0.050	0.036	0.005	0.049	1.000	
CL18-17D	0.018	0.067	0.039	-0.040	0.049	1.000

indicates that difficulties in comparing prospects over time are not closely related to difficulties in comparing prospects across different probability levels.

5.2 Discounting and probability weighting by time horizon

Most empirical studies of probability weighting have focused on estimating these functions either in the gains or loss domains for current risky prospects. Our first contribution is to estimate probability functions for future risky prospects with two different time horizons in the gains domain, with potential payouts 6 months and 12 months into the future for our two samples. We use the DRDU structural model outlined and impose the constraint that utility is linear (DRDEV or discounted dual Yaari (1987)-models). We include the control variables, enumerator FE and CL-order FE, in the noise (Luce error) equation. We have 6 CLs with a 6-month time horizon and 8 CLs with a 12-month horizon in the within-subject design in each sample. We estimate the population-averaged discount rates and the Prelec probability weighting functions separately for each sample's two alternative time horizons. The model results are presented in Tables 6 (student sample) and 7 (rural sample). Graphs of the estimated $w(p)$ functions are presented in Figures 3a and b.

Tables 6 and 7 show that the estimated discount rates are much lower for the 12-month horizon than for the six-month horizon, demonstrating a strong hyperbolic discounting or diminishing impatience pattern in both samples. Table 6 shows an annualized continuous time discount rate of 104.4% in the six-month model and 43.1% in the 12-month model. We also see that the students have significantly lower discount rates than the rural sample (124.9% in the six-month model and 58.3% in the 12-month model).

For the student sample, we find that the $w(p)$ function is more strongly inverse-S-shaped in the six-month than the 12-month model and that it is more elevated (optimistic) in the 12-month horizon (Figure 3a based on models in Table 6). This

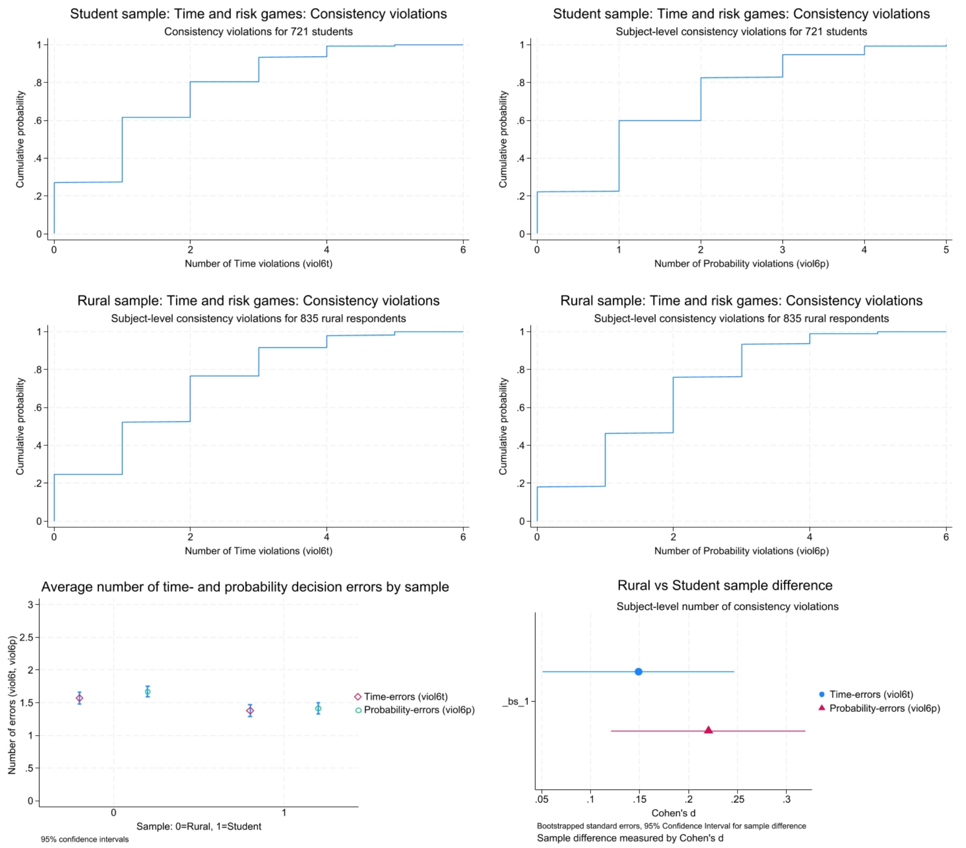

Fig. 1 Student and rural samples: Subject-level number of Time- and Probability consistency violations in the TR games.

indicates that students are more patient and optimistic when judging risky prospects with payouts 12 months into the future than for risky prospects with payouts 6 months into the future. We find a similar tendency in the rural sample, but the level of optimism was higher in the 6-month horizon compared to the student sample and similar to that in the 12-month horizon.

Therefore, the rural sample appears less patient but more optimistic than the student sample. Figures 2a and 3a show the differences across the samples and time horizons. The rural sample has more elevated and less non-linear sample-averaged $w(p)$ functions.

In the next section, we investigate whether these patterns are correlated with the extent of consistency violations in the two samples.

Table 6 Student sample: DRDEV-models: Discounting and probability weighting by time horizon

EQUATION	VARIABLES	(1) 6 months	(2) 12 months
Discount rate	Constant	1.044***	0.431***
		(0.028)	(0.024)
CEMU-θ	Constant	0.000	0.000
Prelec α	Constant	0.518***	0.669***
		(0.045)	(0.044)
Prelec β	Constant	1.044***	0.876***
		(0.047)	(0.044)
Luce error	Constant	3.299***	4.409***
		(0.790)	(0.756)
	CL order FE	Yes	Yes
	Enumerator FE	Yes	Yes
	Observations	8,246	11,016
	Log-likelihood	-5511	-7369
	N_clusters	720	720

Cluster-corrected standard errors in parentheses, clustering on subjects. *** p<0.01, ** p<0.05, * p<0.1.

5.3 Cognitive limitations, time discounting, and probability weighting

5.3.1 Student sample

Table 8 presents the results for the student sample's 6- and 12-month horizons with the $viol6t$ and $viol6p$ variables. We tested for possible non-linear relationships for these two variables but found no significant non-linear relationships. Interestingly, the sign for the $viol6t$ variable goes opposite in the two models. A higher number of violations is associated with significantly higher discount rates in the 6-month model and a significantly lower discount rate in the 12-month model. We predicted these relationships in Figure 4 ($viol6t$) to understand these effects better. Figure 4 demonstrates that a larger number of violations is associated with a larger gap between the 6-month and the 12-month discount rates, indicating that more decision errors are associated with stronger hyperbolic discount rates.

For the Prelec α parameter, only one of the consistency violation variables ($viol6t$) is significant (only at the 10% level) in the 6-month model. Moreover, the sign of the variable is positive such that fewer violations are associated with a more non-linear $w(p)$ function as the constant term for the Prelec α parameter is as low as 0.347 in this 6-month model. The consistency violations cannot explain the large deviation of Prelec α from +1. For Prelec β, both $viol6t$ and $viol6p$ are significant in the six-month model and with negative signs, indicating that more decision errors are associated with more optimistic (more elevated) probability weighting. Figure 5 presents the predicted effects of decision errors on the Prelec β in the six-month student model.

We estimated separate DRDEV models for the sub-sample that did not commit any time consistency errors ($viol6t = 0$). The first two models in Table 9 present the

Table 7 Rural sample: DRDEV-models: Discounting and probability weighting by time horizon

EQUATION	VARIABLES	(1) 6 months	(2) 12 months
Discount rate	Constant	1.249***	0.583***
		(0.038)	(0.031)
CEMU-θ	Constant	0.000	0.000
Prelec α	Constant	0.613***	0.703***
		(0.052)	(0.050)
Prelec β	Constant	0.874***	0.860***
		(0.053)	(0.042)
Luce error	Constant	4.136***	3.627***
		(0.754)	(0.675)
	CL order FE	Yes	Yes
	Enumerator FE	Yes	Yes
	Observations	9,112	12,316
	Log-likelihood	-6149	-8284
	N_clusters	828	830

Models based on switch point rows in each CL. Cluster-corrected standard errors in parentheses, clustering on subjects. *** p<0.01, ** p<0.05, * p<0.1.

results for this sub-sample consisting of 196 students. A discount rate reduction from 91% for the six-month model to 50% in the 12-month model indicates that there is still a remaining hyperbolic effect in this sub-sample, but the gap (41%) is substantially lower than in Table 6 (61%= 104% - 43%).

It has been suggested that the hyperbolic effect could also be due to survival uncertainty or limited confidence related to receiving more distant future prospect payments (T. Epper et al., 2011; T.F. Epper & Fehr-Duda, 2024; Halevy, 2008). We do not have any data on such perceptions of survival or confidence in receiving future payments. We expected that the students would have high confidence in their own survival the next year, even though we carried out the experiment during the third wave of the coronavirus pandemic. On the other hand, their confidence in receiving the payment one year into the future could be lower. We decided to try to calibrate the models above with the extra survival probability and see how its size would affect the discount rates in the six- and 12-month models, assuming the $w(p)$ functions do not change and that the combined survival ($survP$) and risk probabilities are multiplicative for the distant future ($w(p){*}w(survP)$). Table 10 contains the calibrated model results for the sample that did not commit any t-violations with $survP = 0.9$ in Models (1) and (2) and with $survP = 0.75$ in Models (3) and (4). We see a stronger relative reduction in discount rates in the six-month models than in the 12-month models. Therefore, the discount rate gaps for the six- versus 12-month horizon models are further reduced to 24% with $survP = 0.9$ and to about 13% with $survP = 0.75$.

In Figures 2b and 2c, we predicted the $w(p)$ function based on the estimated Prelec parameters for the 196 students with $viol6t = 0$ and the 160 students with $viol6p = 0$ for the 6- and 12-month horizons. The $viol6t = 0$ group is substantially more risk averse in the 6-month horizon and more optimistic (less risk averse) in the 12-month

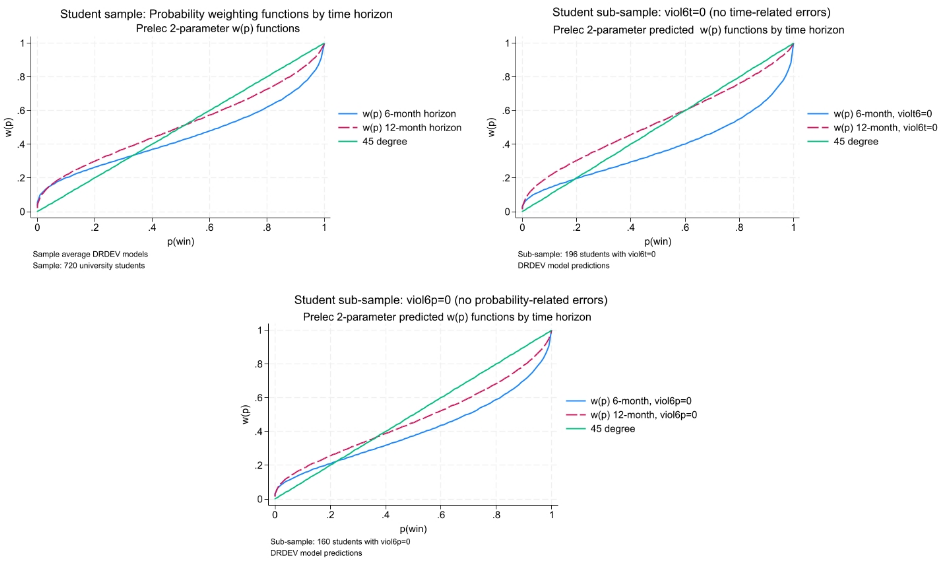

Fig. 2 Student sample: Population-average w(p) functions vs. sub-samples with viol6t=0 and vs. sub-sample with viol6p=0 for 6- and 12-month horizons

horizon perspective. We see the same tendency for the $viol6p = 0$ group, but the gap between the six-month and 12-month $w(p)$ functions is smaller. We can be confident that these estimates are not biased due to decision errors in contrast to Figure 3a, which contains the estimated $w(p)$ functions for the full sample.

5.3.2 Rural sample

We will now investigate how the variation in consistency violations is related to the discount rates and the $w(p)$ function in the rural sample. First, we tested a comprehensive model that included linear and squared $viol6t$ and $viol6p$ in all three equations. However, we found only linear $viol6t$ significant (in most equations). We, therefore, only include these simpler models in Table 11. Table 11 shows that $viol6t$ is significant, with a positive sign in the 6-month model and significant and negative in the 12-month model. These slope effects are similar to those for the student sample and should give a similar predicted pattern to Figure 4 for the student sample but with a slightly stronger downward slope for the 12-month model. Therefore, the number of consistency violations in the time dimension is associated with a strong increase in the degree of hyperbolic discounting in both samples. Like in the student sample, those not committing any such decision errors also had significantly lower discount rates in the 12-month horizon than in the six-month horizon model.

Table 11 shows that for the Prelec α parameter, there is a strong positive and significant correlation with $viol6t$ and a negative and significant correlation with $viol6p$ from an intercept level of Prelec α=0.52. Therefore, those not committing any decision errors exhibit a strong inverse-S-shaped $w(p)$ function, and probability-related errors ($viol6p$) make this worse in the 6-month model. However, these error terms are

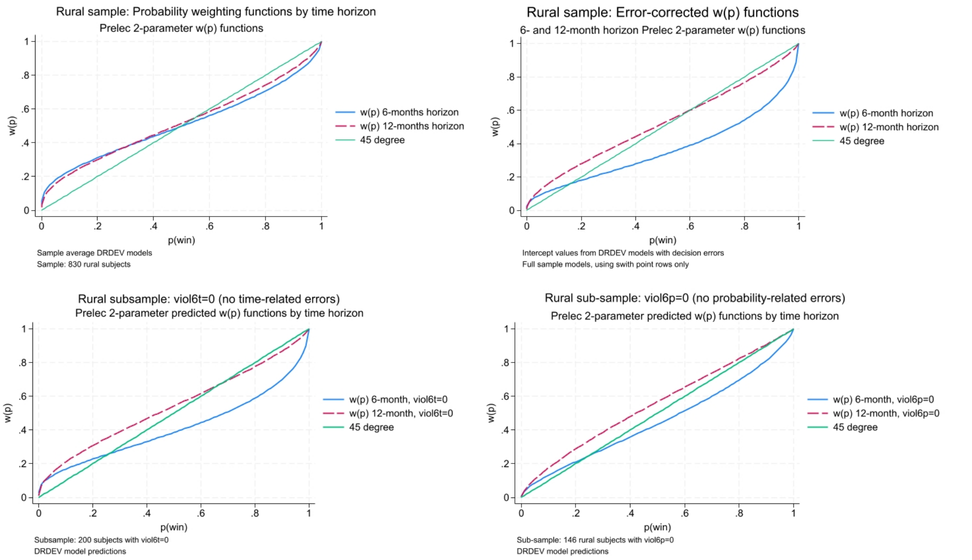

Fig. 3 Rural sample: Uncorrected vs. Error-corrected w(p)-functions vs. error-free sub-samples by time horizon

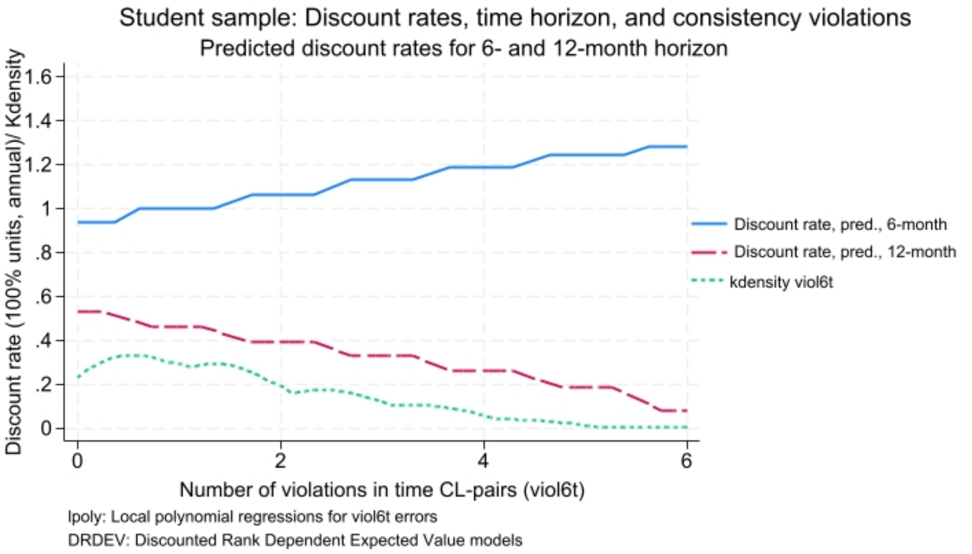

Fig. 4 Student sample: Predicted discount rates by time horizon and number of consistency violations in paired time CLs

Table 8 Student sample: TR consistency violations, student memory index, discounting, and probability weighting (DRDEV models)

EQUATION	VARIABLES	(1) 6 months	(2) 12 months
Discount rate	viol6t	0.067***	-0.061**
		(0.024)	(0.024)
	viol6p	-0.029	-0.028
		(0.025)	(0.041)
	Constant	0.978***	0.558***
		(0.063)	(0.083)
CEMU-θ	Constant	0.000	0.000
Prelec α	viol6t	0.095*	-0.069
		(0.049)	(0.044)
	viol6p	0.013	0.001
		(0.032)	(0.111)
	Constant	0.347***	0.732**
		(0.084)	(0.313)
Prelec β	viol6t	-0.203***	0.015
		(0.034)	(0.079)
	viol6p	-0.098***	0.031
		(0.032)	(0.072)
	Constant	1.491***	0.794***
		(0.090)	(0.105)
Luce error	viol6t	0.045	0.065
		(0.122)	(0.067)
	viol6p		0.357**
			(0.159)
	CL-order FE	Yes	Yes
	Enumerator FE	Yes	Yes
	Constant	3.208***	4.055***
		(0.778)	(0.918)
	Observations	8,246	11,016
	p	0.000346	0.0322
	chi2	15.94	6.869
	Log-likelihood	-5505	-7359
	N_clusters	720	720

Cluster-corrected standard errors in parentheses, clustering on subjects. *** p<0.01, ** p<0.05, * p<0.1.

insignificant in the 12-month model, where the intercept term is substantially higher (0.79).

The models for the sub-sample of rural respondents that did not commit any errors in the time-related CL pairs ($viol6t$=0) are presented in Table 12, models (1) and (2), with $w(p)$ functions in Figure 3. We see a longer time horizon (12 months) is associated with more patience and optimism for the rural sample, as was the case for the student sample.

The hyperbolic effect, measured as the gap in annualized discount rates in the 6- and 12-month models, is reduced from 67% for the full sample (Table 7) to 43% for

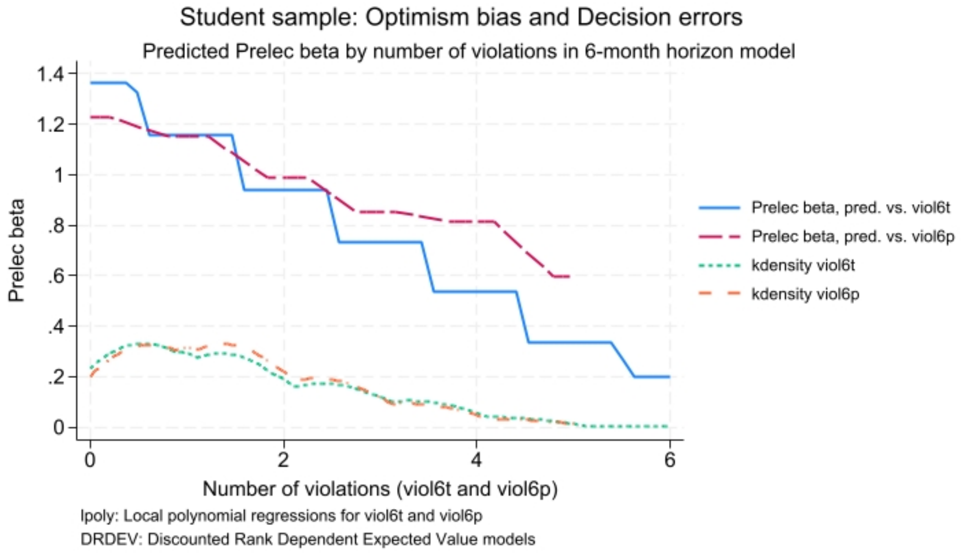

Fig. 5 Predicted Prelec β by number of consistency violations (*viol6t* and *viol6p*) in 6-month horizon DRDEV models

Table 9 Student samples without consistency errors (viol6t=0 or viol6p=0), models with switch point rows only

EQUATION	VARIABLES	(1) 6-month viol6t=0	(2) 12-month viol6t=0	(3) 6-month viol6p=0	(4) 12-month viol6p=0
Discount rate	Constant	0.910***	0.499***	0.982***	0.443***
		(0.052)	(0.038)	(0.051)	(0.048)
CEMU-θ	Constant	0.000	0.000	0.000	0.000
Prelec α	Constant	0.507***	0.743***	0.546***	0.648***
		(0.045)	(0.083)	(0.058)	(0.071)
Prelec β	Constant	1.278***	0.836***	1.200***	1.002***
		(0.078)	(0.066)	(0.091)	(0.080)
Luce error	Constant	2.189***	2.915***	2.869***	3.425***
		(0.395)	(0.618)	(0.807)	(1.093)
	CL-order FE	Yes	Yes	Yes	Yes
	Enumerator FE	Yes	Yes	Yes	Yes
	Observations	2,266	2,986	1,876	2,466
	Log-likelihood	-1519	-1986	-1253	-1646
	N_clusters	196	196	160	160

Cluster-corrected standard errors in parentheses, clustering on subjects. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 10 Student sample (n=196) without consistency errors (viol6t=0) without and with a survival or payment uncertainty rate

EQUATION	VARIABLES	(1) 6-month survP=0.9	(2) 12-month survP=0.9	(3) 6-month survP=0.75	(4) 12-month survP=0.75
Discount rate	Constant	0.635***	0.397***	0.398***	0.270***
		(0.100)	(0.054)	(0.142)	(0.071)
CEMU-θ	Constant	0.000	0.000	0.000	0.000
Prelec α	Constant	0.507***	0.743***	0.507***	0.743***
		(0.045)	(0.083)	(0.045)	(0.083)
Prelec β	Constant	1.278***	0.836***	1.278***	0.836***
		(0.078)	(0.066)	(0.078)	(0.066)
Luce error	Constant	2.189***	2.915***	2.189***	2.915***
		(0.395)	(0.618)	(0.395)	(0.618)
	CL-order FE	Yes	Yes	Yes	Yes
	Enumerator FE	Yes	Yes	Yes	Yes
	Observations	2,266	2,986	2,266	2,986
	Log-likelihood	-1519	-1986	-1519	-1986
	N_clusters	196	196	196	196

Models (1) and (2) assume a survival (or payment probability) rate of 0.9, models (3) and (4) assume a survival rate of 75% one year into the future as added risk on future payments. Cluster-corrected standard errors in parentheses, clustering on subjects. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

the $viol6t = 0$ sample (n=200) in Table 12 and to 62% for the $viol6p = 0$ sample (n=146) in Table 12.

We explored further by simulated prediction of survival probability or payment risk on the discount rates following the same approach as for the student sample. The models with $survP = 0.9$ and 0.75 are presented in Table 13. We see that the discount rate gap is reduced to 31 and 25% for the $viol6t = 0$ and with $survP = 0.9$ and 0.75.

Figures 4b, 4c, and 4d show the predicted $w(p)$ functions for the "intercept zero error" (4b) models in Table 11, the $viol6t = 0$ sample (196 subjects) (4b), and the $viol6p = 0$ sample (160 subjects) (4b), based on the estimated models in Table 12.

Those not committing any decision errors are more pessimistic in the six-month model, but time-related errors are associated with a less pessimistic (lower Prelec β) $w(p)$, while probability-related errors pull in the direction of more optimism in the 12-month model.

In both samples, those committing more mistakes are relatively more optimistic. In the 12-month models, all were substantially more optimistic. Those demonstrating the highest level of cognitive ability to make consistent decisions have a strong inverse-S-shaped and quite pessimistic (risk averse) $w(p)$ function in the 6-month horizon. As for the student sample, the rural subjects, also those committing few errors, had a less non-linear and more optimistic $w(p)$ function for the more distant 12-month time horizon.

Table 11 Rural sample: TR consistency violations and parameter bias: Models including switch point rows only from CLs

EQUATION	VARIABLES	(1) 6 months	(2) 12 months
Discount rate	viol6t	0.069***	-0.085**
		(0.025)	(0.035)
	viol6p	-0.017	-0.017
		(0.033)	(0.033)
	Constant	1.145***	0.739***
		(0.099)	(0.095)
CEMU-θ	Constant	0.000	0.000
Prelec α	viol6t	0.163***	-0.035
		(0.046)	(0.042)
	viol6p	-0.097**	-0.010
		(0.038)	(0.052)
	Constant	0.520***	0.794***
		(0.093)	(0.110)
Prelec β	viol6t	-0.191***	0.074
		(0.039)	(0.056)
	viol6p	-0.084	-0.088**
		(0.058)	(0.042)
	Constant	1.340***	0.875***
		(0.117)	(0.125)
Luce error	viol6t	0.361**	0.403*
		(0.166)	(0.211)
	viol6p	-0.002	0.176
		(0.284)	(0.289)
	CL-order FE	Yes	Yes
	Enumerator FE	Yes	Yes
	Constant	3.433***	2.320*
		(0.757)	(1.186)
	Observations	9,088	12,284
	p	0.00902	0.0385
	chi2	9.417	6.517
	Log-likelihood	-6127	-8254
	N_clusters	826	828

Cluster-corrected standard errors in parentheses, clustering on subjects. *** p<0.01, ** p<0.05, * p<0.1.

6 Discussion

We have estimated discount rates and probability weighting functions for a large university student sample (high education) and a large rural (low education) sample in an African context (Malawi). We were inspired by the recent literature that has suggested that the behavioral phenomena described as hyperbolic discounting and non-linear (inverse-S-shaped) probability weighting may be the outcome of systematic decision errors (cognitive noise and uncertainty) Enke and Graeber (2023); Enke et al. (2023). We used an innovative experimental design comprising 20 Choice Lists (CLs) with integrated decisions combining risk and time with a rapid binary choice eliciting procedure as a basis for the identification of within-subject decision errors and for

Table 12 Rural samples without consistency errors (viol6t=0 or viol6p=0)

EQUATION	VARIABLES	(1) 6-month viol6t=0	(2) 12-month viol6t=0	(3) 6-month viol6p=0	(4) 12-month viol6p=0
Discount rate	Constant	1.061***	0.630***	1.243***	0.624***
		(0.058)	(0.044)	(0.064)	(0.056)
CEMU-θ	Constant	0.000	0.000	0.000	0.000
Prelec α	Constant	0.521***	0.777***	0.738***	0.936***
		(0.066)	(0.086)	(0.114)	(0.115)
Prelec β	Constant	1.156***	0.815***	1.094***	0.798***
		(0.089)	(0.083)	(0.118)	(0.134)
Luce error	Constant	3.315***	2.525***	4.074***	3.350***
		(0.379)	(0.421)	(0.590)	(0.589)
	CL-order FE	Yes	Yes	Yes	Yes
	Enumerator FE	Yes	Yes	Yes	Yes
	Observations	2,186	2,978	1,566	2,112
	Log-likelihood	-1470	-1990	-1053	-1418
	N_clusters	199	200	145	146

Cluster-corrected standard errors in parentheses, clustering on subjects. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 13 Rural sample (n=200) without consistency errors (viol6t=0) with alternative survival or payment uncertainty rates of 0.9 and 0.75

EQUATION	VARIABLES	(1) 6-month SurvP=0.9	(2) 12-month SurvP=0.9	(3) 6-month SurvP=0.75	(4) 12-month SurvP=0.75
Discount rate	Constant	0.863***	0.550***	0.700***	0.446***
		(0.097)	(0.055)	(0.127)	(0.070)
CEMU-θ	Constant	0.000	0.000	0.000	0.000
Prelec α	Constant	0.521***	0.777***	0.521***	0.777***
		(0.066)	(0.086)	(0.066)	(0.086)
Prelec β	Constant	1.156***	0.815***	1.156***	0.815***
		(0.089)	(0.083)	(0.089)	(0.083)
Luce error	Constant	3.315***	2.525***	3.315***	2.525***
		(0.379)	(0.421)	(0.379)	(0.421)
	CL-order FE	Yes	Yes	Yes	Yes
	Enumerator FE	Yes	Yes	Yes	Yes
	Observations	2,186	2,978	2,186	2,978
	Log-likelihood	-1470	-1990	-1470	-1990
	N_clusters	190	200	199	200

Models (1) and (2) assume a survival (or payment probability) rate of 0.9, models (3) and (4) assume a survival rate of 75% one year into the future as added risk on future payments. Cluster-corrected standard errors in parentheses, clustering on subjects. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

joint estimation of discount rates and probability weighting functions 6 and 12 months into the future. Subject-level decision errors were recorded based on paired CLs that differed only in time horizon or probability. We have stated several hypotheses and will summarize and discuss the test results here.

Hypothesis H1. *Students commit fewer decision errors than the rural (low education) subjects.* We cannot reject this hypothesis as the difference in mean time- and probability-related errors significantly differed in the two samples. However, the differences in the mean number of errors for the two samples were surprisingly small (Cohen's *d*s 0.15-0.23), indicating a surprisingly small effect of higher education on the propensity to commit errors with our experimental tool.

Hypothesis H2a. *The rural sample exhibits stronger hyperbolic discounting than the student sample.* While we found weak evidence in this direction, we found a strong hyperbolic pattern in both samples. The gaps between the annualized discount rates in the rural versus student samples were 67% and 61%.

Hypothesis H2b. *The rural sample exhibits a stronger inverse-S-shaped $w(p)$ function than the student sample.* We have to reject this hypothesis. Tables 6 and 7 show that the Prelec α parameters are slightly lower for the student sample than for the rural sample both in the six- and the 12-month models.

Hypothesis H3a. *More time-related decision errors are associated with stronger hyperbolic discounting in both samples.* We find strong evidence in support of this hypothesis in both samples. Decision errors, therefore, appear to contribute to the apparent diminishing impatience with an extended time horizon. However, we found that the sub-samples that did not commit any decision errors also exhibited diminishing impatience, although to a lower degree. This may indicate that there is more than one explanation for the phenomenon.

Hypothesis H3b. *More probability-related decision errors are associated with stronger inverse-S-shaped $w(p)$ functions in both samples.* We have to reject this hypothesis. While the results are a bit mixed, the subjects that did not commit any probability-related decision errors have stronger inverse-S-shaped $w(p)$ functions, especially in the six-month horizon models.

Overall, we found that future optimism bias is associated with more inconsistent decisions for our subjects. Our findings indicated that the $w(p)$-function parameters were more sensitive to the decision error variables in the 6-month than in the 12-month models, with more decision errors associated with stronger optimism in the 6-month horizon. Optimism was stronger in the 12-month horizon models but did not vary significantly with the number of decision errors except for p-violations in the rural sample.

This is the first study to estimate such probability weighting functions for different time horizons both in the lab (student sample) and in the field (rural sample) in a developing country (Malawi). Our findings are consistent with earlier studies that state that subjects become more risk-tolerant when the outcomes occur further into the future. It may appear surprising that people become more optimistic and willing to take risks related to more distant future prospects when uncertainty should grow with distance into the future. We are not sure about the psychology and heuristics behind this finding. It requires further research. This result remains strong for the sub-samples of students and rural subjects that did not make any decision errors in our experiment. We cannot, therefore, blame it away on decision errors. Why are the more rational (more consistent) decision-makers fairly risk-neutral regarding risky prospects with payouts one year into the future but strongly risk-averse in risky prospects with a payout six months into the future? This is a striking result that we cannot explain.

We find the same result for both the student and rural samples. The result that delay is associated with higher risk tolerance is not a new finding (Abdellaoui et al., 2011; Coble & Lusk, 2010; Kemel & Paraschiv, 2023; Noussair & Wu, 2006; Shelley, 1994). Shelley (1994) found that subjects were more risk-tolerant towards large distant future losses. Noussair and Wu (2006) found the same without considering probability weighting, based on an incentivized experiment with a fairly small student sample (63 undergraduate students in Emory University, Atlanta). Coble and Lusk (2010) found the same in a sample of 47 undergraduate and graduate students in the US and associated this with a less concave utility function (lower risk aversion). Abdellaoui et al. (2011) also found subjects more risk tolerant in delayed lotteries. A difference between their study and ours is that they also delayed the time for the lottery. We played out the lottery immediately after the games were played, but the payouts would occur at different times. In our experiment, the subjects had a 10% chance of winning in the game in a randomly drawn CL out of 20 CLs. Nevertheless, our results are strikingly similar to those of Abdellaoui et al. (2011). They found that utility curvature does not explain the result, which the probability weighting function absorbed. Their finding is that time delay results in probabilistic optimism and, therefore, higher risk tolerance for delayed lotteries. They had a small sample (52 undergraduate students from a university in Turkey), and one may wonder about the external validity of their results. Our finding of similar results in two large samples, including a university student sample and a rural sample with limited education, attests to their results' external validity. Furthermore, we find that decision errors do not drive the result as the result is even strengthened when we limit our analysis to the sub-samples that did not commit any time-horizon-related decision errors.

We may wonder what difference the timing of the risk resolution makes compared to the timing of payouts for the risky prospects. Abdellaoui et al. (2022) made an explicit study of this. They considered cases where a lottery could be a) resolved and paid immediately, b) resolved and paid later, and c) resolved immediately but paid later. Our experiment belongs to the last category. Noussair and Wu (2006) and Abdellaoui et al. (2011) compared cases a) and b) and showed that b) was associated with more risk tolerance than a). Our contribution is finding the same in the case of c). The timing of the resolution, whether it is immediate or delayed, seems to be less important than the timing of the payout for the effect on risk tolerance. Abdellaoui et al. (2022) compared cases b) and c). They found a general preference for early resolution of the risk, and this preference increased with the probability of winning. They also found that the probability weighting dominated the utility-related effects of temporal risk on preferences and suggested that a linear relationship ($U_0 = U_t$) between the utilities at the alternative points in time is adequate based on a comprehensive assessment of alternative transformation functions.

Kemel and Paraschiv (2023) experimented on risk attitudes with immediate versus delayed outcomes while excluding discounting as a covariate in their design. Their sample consisted of 70 undergraduate students from the University of Paris. They also found that delayed outcomes were associated with higher risk tolerance and that this effect largely came through the probability weighting function in the form of a more elevated (optimistic) function for delayed prospects.

We used models with linear utility as the main models in our analysis because the concave utility was found to lead to negative discount rates for our data's longest time horizon (2 years). After selecting the sub-samples that did not commit any decision errors, our result was similar: the subjects were more optimistic in the 12-month than in the six-month horizon models (Tables 10 and 12). We found the degree of optimism to be even stronger in the rural sample than in the student sample. This is striking as these rural subjects live in an environment with frequent severe climate shocks and poverty. A recent study in Ethiopia found that poor rural subjects became more willing to take risks after being exposed to a severe climate shock (drought) (Holden & Tilahun, 2024).

The rural sample had higher discount rates than the student sample. We investigated the effect of imposing a survival rate or limited trust in receiving payment of late outcomes as proposed by Halevy (2008). Including such survival constraints resulted in a substantial reduction in the discount rates, especially in the six-month horizon models (Tables 10 and 13). We showed with simulations that such survival constraints or additional risks associated with future payments also may contribute to explaining the hyperbolic pattern in the data in line with the findings of (T. Epper et al., 2020, 2011; T.F. Epper & Fehr-Duda, 2024; Halevy, 2008).

Our study also provides an interesting finding related to earlier studies finding that certain future outcomes are discounted more heavily than uncertain future outcomes(Andreoni & Sprenger, 2012; T.F. Epper & Fehr-Duda, 2024). Our data reveal the same result if we assume linear probability weighting and linear utility (DEV models). The discount rate is then strongly positively correlated with the probability of winning. However, when we allow non-linear probability weighting, this positive and significant result disappears and can even turn in the opposite direction in DRDEV models (see models in Tables B4-B11 in Appendix B). This is, therefore, not a robust result but may be a result of not considering non-linear probability weighting. We, therefore, assumed that discounting was independent of the probability of winning in our DRDEV models, which form the backbone of our analyses.

7 Conclusion

In our cognitive limitations approach, we allow errors because of prior beliefs, imprecise and unstable preferences due to uncertainties, and calculation errors due to limited numeracy skills. We have used an experiment with many binary decisions in a within-subject design to measure the consistency in decision-making related to simple preference ranking of prospects over risk and time. We have used the frequency of decision errors in the form of consistency violations to assess whether such errors can explain hyperbolic discounting and non-linear (inverse-S-shaped) probability weighting. If decision errors are the sole reason for these phenomena, subjects not committing such errors should not exhibit these phenomena. On the other hand, if decision errors associated with cognitive limitations are one of several reasons for these phenomena, these phenomena may be positively correlated with the frequency of decision errors but only partially explain these. Our results indicate that decision errors as measures of cognitive limitations explain a large part of the hyperbolic discounting pattern. Uncertainty about future payments may possibly contribute to explaining an additional part of the hyperbolic pattern. However, when it came to the inverse-S-shaped probability weighting, we did not find that the frequency of decision errors in our experiment could explain this phenomenon, which remained persistent and strong for those not committing any decision errors in the high-education student sample and the low-education rural sample. While the student sample, on average, made fewer decision errors than the rural sample, Cohen's ds for the differences in error-making in time and probability comparisons were small, in the range of 0.15-0.23. This shows a weak influence of formal schooling on subjects' ability to make consistent decisions across a large number of binary choices.

Many types of decisions are associated with substantial delays before the outcomes of the decisions materialize. Climate change policies represent one example of this. People's time and risk preferences may substantially impact their attitudes toward future climate change risks. Our study focuses on the delayed outcomes materializing six months to two years after the decisions were taken and mostly on decisions with payout 6 and 12 months into the future. These horizons fit well with the annual cycles of students and rural agricultural households in our two samples. The decisions to invest in agricultural production must be made early in the rainy season before the weather has been revealed.[15] Exposure to such climate shocks and information about climate change and the need for adaptation to climate change imply that they must make decisions over risk and time that are vital for survival. A better understanding of their decisions is important for climate and agricultural policies that can better facilitate adaptation to climate change.

Our study reveals two counter-acting elements regarding people's motivation to invest in the future: their discounting behavior related to risky returns and how they weigh future risks. A hyperbolic discounting function should indicate increasing patience related to the receipts of future returns and a willingness to invest when far future returns are relatively low. This may indicate a stronger willingness to invest in future climate change mitigation. Our finding that hyperbolic discounting, to a large extent, may be an experimental artifact due to decision errors gives reason to be cautious about assuming that hyperbolism can help promote climate action. Lack of trust in future returns to the investment may further eliminate the hyperbolic pattern in discount rates. After correcting decision errors, our study revealed that the average discount rates of students and rural household members remained high in the six- to 12-month perspective. The fact that their risk tolerance increased substantially in the

[15] Rainfed agriculture, which dominates in Malawi, is exposed to climate risks in terms of droughts and floods that may occur between the time of cultivation and planting and the harvesting five to six months later. With only one rainy season per year, rural households must plan for a full year for production and consumption.

12-month horizon compared to the 6-month horizon indicates considerable optimism in the longer horizon and substantial risk aversion in the shorter 6-month perspective. This finding is consistent across our two large samples, and similar results have been found in several other studies with relatively small student samples in the US and Europe, attesting to their external validity. This indicates that people are less worried about the distant future, which could cause a laissez-faire attitude and a tendency to postpone actions. While procrastination behavior has been associated with present bias, our study indicates that optimism bias related to future outcomes may result in a similar tendency to procrastinate actions related to more distant future risks. In Malawi, such optimism bias may lead to insufficient climate actions and adaptations to prevent catastrophic future outcomes.

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Declarations

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- Conflict of interest/Competing interests: The authors declare no conflicts of interest.
- Ethics approval: Norwegian Agency for Development Cooperation (NORAD) approved the project that aims to enhance collaborative research between the Norwegian University of Life Sciences (NMBU) and Lilongwe University of Agriculture and Natural Resources (LUANAR) and to contribute to capacity-building within Behavioral and Experimental economics in LUANAR. At the time of the project's establishment, the two universities did not have review boards for the ethical assessment of experimental protocols in experimental economics. The experiments used in the project are standard incentivized experiments used in many research projects in behavioral and experimental economics. The researchers in the project push for the establishment of Institutional Review Boards in both universities and have used general guidelines to meet all ethical requirements associated with the types of experiments used in the project, including prior informed consent and ensuring the anonymity of all respondents in all shared data and publications. Special care was taken as the experiments took place during the fourth round of the coronavirus pandemic in Malawi to satisfy all safety measures needed to avoid contributing to the spread of the virus.
- Consent to participate: After receiving an introduction, all subjects were explicitly asked at the beginning of each round about their consent to participate.
- Consent for publication: All authors are project members who have participated and agreed to publish the work jointly.
- Availability of data and materials: Experimental protocols and data will be made available upon the paper's publication and can be made available for reviewers upon request.
- Code availability: Codes for data analyses will be made available upon the publication of the paper and can be made available for reviewers upon request.

Table A1 Certainty Equivalent statistics for each sample by CL (mean, median, and standard deviations

CL No.	Student CE-Mean	sample CE-p50	n=721 CE-SD	Rural CE-Mean	sample CE-p50	n=835 CE-SD
1	766	450	734	885	450	908
2	1192	1050	844	1235	1050	1002
3	965	750	791	1073	750	954
4	3475	2250	3848	3667	1000	4438
5	5561	5250	4354	5235	3750	4789
6	4474	3750	4001	4465	2250	4565
7	1417	1050	1495	2069	1050	2080
8	1612	1050	1537	2176	1350	2044
9	1447	1050	1453	2217	1350	2030
10	1723	1050	1567	2350	1750	2059
11	1888	1050	1759	2889	2500	2316
12	2305	1750	1825	3172	3500	2257
13	3508	2250	3690	3800	2250	4279
14	3041	2250	3483	3517	1000	4133
15	4545	3750	3782	4692	2250	4492
16	3996	2250	3594	4500	2250	4355
17	4463	3750	3963	4370	2250	4432
18	3700	2250	3574	4199	2250	4366
19	2087	1500	1689	2060	1500	1920
20	10215	7500	8760	10317	7500	9882

- Authors' contributions: Stein T. Holden (First author). The initial design of experimental protocols, conceptual ideas, data checking and cleaning, variable construction, statistical analysis, and paper write-up. Sarah Tione. Comments on experimental protocol, training of enumerators, implementation of experiments, data checking, and corrections. Mesfin Tilahun. Comments on experimental protocol, training of enumerators, piloting and implementation of experiments, commenting on drafts. Samson Katengeza. Comments on experimental protocol, recruitment of enumerators, and implementation of experiments, comments on drafts.

Appendix A Certainty Equivalent statistics by CL

The CLs are constructed to facilitate pairwise consistency checks for the CEs. CLs 1-3 have far future and near future amounts that are one-fifth in value of those in CLs 4-6. All the amounts are the same within CLs 1-3 and within CLs 4-6. Similarly, CLs 19 and 20 have values in CL 19 that are one-fifth of CL20. As both these lists have a p(win)=0.5, their expected values for near and far future amounts are identical to those for CLs 1-3 and 4-6, respectively. These differences in amount levels provide an opportunity to assess the concavity of the utility function. With linear utility, the near future CEs should be one-fifth in CLs 1-3 vs. CLs 4-6 and for CL19 vs. CL20.

To more easily compare and assess whether the linear utility is a reasonable assumption, we compare CLs 1-6 and CLs 19-20 after multiplying all values in CLs 1-3 and 19 with five. We compare the means, medians, and standard deviations for

Table A2 Adjusted Certainty Equivalent statistics for each sample by CL (mean, median, and standard deviations

CL No.	FFT	Student CE-Mean	sample CE-p50	n=721 CE-SD	Rural CE-Mean	sample CE-p50	n=835 CE-SD
1	24	3830	2250	3670	4423	2250	4542
4	24	3475	2250	3848	3667	1000	4438
3	12	4823	3750	3957	5365	3750	4768
6	12	4474	3750	4001	4465	2250	4565
2	6	5962	5250	4220	6175	5250	5008
5	6	5561	5250	4354	5235	3750	4789
19	12	5218	3750	4224	5150	3750	4799
20	12	5108	3750	4380	5158	3750	4941

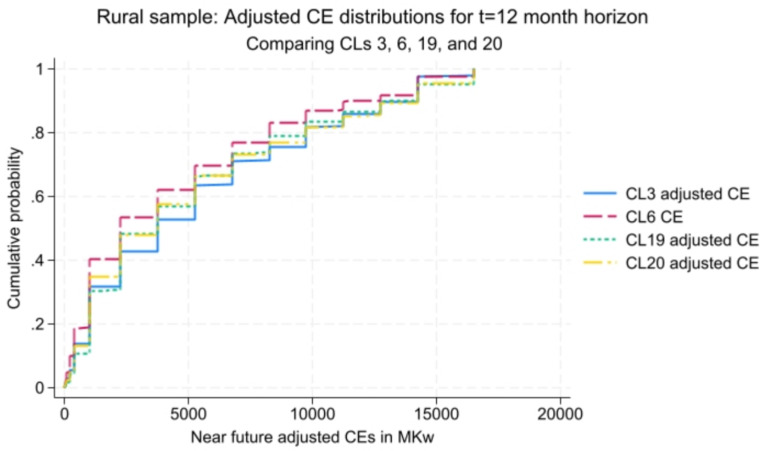

Fig. A1 Rural subjects with high cognitive ability: Estimated w(p) functions by time horizon

these after this adjustment in Table A2, where we have reorganized the CLs' order to pair CLs with the same time horizon.

Table A2 indicates that the linear utility assumption is reasonable for the student sample, as the median CEs match perfectly. The mean values for the students point in the direction of a weak concave utility. For the rural sample, we have stronger indications of utility being concave. This may also be one reason for the finding of higher discount rates in the rural sample than in the student sample in our DRDEV models with linear utility.

Figure A1 presents the adjusted CE cumulative distributions for the 12-month horizon CLs 3, 6, 19, and 20 as an additional inspection for the rural sample. While CLs 3 and 6 indicate concave utility, CLs 19 and 20 do not.

Based on CLs 1-6 evidence for the rural sample, we also run DRDU models for the rural sample without consistency violations (n=200) with a CEMU-θ=0.2, see Table A3. The results are with two alternative survival/future payment risk rates. This concave utility function brought the sample discount rates down and more closely to the levels of the student sample models with linear utility in the models with the

Table A3 Rural sample (n=200) without consistency errors (viol6t=0): DRDU models (CEMU-θ=0.2) with a survival or payment uncertainty rates of 0.9 and 0.75

EQUATION	VARIABLES	(1) 6-month SurvP=0.9	(2) 12-month SurvP=0.9	(3) 6-month SurvP=0.75	(4) 12-month SurvP=0.75
Discount rate	Constant	0.644***	0.331***	0.482***	0.227***
		(0.097)	(0.055)	(0.126)	(0.070)
CEMU-θ	Constant	0.200	0.200	0.200	0.200
Prelec α	Constant	0.523***	0.781***	0.523***	0.781***
		(0.067)	(0.086)	(0.067)	(0.086)
Prelec β	Constant	0.926***	0.654***	0.926***	0.654***
		(0.072)	(0.067)	(0.072)	(0.067)
Luce error	Constant	2.660***	2.024***	2.660***	2.024***
		(0.304)	(0.337)	(0.304)	(0.337)
	CL-order FE	Yes	Yes	Yes	Yes
	Enumerator FE	Yes	Yes	Yes	Yes
	Constant	1.041***	0.869***	1.041***	0.869***
		(0.242)	(0.239)	(0.242)	(0.239)
	Observations	2,186	2,978	2,186	2,978
	Log-likelihood	-1470	-1990	-1470	-1990
	N_clusters	199	200	199	200

Models with concave utility and survival constraints by time horizon. Can be compared with Table 13 (models with linear utility). Cluster-corrected standard errors in parentheses, clustering on subjects. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

survival constraint (Tables 9 vs. 10). The hyperbolic effect remained stronger in the rural sample.

Appendix B Discounted Expected Value (DEV) models for all time horizons

Tables B4 (student sample) and B5 (rural sample) present Discounted Expected Value models for each time horizon (6, 12, and 24 months) with contextual Luce errors. They demonstrate the sharp decline in discount rates (hyperbolic discounting) as time horizons are extended. With the 24-month horizon, the discount rate is close to zero in the student sample. Imposing a concave utility function would make these long-term discount rates negative. We have, therefore, retained a linear utility function in all models presented in this paper.

It has been found that certain outcomes are discounted more heavily than risky ones (T.F. Epper & Fehr-Duda, 2024; Keren & Roelofsma, 1995). We investigate this in the DEV framework below in Tables D8 and D9. We see in both tables (five of six models) that the p(win) is significantly positively correlated with the discount rate in line with this. We may, however, wonder whether this phenomenon is associated with non-linear probability weighting. We investigate this by allowing for a one-parameter Prelec $w(p)$ function. Tables B8 and B9 test what happens to the sign and significance of the p(win) variable. We see that the sign changes in the opposite direction in two of the three models in Table B8 and is only weakly significant and positive in one of

Table B4 Student sample: Discounted Expected Value models

EQUATION	VARIABLES	(1) 6-month	(2) 12-month	(3) 24-month
Discount rate	Constant	1.059***	0.404***	-0.054
		(0.025)	(0.025)	(0.036)
Luce error	probwin1	-1.691***	-1.614***	
		(0.237)	(0.279)	
	Constant	4.903***	6.183***	4.427***
		(0.835)	(0.884)	(0.711)
	Observations	8,246	11,016	5,594
	Log-likelihood	-5520	-7377	-3704
	N_clusters	720	720	718

Cluster-corrected standard errors in parentheses, clustering on subjects.
*** p<0.01, ** p<0.05, * p<0.1.

the models in Table B9. We interpret this cautiously as a sign that this phenomenon is not a robust finding independent of whether probability weighting is non-linear. Allowing for the 2-parameter Prelec $w(p)$ function is also tested in Tables B10 and B11. This further strengthens the evidence that non-linear probability weighting is the basic reason for the apparent phenomenon that certain outcomes are discounted more heavily than risky ones. The models generate implausible results when the time horizon is 6 months (very low Prelec α and the discount rates becoming strongly negatively correlated with p(win), opposite of the DEV model). The results are similar if we run these models for the sample that did not commit any decision errors ($viol6t$=0). We interpret the risk-dependent discount rate result as an artifact associated with not considering non-linear probability weighting of risk. Consequently, all our main DRDEV models assume that the discount rate does not vary with risk.

Table B5 Student sample: Discounted Expected Value models

EQUATION	VARIABLES	(1) 6-month	(2) 12-month	(3) 24-month
Discount rate	viol6t	0.000	-0.047**	-0.068**
		(0.024)	(0.019)	(0.032)
	viol6p	-0.057***	-0.035*	-0.086**
		(0.021)	(0.018)	(0.039)
	Constant	1.137***	0.513***	0.084
		(0.059)	(0.043)	(0.067)
Luce error	probwin1	-1.689***	-1.574***	
		(0.240)	(0.252)	
	Constant	4.975***	6.147***	4.234***
		(0.828)	(0.839)	(0.742)
	Observations	8,246	11,016	5,594
	p	0.0157	0.00992	0.000201
	chi2	8.304	9.226	17.02
	Log-likelihood	-5518	-7375	-3699
	N_clusters	720	720	718

Cluster-corrected standard errors in parentheses, clustering on subjects.
*** p<0.01, ** p<0.05, * p<0.1.

Table B6 Student sample: Discounted Expected Value models

EQUATION	VARIABLES	(1) 6-month	(2) 12-month	(3) 24-month
Discount rate	viol6t	0.000	-0.054***	-0.067*
		(0.025)	(0.020)	(0.034)
	viol6p	-0.056***	-0.023	-0.086**
		(0.022)	(0.020)	(0.039)
	probwin1	0.361***	0.383***	-0.022
		(0.053)	(0.044)	(0.281)
	Constant	0.845***	0.228***	0.104
		(0.083)	(0.057)	(0.283)
Luce error	viol6t	0.068	0.089	
		(0.078)	(0.069)	
	viol6p		0.251***	
			(0.064)	
	probwin1	-1.177***	-1.007***	
		(0.239)	(0.279)	
	Constant	4.494***	5.073***	4.237***
		(0.863)	(0.951)	(0.746)
	Observations	8,246	11,016	5,594
	p	0	0	0.000516
	chi2	59.97	83.77	17.66
	Log-likelihood	-5514	-7364	-3699
	N_clusters	720	720	718

Cluster-corrected standard errors in parentheses, clustering on subjects.
*** p<0.01, ** p<0.05, * p<0.1.

Table B7 Rural sample: Discounted Expected Value models

EQUATION	VARIABLES	(1) 6-month	(2) 12-month	(3) 24-month
Discount rate	Constant	1.197***	0.553***	-0.022
		(0.034)	(0.032)	(0.041)
Luce error	probwin1	-2.756***	-2.510***	0.061
		(0.338)	(0.372)	(0.865)
	Constant	6.642***	6.173***	2.936***
		(0.866)	(0.787)	(0.998)
	Observations	9,112	12,316	6,508
	Log-likelihood	-6150	-8283	-4343
	N_clust	828	830	831

Models including only switch point rows. Cluster-corrected standard errors in parentheses, clustering on subjects. *** p<0.01, ** p<0.05, * p<0.1.

Table B8 Rural sample: Discounted Expected Value models: Decision error (viol6t) correlation with discount rates

EQUATION	VARIABLES	(1) 6-month	(2) 12-month	(3) 24-month
Discount rate	viol6t	0.019	-0.075***	-0.117***
		(0.020)	(0.022)	(0.030)
	Constant	1.165***	0.674***	0.159***
		(0.051)	(0.051)	(0.057)
Luce error	probwin1	-2.769***	-2.725***	0.348
		(0.339)	(0.391)	(1.282)
	Constant	6.630***	6.239***	2.625
		(0.875)	(0.733)	(1.787)
	Observations	9,088	12,284	6,492
	p	0.339	0.000752	0.000113
	chi2	0.915	11.36	14.91
	Log-likelihood	-6133	-8258	-4327
	N_clusters	826	828	829

Models including only switch point rows. Cluster-corrected standard errors in parentheses, clustering on subjects. *** p<0.01, ** p<0.05, * p<0.1.

Table B9 Rural sample: Discounted Expected Value models with p(win) dependent discount rates and time-related decision error correlations, with Luce error correlated with p(win)

		(1)	(2)	(3)
EQUATION	VARIABLES	6-month	12-month	24-month
Discount rate	viol6t	0.020	-0.078**	-0.122***
		(0.021)	(0.030)	(0.035)
	probwin1	0.457***	0.316***	0.415**
		(0.055)	(0.071)	(0.184)
	Constant	0.800***	0.448***	-0.212
		(0.072)	(0.053)	(0.180)
Luce error	probwin1	-2.235***	-2.592***	0.514
		(0.336)	(0.657)	(1.344)
	Constant	6.238***	6.141***	2.404
		(0.885)	(1.102)	(1.657)
	Observations	9,088	12,284	6,492
	p	0	5.43e-05	0.00208
	chi2	70.03	19.64	12.35
	Log-likelihood	-6130	-8255	-4327
	N_clusters	826	828	829

Probwin included in the Luce error. Cluster-corrected standard errors in parentheses, clustering on subjects. *** p<0.01, ** p<0.05, * p<0.1.

Table B10 Student sample: Discounted Rank Dependent Expected Value models with 1-parameter Prelec w(p) and p(win) dependent discount rates, with Luce error correlated with p(win)

EQUATION	VARIABLES	(1) 6-month	(2) 12-month
Discount rate	viol6t	-0.003	-0.054***
		(0.017)	(0.019)
	viol6p	-0.031	-0.024
		(0.026)	(0.020)
	probwin1	-0.034	0.089*
		(0.082)	(0.049)
	Constant	1.150***	0.443***
		(0.104)	(0.059)
Prelec alpha	viol6t	-0.058	-0.020
		(0.037)	(0.034)
	viol6p	0.000	-0.032
		(0.032)	(0.022)
	Constant	0.644***	0.709***
		(0.132)	(0.065)
Luce error	viol6t	-0.102***	0.070
		(0.024)	(0.073)
	viol6p	0.341***	0.262***
		(0.047)	(0.064)
	probwin1	-0.557**	-0.692**
		(0.227)	(0.315)
	Constant	3.534***	4.836***
		(0.848)	(0.971)
	Observations	8,246	11,016
	p	0.684	0.00420
	chi2	1.491	13.21
	Log-likelihood	-5503	-7359
	N_clust	720	720

Probwin included in the discount function and the Luce error. Cluster-corrected standard errors in parentheses, clustering on subjects. *** p<0.01, ** p<0.05, * p<0.1.

Table B11 Rural sample: Discounted Rank Dependent Expected Value models with p(win) dependent discount rates, with Luce error correlated with p(win)

EQUATION	VARIABLES	(1) FFT=6	(2) FFT=12
Discount rate	probwin1	0.067	0.086*
		(0.061)	(0.046)
	Constant	1.141***	0.523***
		(0.057)	(0.044)
CEMU-θ	Constant	0.000	0.000
Prelec α	Constant	0.514***	0.587***
		(0.045)	(0.040)
Prelec β	Constant	1.000	1.000
		(0.000)	(0.000)
Luce error	probwin1	-0.140***	-0.087*
		(0.051)	(0.051)
	startptno	0.042***	0.038***
		(0.007)	(0.006)
	Constant	1.012***	1.017***
		(0.110)	(0.120)
	Observations	50,970	69,142
	p	0.274	0.0592
	chi2	1.196	3.558
	Log-likelihood	-25218	-33303
	N_clust	828	830

Probwin included in the Luce error. Cluster-corrected standard errors in parentheses, clustering on subjects. *** p<0.01, ** p<0.05, * p<0.1.