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Does luck make people more optimistic and patient? - Lessons from an experiment with students and rural subjects in Malawi

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Abstract

We investigate how random luck in repeated variants of the risky investment game of Gneezy, Leonard, and List (2009); Gneezy and Potters (1997) influences risk-taking and discounting behavior in future risky prospects with probabilistic payouts one week, six, 12, and 24 months into the future. We test non-parametrically whether luck enhances risk-taking and patience (reduces the discount rate) in risky prospects with delayed payouts. To investigate whether luck influences probability weighting (w(p) function), we estimate structural models with two-parameter Prelec probability weighting functions to decompose risk-taking in prospects with potential payouts six and 12 months into the future. We find that luck results in more optimistic (reduces the Prelec $\boldsymbol{\beta}$ parameter) and less non-linear (inverse-S-shaped) (increases the Prelec $\boldsymbol{\alpha}$ parameter) w(p) function. We assess this for two samples from Malawi: one is a random sample of university students (n=721), and the other is a random sample (n=835) of rural

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subjects with limited education. The students were found to be more patient but had similar probability weighting functions.

Keywords: Luck, Discounting, Risk-taking, Probability weighting

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

1 Introduction

There has been a rapid expansion of the literature on behavior under risk and over time in recent years. Three important lessons from the recent experimental literature are that a) the appropriateness of framing utility over time and risk under a common utility function based on Expected Utility Theory (EUT) is questioned. Several studies have found utility in time to be close to linear and not to be matching the utility curvature estimated based on risky prospects within an EUT framework for the same subjects (Abdellaoui, Bleichrodt, l'Haridon, & Paraschiv, 2013; Abdellaoui, Diecidue, & Öncüler, 2011; Abdellaoui, Kemel, Panin, & Vieider, 2019; Andreoni, Kuhn, & Sprenger, 2015; Cheung, 2016, 2019); b) patience of subjects is increasing with the length of the time horizon, and this is not only caused by present bias (Cohen, Ericson, Laibson, & White, 2020; Enke & Graeber, 2021, 2023; Enke, Graeber, & Oprea, 2023; Grijalva, Lusk, Rong, & Shaw, 2018; Grijalva, Lusk, & Shaw, 2014; Holden & Quiggin, 2017) and c) probabilistic insensitivity is a commonly found characteristic for a large range of intermediate probability levels (p=[0.1,0.9]) in many studies Holden and Tilahun (2024); l'Haridon and Vieider (2019); Vieider, Martinsson, Nam, and Truong (2019).

This points towards the use of alternative theoretical models such as Cumulative Prospect Theory or Rank Dependent Utility (RDU), and the special case with a linear utility function, the Yaari (1987) model, where risk-taking is modeled with a non-linear probability weighting function rather than through utility function curvature. This approach facilitates the incorporation of probabilistic insensitivity and (near-)linear utility in time and risk and may be combined with time-horizon-specific discounting.

In this study, we combined several rounds of variants of the risky investment (RI) game of Gneezy et al. (2009); Gneezy and Potters (1997) and a loss aversion (LA) game followed by a Multiple Choice List (MCL) design that integrates risk and time (TR experiment) by obtaining near future certainty equivalent (CE) income for more far future risky prospects that vary in time delay and risk. The risky prospects are placed one week, six, 12, and 24 months into the future, and the probability of winning in each prospect varies with p(win) values 0.1, 0.25, 0.5, 0.75, 0.9, and 1. We also included two magnitude levels for future safe and risky amounts to test for potential utility curvature effects. The high magnitude level was five times (5x) the low magnitude level. Combining all probability, time horizons, and magnitude levels would lead to too many choice lists (CLs). We prioritized getting good measures of the discount rates to estimate probability weighting functions for six- and 12-month horizons. The time and risk MCL (TR) game was played with a 10% chance of winning in one of the 20 choice lists (CLs) and with the near future time certainty equivalent (CE) amounts being paid one week into the future. Payouts to lucky winners were based on the actual choices made by the subjects to ensure that the game was incentive-compatible. The delay in payout was done to avoid present bias in the estimates from the TR experiment. The TR game's 10% probability of payout was used to keep the experimental budget down and reduce the logistical costs of arranging future payments to an affordable level. The experiments were implemented with a large student (n=721) and rural (n=835) sample in Malawi. Except for the first RI game round[1], half of the sample played the TR game after the RI and LA games, while the other half played the TR game before the RI and LA games. Those who played the TR game after the RI and LA games did not receive a payout for these games till after they also had played the TR game to avoid a liquidity/cash effect that could otherwise be confounded with the luck effect.

We aimed to answer the following research questions (RQs) based on the three experimental designs and the sequential implementation:

RQ1) Is experimental luck in the RI and LA games enhancing risk-taking in the following TR games?

RQ2) Is experimental luck in the RI and LA games enhancing patience (reducing the discount rate) in the following TR games?

RQ3) Given a luck effect on risk-taking in the following TR game, does this effect decline with the length of the time horizon in the TR game?

RQ4) Is experimental luck enhancing optimism in the following TR game (resulting in a more elevated probability weighting function?[2]

RQ4) Is experimental luck reducing small-stakes risk aversion by reducing the degree of non-linear (inverse-S-shaped) probability weighting for prospects with payout six and 12 months into the future?[3]

Based on non-parametric tests, subjects' risk-taking behavior in the TR game responded significantly to luck in the RI game but not to luck in the LA game, while luck did not significantly affect patience (discount rates). Luck in the RI games made subjects significantly more willing to take risks in the following TR games for risky prospects with near-future (one week), six-month, and 12-month payout delays. Based on structural models with two-parameter Prelec w(p) functions, we found that the luck effects could be decomposed into more optimistic (more elevated) and less non-linear (less inversely-S-shaped) utility functions for prospects with payouts six and 12 months into the future.

The paper is organized as follows. Part 2 outlines the experimental designs...

2 Experimental designs

The elicitation of risk-taking behavior included three experimental designs. These are variants of the risky investment game (RI) of Gneezy et al. (2009); Gneezy and Potters (1997), a loss aversion (LA) game inspired by Tanaka, Camerer, and Nguyen (2010)

[1] All subjects played this round before any other games.

[2] Measured with the Prelec β parameter in the two-parameter Prelex w(p) function. We estimate such functions for six- and 12-month time horizon CLs in the TR game.

[3] This implies an increase in the Prelec α parameter within the interval 0-1.

and an integrated time and risk choice list design (TR) developed by the authors in the form of a Certainty-Equivalent approach framed in an inter-temporal setting.

Four rounds of the RI game were used.[4] The first round of the RI game was jointly played in a separate session with a survey focusing on students' perceptions of the coronavirus pandemic. The order of the TR games versus the second round of the RI games was randomized at the class level. This facilitates the assessment of the possible effects of the outcomes in the RI game on risk-taking in the TR game.[5] We should note that the outcome of the RI games was revealed for each game before the next game was played, but no cash payment was made for the second round of the RI game till after the TR game had also been completed. We are, therefore, testing the effects of winning/losing but not the effects of cash payments associated with this. For the TR games, there was a 10% chance of winning in one of the games, but all payments for the lucky winners were delayed by one week or more (depending on the randomly chosen CL for payout and the choices made by the subject for the real game). A more detailed description of each game follows.

2.1 The risky investment (RI) game

Four rounds of a version of the risky investment game of Gneezy et al. (2009); Gneezy and Potters (1997) with real payouts were played sequentially with the subjects. The outcomes of each round were determined by the throwing of a die, with the probability of winning being 0.5 in the first two rounds, 0.4 in the third round, and 0.3 in the fourth round. The third and fourth rounds had an equal chance of becoming real (lottery between the two). The respondents could choose between six risk-taking levels in the game. They could also choose a safe amount, X. The most risky option implied a 0.5[6] probability of winning $3X$. The safe amount is $X = 1000$ MKw.[7] The subjects were free to invest nothing, some, or all of the endowment (in multiples of 200 MKw) in the lottery, with the researchers tripling the amount invested. The intermediate options between these are listed below, and subjects had to choose one of the six options in each round:

1) $0.5u(3X)$
2) $0.5u(12/5X) + u(X/5)$
3) $0.5u(9/5X) + u(2X/5)$
4) $0.5u(6/5X) + u(3X/5)$
5) $0.5u(3/5X) + u(4X/5)$
6) $u(X)$

The risky investment game data are analyzed in a separate paper. Here, we only use the random luck results to analyze how random luck as a treatment influences risk-taking behavior in the TR experiment.

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[4] There was one difference in how the experiments were implemented for the student and rural samples. In the student sample, there was a 1-2 months delay from an initial survey combined with the first round of the RI game until the remaining three RI, the LA, and the TR games were played. For the rural sample, the survey and all the RI and LA game rounds were played within the same week.

[5] We may separate the effect of having played the RI game first and the effect of luck in the RI game, given that it was played first.

[6] p=0.5 in rounds 1 and 2, and reduced to 0.4 and 0.3 in rounds 3 and 4.

[7] MKw is Malawian Kwacha, the local currency. 1000 MKw is approximately 30% above the daily PPP income in Malawi in 2022 at the time of the experiments.

2.2 Loss aversion (LA) game

This game was inspired by Tanaka et al. (2010). After the risky investment game, where all participants had won some money (but not received the payout yet for Rounds 2, 3, and 4), they were introduced to this game where they risked losing some of the money they had won. In this game, they had to choose between two risky prospects, one riskier than the other. In the riskier prospect, they could win more but also lose more. Both prospects had a 50-50 chance of winning or losing. Nine ordered prospect combinations are arranged in the CL, where the amounts they can win or lose change, see Table 1. The CL is used to identify a switch point where subjects switch from the less risky (with lower potential loss) and lower expected return to the more risky (with larger potential loss) and higher expected return. The switch point can be used as an indicator of loss aversion. All participants also played this game as a real game.

Table 1 Choice List in Loss aversion experiment

CL no.	Start point	Task no.	Prob. Win	Prospect Win	A (MKw) Loss	Choice	Prospect Win	B (MKw) Loss
21		1	0.5	2000	-400		2400	-1600
21		2	0.5	1500	-400		2400	-1600
21		3	0.5	1000	-400		2400	-1600
21		4	0.5	400	-400		2400	-1600
21		5	0.5	200	-400		2400	-1600
21		6	0.5	200	-400		2400	-1200
21		7	0.5	200	-600		2400	-1200
21		8	0.5	200	-600		2400	-1000
21		9	0.5	200	-600		2400	-800

2.3 The time and risk (TR) multiple choice list games

An overview of the TR choice lists (CLs) is given in Table 2.[8] The order of the CLs was randomized with the first six CLs (in random order) for the elicitation of time preferences, presented first, then followed by the remaining 14 CLs (in random order) that include both risk and time afterward.[9] However, the respondents face an overall risk. The respondents are informed that each has a 10% chance of winning in the TR game, with each CL out of 20 CLs having an equal chance of being drawn as the real game for the lucky winners. A random row in the selected CL is then drawn, and the choice made by the subject determines whether the subject will receive the preferred near-future safe amount or whether the CL contains a risky far-future preferred

[8] The authors also use the same experimental designs and data in two other papers. One of the papers utilizes the RI data, and the other utilizes the TR data. This paper combines the two experimental games in a joint analysis. The objectives of the three papers are different, but the experimental design descriptions are, by necessity, overlapping.

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

prospect. In the latter case, a 20-sided die is used when playing the (preferred) risky lottery. The outcome determines whether the subject will receive the future amount. The experiment is, therefore, incentive-compatible. 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 five times larger than for lists 1-3 to facilitate careful comparison of switch points across lists to assess utility curvature, stochastic dominance, and within-subject consistency of decisions across CLs. Risky prospects included CLs 7-12 for $p(win)$=0.1-0.25 future prospects and for CLs 13-18 in CLs for $p(win)$=0.75-0.9. CLs 19-20, with CL20 having all five times the amounts in CL19, are in expectations are equivalent to CLs 3 and 6, with double amounts and $p(win)$=0.5 for near and far future amounts, allowing another assessment of utility curvature and assessment of whether another layer of probabilities makes a difference. CLs 11 and 12 have the property that the risky and the safe prospects have the same time horizon, one week. These two CLs allow us to $p(win)$=0.1 and 0.25 can be used to assess whether luck influences the share of risk-lovers in the sample and whether luck influences this share.

Table 2 Time and risk preference choice list overview

CL No.	P(good) FFT	FFT months	FFA MKw	P(good) NFT	NFT months	NFA MKw
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.

Table 3 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	

3 Sampling, data, and ethical issues

3.1 Sampling

3.1.1 Student sample

Our student sample consisted mainly of BSc students at the Lilongwe University of Agriculture and Natural Resources (LUANAR), Lilongwe, Malawi. The university recruits students from the whole country. Unlike most experiments with students, we did not allow self-selection in our study; instead, we used a stratified random sample stratified by study programs and year of study, and we randomly sampled up to 16 students from each class. We also included a few classes with MSc students. In total, we included 48 classes and 764 students in the first round. We faced some attrition in the second round of experiments and managed to include 721 of the same students.

3.1.2 Rural sample

Our rural sample consists of stratified random household members from 64 villages in two districts in the Central Region of Malawi and four districts in the Southern Region of Malawi. These two regions contain 89% of the population in the country. Our rural sample, therefore, gives a good representation of the rural population in the country. We sampled up to four members above 16 years old from each household to achieve more variation in age distribution than if we only had selected household heads. The original household sample consists of typical smallholder farming households dominating Malawi's rural sector. We conducted the survey and the experiments within the same week in each village. The rural sample consists of 835 subjects.

3.2 Data management

The data from the two samples have been managed and analyzed separately. One of the co-authors from LUANAR has taken main responsibility for the data collection, cleaning, anonymizing, and safe data storage at LUANAR. The first author is responsible for the safe storage of anonymized data at NMBU. The data are intended for collaborative research for the NMBU and LUANAR researchers involved in the project and for providing access for MSc and Ph.D. students in the two universities and possibly students from elsewhere to utilize the data to write papers and theses.

3.3 Ethical issues

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. The guidelines used for this are available at:

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 important challenge was that the project started during the coronavirus pandemic. This 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 in classrooms and the field.

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

Accordance: All the experiments were carried out following the relevant guidelines and regulations.

Informed consent: Prior informed consent was obtained from all the students and rural subjects after being introduced to the project, survey, and experiments.

4 Theory and Estimation Strategy

Recent literature has found that risk preferences or risk-taking behavior respond to shocks. The evidence is mixed in terms of whether negative shocks make subjects more or less willing to take risks. Most studies of real-world shock effects on risk-taking behavior have relied on the Expected Utility Framework. We utilize both non-parametric and parametric methods to answer our research questions. Especially our RQs 4) and 5) require the estimation of structural parametric models.

Holden and Tilahun (2024) found that poor and vulnerable rural youth relying on income from natural resource utilization in Ethiopia became more willing to take risks after a severe drought. The response was associated with the subjects having near linear utility functions and inverse-S-shaped probability weighting functions. The more severe shocks made them more optimistic (more elevated $w(p)$ functions) in experimental risk games they played two years after the drought shock. We build on the same theoretical modeling approach by designing our TR game so that we can estimate the $w(p)$ function of subjects. While most studies of shock effects on risk-taking behavior rely on natural experiments in the form of severe negative shocks, in this study, we investigate whether risk-taking and discounting behavior are affected by recent small-stakes shocks in terms of random luck that may affect the expectations in the following games.

Based on our research questions, we aim to test the following hypotheses: RQ 1): Hypothesis H1: Luck in the RI and LA games enhances the willingness to take risks in TR game CLs.

RQ 2): Hypothesis H2: Luck in the RI and LA games enhances patience (reduces the discount rate) in the TR game.

RQ 3): Hypothesis H3: The luck effect from winning in the RI and LA games diminishes with a longer time horizon in the future prospects in the TR game CLs.

RQ 4): Hypothesis H4: Luck in the RI and LA games make subjects more optimistic in their TR game decisions (reduce the Prelec β parameter in the $w(p)$ function.[10]

RQ 5): Hypothesis H5: Luck in the RI and LA games reduces the degree of nonlinearity (inverse-S-shaped) of the $w(p)$ function (increases the Prelec α parameter in the $w(p)$ function). We build this hypothesis assuming that luck reduces irrational small gamble risk aversion (Rabin, 2000).

While we can test hypotheses H1-H3 using non-parametric tests on our experimental data, we rely on structural models for testing hypotheses H4 and H5. We outline the methods applied for the hypotheses testing in the next section.

4.1 Empirical strategy

4.1.1 Non-parametric tests

For Hypotheses H1-H3, we use between-subject non-parametric tests using Cohen's ds for the luck treatment effects. These tests have the advantage of measuring the treatment effects in within-sample standard deviation units. We complement these with cumulative probability distributions for the switch point distributions in the CLs to assess stochastic dominance for the effects of luck treatments.

Testing of H1: Luck in the RI and LA games enhances the willingness to take risks in TR game CLs.

All subjects played the first RI game before the TR games, and we can assess whether they won or not in the RI game, round 1 with luck treatment (p=0.5) T1=0 (loss), T1=1 (win). Risk-taking behavior in CLs 11 and 12 is measured by the near-future certainty equivalent (CE) for these risky prospects identified by the switch points in these CLs. A significant luck effect is identified if $CE(T1 = 1) > CE(T1 = 0)$

[10]This is equivalent of lifting the $w(p)$ function.

in CL 11 and 12. We estimate this by using Cohen's ds to take sample variation into account. We apply the same test for luck (T2) in round 2 of the RI game. We make a further stochastic dominance assessment of the distributions of the CEs in CLs 11 and 12 for the T1 and T2 luck effects. We assess how the cumulative distributions change with the number of wins. We should note that the RI game luck effects are tested for select samples of the subjects who did not choose the safe option in each RI game round. The fact that RI game rounds 2, 3, and 4 were played before the TR game only for about half the sample further reduces the sample sizes for the testing of the luck effects from these game rounds. One of the third and fourth RI game rounds was randomly chosen as real and, therefore, combined as the third luck treatment effect (T3) test. We specify luck in the LA game as T4.

Luck in the RI game enhances the willingness to take risks in the near-future TR game CLs. We use a non-parametric approach for the two near-future risky prospects in the TR games, CLs 11 and 12.

Testing of H3: Luck in the RI game reduces the discount rate (increases patience) in the TR game. We use the first six risk-free CLs in Table 1 to assess whether luck effects influence the discount rates. We construct Cohen's ds for potential luck effects in each RI and LA game. This gives 6*4 such significance tests.

Testing of H2: The luck effect from winning in the RI game diminishes with a longer time horizon in the TR game CLs, ceteris paribus. We assess whether the Cohen's ds are reduced with the length of the time horizon for the payouts of the risky prospects in the TR game for the low $p(win)$ for luck in the first two rounds of the RI game. This implies comparing the Cohen's ds for CLs 11 and 12 (t=1 week) vs. CLs 9 and 10 (t=6 months vs. CLs 7 and 8 (t=12 months). If the luck effects in the parametric models are also smaller in the models with a 12-month horizon than in the models with a six-month horizon, this provides additional support for the hypothesis.

4.1.2 Structural model integrating time and risk

To test Hypotheses H4 and H5, we must disaggregate the risk and time responses into discounting, utility, and probability weighting and rely on structural rank-dependent utility (RDU) models with two-parameter Prelec probability weighting functions.

The inter-temporal binary choice between the two time-dated (t_1 and t_2) future prospects can be formulated as follows:

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

where δ is the exponential continuous time discount rate. t_0 represents the day of the experiment, t_1 represents the near-future option (one week into the future), and t_2 represents the far-future option (six, 12, or 24 months into the future). This choice problem allows for asset integration in the sense that $u(b)$ is the base utility or utility of baseline consumption. Experimental money comes on top of this baseline consumption. Alternatively, we can do like in Prospect Theory and assume $b = 0$ and $u(b)$=0.

The far-future prospect (M_B) or the near-future prospect (M_A) can be risky. In most CLs, the far-future prospect is risky, and the near-future prospect is a safe amount that varies within a CL. A risky prospect has a probability $p < 1$ of a positive outcome and a 1-p probability of zero outcome.[11] 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 utilities associated with the binary choice between a risky far-future prospect (U_B) and a certain (safe) near-future prospect ($U_A = u(s)$) are modeled as follows:

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

Under Cumulative Prospect Theory (CPT) (Tversky & Kahneman, 1992), which is equivalent to Rank Dependent Utility (RDU) (Quiggin, 1982) without asset integration in the gains domain that we operate in with our CLs, 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:

$$\begin{aligned} NPU_A &= e^{-\delta(t_1-t_0)}u(s) \\ NPU_B &= e^{-\delta(t_2-t_0)}(w(p)u(X)) \end{aligned} \tag{3}$$

We eliminate potential present bias by avoiding present-time valuation by offering the choices between:

$$\begin{aligned} NFU_A &= u(s) \\ NFU_B &= e^{-\delta(t_2-t_1)}(w(p)u(X)) \end{aligned} \tag{4}$$

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 and CPT theories are typically framed in an atemporal setting, we apply them 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.

Given zero asset integration, the model nests the discounted expected utility of experimental income (DEU) when $w(p) = p$ and the discounted expected value (DEV) when $w(p) = p$ and utility is linear. We allow the $w(p)$ function to be determined freely with a two-parameter Prelec function. We utilize the magnitude variation in future prospects in CLs without risk to assess the functional form of the utility in time curvature and whether discounted rank-dependent expected value (DRDEV) (linear utility) vs. discounted rank-dependent utility (DRDU) (concave utility) is more appropriate.

[11] For ethical reasons, we have avoided prospects with negative outcomes.

Some recent studies of utility in time have concluded that it is close to linear or slightly concave (Cheung, 2019). We use the Discounted Rank Dependent Expected Value (DRDEV) model as our baseline model. The interval for the safe amount at the switch point for a CL then represents the near-future CE = DRDEV of the risky far-future prospect.

The sizes of the discount rates for the longer time horizons (six, 12, and 24-month horizons) that are of particular interest to us in this study capture the possible (degree of) diminishing impatience. We need to consider this when assessing potential luck's effects on patience. We are interested in assessing whether recent luck in the RI and LA games carries over to risk-taking in future risky prospects and whether this changes with the time horizon of the future prospects.

We also allow the probability weighting function to vary with time horizon [12] and the $w^t(p)$ function is modeled with a Prelec (1998) 2-parameter weighting function:

$$w_t(p) = exp(-\beta_t(-\ln p)^{\alpha_t}), \alpha_t > 0, \beta_t > 0 \quad (5)$$

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 $w(p)$ function is strictly increasing and continuous within the interval $[0, 1]$[13].

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[14]:

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

where θ captures the constant elasticity of marginal utility, b captures eventual asset integration, but we assume $b = 0$ in line with CPT in our base models. The utility function is linear for $\theta = 0$. 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. The linear utility assumption could not be rejected for the student sample when doing a pair-wise comparison of CLs with the same time horizon, p=1, and with future amounts of 3000 vs. 15000 MK. We also tested parametric models with concave utility, but these models produced implausible negative discount rates for the longest time horizon (24 months). We found indications of weak concave utility in the rural sample. 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.

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.

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

[13] 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 $\alpha = \beta = 1$

[14] 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.

$$\nabla DRDU = \frac{NFU_A^{\frac{1}{\mu}}}{NFU_A^{\frac{1}{\mu}} + NFU_B^{\frac{1}{\mu}}} \tag{7}$$

Equation (7) 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:

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

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

The structural model allows us to decompose eventual luck effects into the effect on the elevation of the $w(p)$ function and its degree of non-linear (inverse-S-shape) by allowing the Prelec α and β parameters to vary linearly in the random luck treatments:

$$\begin{aligned} &\beta_t = \beta_t(Luck) \\ &\alpha_t = \alpha_t(Luck) \\ &Luck = [T1, T2, T3, T4] \end{aligned} \tag{9}$$

These structural models may now be used to test our hypotheses H4 and H5.

Testing of H4: Luck in the RI and LA games makes subjects more optimistic in their TR game decisions (reduce the Prelec β parameter in the $w(p)$ function. We apply these structural models with a two-parameter Prelec $w(p)$ function to separate possible effects on the degree of inverse-S-shape of the $w(p)$ function and its elevation. If luck is associated with a significantly lower Prelec β, people have become more optimistic in the TR game based on luck in the RI and LA games.

Testing of H5: Luck in the RI and LA games reduces the degree of nonlinearity (inverse-S-shape) of the $w(p)$ function (increases the Prelec α parameter in the $w(p)$ function). Like for hypothesis H4, we rely on estimating structural models with the two-parameter Prelec $w(p)$ function to test this hypothesis. Hypotheses H4 and H5 are tested jointly by making the two estimated Prelec parameters in the TR game CLs with six- and 12-month time horizons linearly related to each of the RI and LA luck dummy variables.

5 Results

5.1 Non-paramteric assessment of luck effects

We apply non-parametric tests to test hypotheses H1-H3 and measure the luck effects in Cohen's d units based on the near future values of the future risky prospects.

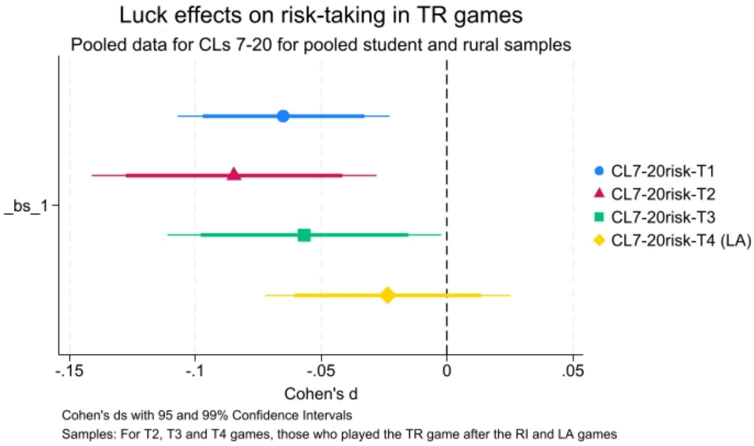

Fig. 1 Luck in the RI and LA games and effects on risk-taking in in the TR game

Testing of H1: Luck in the RI game enhances the willingness to take risks in the following TR game CLs.

Figure 1 presents Cohen's *d*s for the four luck treatments across all the future risky prospects with 95% and 99% confidence intervals. We see that the luck effects are significant at the 1% level for T1, T2, and T3, while they are insignificant for T4, the LA game. We, therefore, find strong evidence in favor of hypothesis H1, which cannot be rejected.

Testing of H2: Luck in the RI and LA games enhances patience (reduces the discount rate) in the TR game.

Figure 2 presents Cohen's *d*s for the luck treatments on the near-future values of the six distant future prospects in CLs 1-6. The graph shows that three of the four treatments had an insignificant effect on patience, while luck in round 2 of the RI game is associated with a significant (at the 1% level) effect on patience in the direction of the hypothesis. Therefore, we find less support for hypothesis H2 and reject it.

Testing of H3: The luck effect from winning in the RI and LA games diminishes with a longer time horizon in the future prospects in the TR game CLs.

Figure 3 presents Cohen's *d*s by time horizons of one week, six months, and 12 months for each of the three random luck treatments in the RI games. The three graphs give significant luck effects in seven out of nine paired comparisons, and five are significant at the 1% level. However, we see no clear indication that the luck effect is myopic in the sense that it is stronger for near-future prospects than far-future prospects. Therefore, we reject hypothesis H3.

We present the cumulative distributions in Figure 4 to inspect the stochastic dominance of the T1 and T2 luck effects on the switch point distributions in CL11 and CL12 (near-future prospects). The results show a clear pattern of enhanced risk-taking by luck through the distributions. The vertical dotted lines represent the risk-neutral switch points in these CLs. We see that 38-45% of the samples are risk-lovers (CE¿EV)

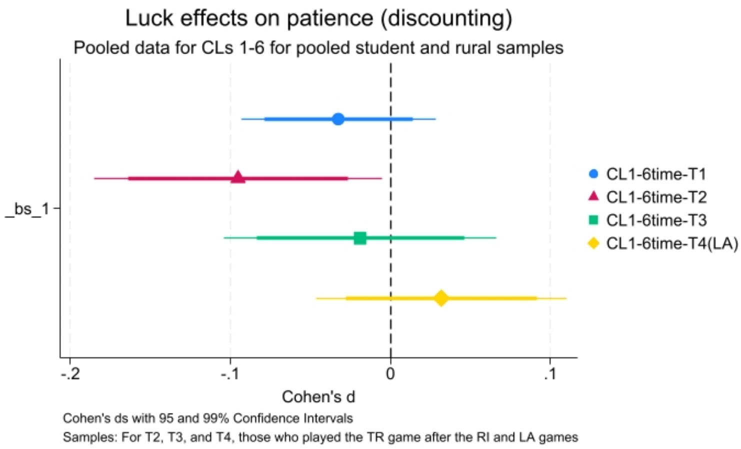

Fig. 2 Luck in the RI and LA games and patience in the TR game

in CL11, where $p(win) = 0.1$, and 25-30% are risk-lovers in CL12 with $p(win) = 0.25$, where the gaps in these ranges represent the luck effects in these CLs.

5.2 Parametric decomposition of luck effects with two-parameter Prelec *w(p)* functions

H4: Luck in the RI and LA games makes subjects more optimistic in their TR game decisions (reduce the Prelec β parameter in the $w(p)$ function.

Testing of H4: Luck in the RI and LA games makes subjects more optimistic in their TR game decisions (reduce the Prelec β parameter in the $w(p)$ function.

In Table 4, we have estimated separate models for the six- and 12-month time horizon CLs and for luck in the first two rounds of the RI game. The table shows that T1 luck in the first round of the RI game is highly significant, with a negative sign in the 12-month model. The same is found for T2 luck in the second round RI game in the six-month time horizon model. The coefficients on Prelec β are insignificant, but there is also a negative sign in the other two models. Based on this, we cannot reject the hypothesis that luck in the RI games leads to more optimistic responses in the TR game with delayed payouts six and 12 months into the future. Further support for this is also provided for luck in the combined third and fourth rounds of the RI game (T3) in the six-month model in Table 5. The Prelec β parameter change for T3 is significant at the 5% level. The LA game had no significant luck effects on the $w(p)$ function Prelec β parameters, although the signs of the coefficients there were also negative.

Testing of H5: Luck in the RI game increases the Prelec α parameter in the $w(p)$ function.

We also examine the results for this hypothesis by inspecting Tables 4 and 5 for the treatment effects on the Prelec α parameter. Table 4 finds a strong and highly significant positive effect of T1 in the 12-month model and the same for T2 in the six-month model. For T3 in Table 5, there was also a weakly significant (at the 10% level) and positive effect in the six-month model. The other models had positive but

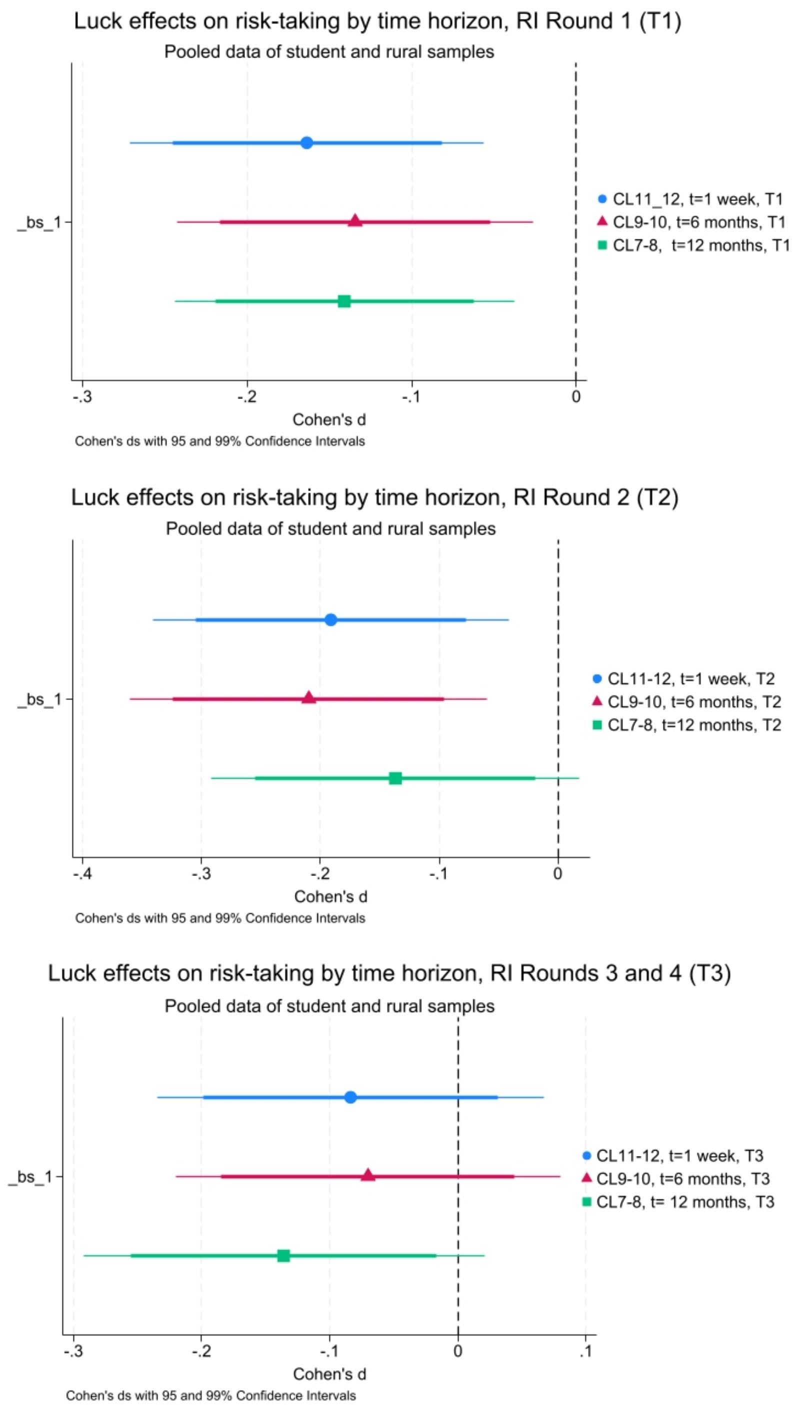

Fig. 3 Is the luck effect diminishing with time horizon in the TR game?

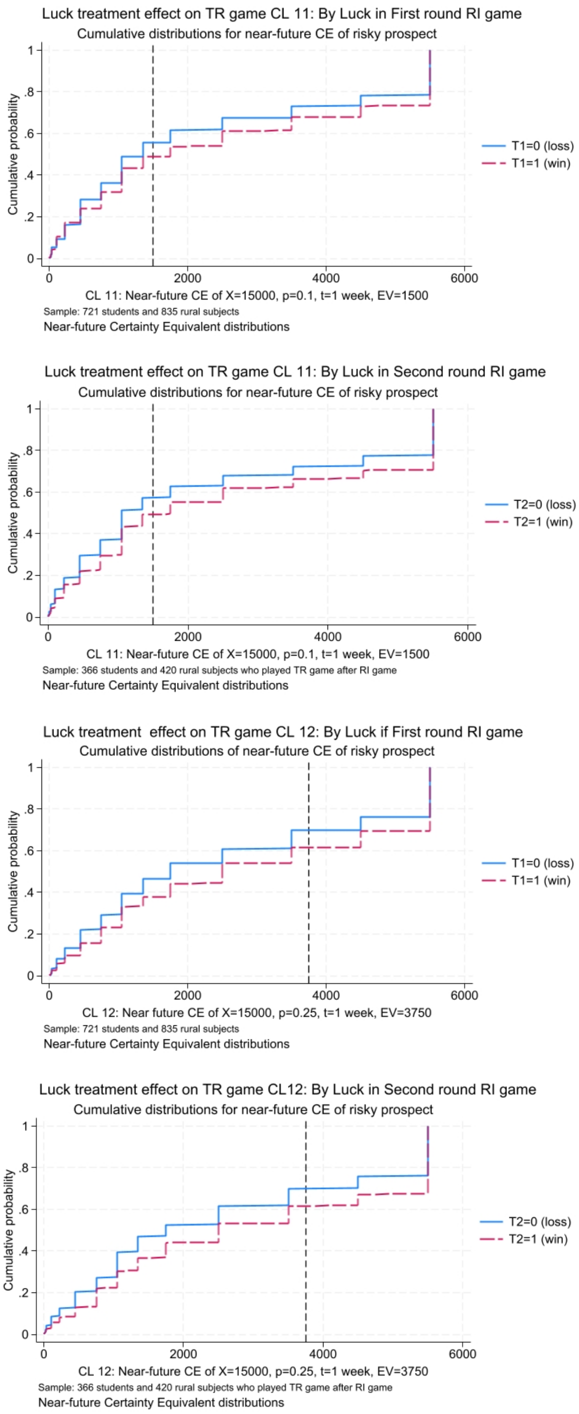

Fig. 4 Assessment of stochastic dominance of luck effects in CL11 and CL12

insignificant parameters for the luck treatment variables. The significant luck treatment effects on Prelec α and β were found in the same models. To better understand the size of these shifts in the $w(p)$ functions associated with the luck treatments, they are predicted in Fig. 6 for the models where they were found to be significant. We see the luck effects as substantial upward shifts and less non-linear forms of the functions.

We included controls with a dummy for the student sample and the random starting row in each CL. These show that students, on average, had significantly lower discount rates than the rural sample and significantly smaller Luce error, while the $w(p)$ functions were not significantly different. We also found that the estimated parameters were sensitive to some of the models' starting rows in the elicitation in the CLs. However, we do not think this affected our main results and conclusions in any major way.

6 Discussion and conclusions

Most experimental studies on risk-taking behavior have been conducted in an atemporal framing. However, the risky investment (RI) game of Gneezy and Potters (1997) was initially used to study myopic loss aversion in repeated versions of the game. While we used four single-round versions of their game, followed by a loss aversion (LA) game, our purpose differed. We utilize the random luck in these repeated games to assess whether it affected risk-taking and discounting behavior in the following time and risk (TR) CLs with delayed payouts but immediate risk resolution. Our evidence shows that subjects became significantly more willing to take risks after winning the previous RI games. This luck effect did not decline significantly with a delay in the TR game's payout time. As the payout for the RI and LA games played just before the TR game was delayed till after the TR game, the luck effect is not a cash or liquidity effect.

Our paper contributes to the literature investigating how shocks affect risk-taking behavior. Much of this literature has focused on natural shocks and disasters and found that such large shocks can alter people's risk-taking responses, although the results are mixed. Our approach is different as we investigate whether and how even small random shocks can alter behavior in following experiments with risk and delayed payouts. It allows us to decompose the effects into potential changes in patience and risk-taking and to disaggregate the risk-taking responses into changes in optimism and probabilistic sensitivity. We find novel evidence that luck without immediate cash supply enhances optimism and probabilistic sensitivity, while the impact on patience is insignificant in most tests.

While we did not find that the luck effect made subjects more patient, we found strong evidence of diminishing impatience, with discount rates being substantially lower in the 12-month than the six-month time horizon. The students were also, on average, more patient than the rural sample. The variation in magnitude levels of the future amounts in our within-subject experimental design allowed us to assess the utility-in-time curvature for our subjects. We found the utility-in-time curvature to be close to linear for our student sample, while it was weakly concave for the rural sample. While our baseline structural models estimated the discount rates and the

Table 4 Testing for luck effects in RI game Rounds 1 and 2 on w(p) functions based on six- and 12-month horizon CLs in TR games

EQUATION	VARIABLES	(1) 6-month	(2) 12-month	(3) 6-month	(4) 12-month
Discount rate	stud	-0.140***	-0.102***	-0.118**	-0.053
		(0.040)	(0.034)	(0.057)	(0.048)
	strow	0.005	0.010**	0.027***	0.003
		(0.005)	(0.004)	(0.008)	(0.006)
	Constant	1.122***	0.456***	0.943***	0.471***
		(0.046)	(0.034)	(0.067)	(0.042)
CEMU-θ	Constant	0.000	0.000	0.000	0.000
Prelec α	T1, Luck in RI1	0.113	0.259***		
		(0.071)	(0.084)		
	T2, Luck in RI2			0.308***	0.002
				(0.111)	(0.140)
	strow	0.010	-0.002	0.053***	-0.063***
		(0.011)	(0.014)	(0.019)	(0.024)
	stud	-0.157**	-0.071	-0.052	0.140
		(0.079)	(0.071)	(0.111)	(0.129)
	Constant	0.665***	0.686***	0.310**	1.192***
		(0.114)	(0.109)	(0.153)	(0.178)
Prelec β	T1, Luck in RI1	-0.105	-0.259***		
		(0.072)	(0.077)		
	T2, Luck in RI2			-0.324***	-0.155
				(0.094)	(0.103)
	strow	0.003	0.003	-0.034**	0.038**
		(0.011)	(0.011)	(0.015)	(0.016)
	stud	0.181**	0.040	0.132	0.002
		(0.078)	(0.064)	(0.094)	(0.093)
	Constant	0.866***	0.937***	1.219***	0.615***
		(0.111)	(0.092)	(0.136)	(0.113)
Luce error	probwin1	-1.604***	-1.173***	-2.103***	-1.382***
		(0.188)	(0.169)	(0.282)	(0.250)
	strow	-0.080***	-0.036**	-0.029	-0.041**
		(0.019)	(0.016)	(0.030)	(0.020)
	stud	-1.197***	-0.906***	-1.386***	-0.566**
		(0.169)	(0.182)	(0.273)	(0.284)
	CL-order FE	Yes	Yes	Yes	Yes
	Constant	6.324***	6.275***	6.521***	6.330***
		(0.450)	(0.605)	(0.513)	(0.703)
	Observations	13,102	17,606	6,582	8,786
	p	0.00108	0.00132	0.000108	0.533
	chi2	13.67	13.26	18.26	1.259
	ll	-8796	-11815	-4424	-5893
	N_clusters	1108	1110	571	572

Note: stud=student sample dummy, strow=starting row in CL, probwin1 is probability of winning in CL. Cluster-corrected standard errors in parentheses, clustering on subjects. Significance levels: *** p<0.01, ** p<0.05, * p<0.1

Table 5 Testing for luck effects from RI game rounds 3 and 4 and LA game on $w(p)$ functions based on six- and 12-month horizon CLs in TR games

EQUATION	VARIABLES	(1) 6-month	(2) 12-month	(3) 6-month	(4) 12-month
Discount rate	stud	-0.127**	-0.087*	-0.195***	-0.120***
		(0.060)	(0.050)	(0.052)	(0.044)
	strow	0.016*	0.011	0.008	0.009*
		(0.009)	(0.007)	(0.008)	(0.005)
	Constant	1.013***	0.452***	1.135***	0.508***
		(0.076)	(0.044)	(0.068)	(0.039)
CEMU-θ	Constant	0.000	0.000	0.000	0.000
Prelec α	T3, Luck in RI3-4	0.230*	0.047		
		(0.121)	(0.181)		
	Luck in LA game			0.052	0.089
				(0.094)	(0.125)
	stud	-0.024	0.002	-0.106	0.035
		(0.120)	(0.153)	(0.110)	(0.106)
	strow	0.027	-0.020	0.017	-0.021
		(0.021)	(0.034)	(0.020)	(0.023)
	Constant	0.447**	0.944***	0.616***	0.909***
		(0.188)	(0.234)	(0.160)	(0.148)
Prelec β	T3, Luck in RI3-4	-0.222**	-0.140		
		(0.104)	(0.124)		
	Luck in LA game			-0.053	-0.060
				(0.093)	(0.103)
	stud	0.129	0.031	0.189*	0.015
		(0.118)	(0.109)	(0.104)	(0.085)
	strow	-0.004	0.012	0.001	0.016
		(0.018)	(0.022)	(0.018)	(0.017)
	Constant	0.972***	0.721***	0.871***	0.721***
		(0.173)	(0.154)	(0.159)	(0.109)
Luce error	probwin1	-1.853***	-1.134***	-2.060***	-1.732***
		(0.293)	(0.247)	(0.280)	(0.262)
	stud	-1.323***	-0.698**	-1.797***	-0.917***
		(0.276)	(0.299)	(0.332)	(0.289)
	strow	-0.021	-0.037*	-0.040	-0.026
		(0.031)	(0.021)	(0.030)	(0.019)
	CL-order FE	Yes	Yes	Yes	Yes
	Constant	6.183***	6.643***	7.020***	6.799***
		(0.522)	(0.773)	(0.554)	(0.629)
	Observations	6,664	8,874	8,668	11,550
	p	0.00335	0.124	0.000166	0.0149
	chi2	11.40	4.181	17.40	8.407
	ll	-4478	-5949	-5835	-7756
	N_clusters	577	578	740	741

Note: stud=student sample dummy, strow=starting row in CL, probwin1 is probability of winning in CL. Cluster-corrected standard errors in parentheses, clustering on subjects. Significance levels: *** p<0.01, ** p<0.05, * p<0.1

$w(p)$ functions assuming linear utility, we relaxed this assumption and allowed for concave utility in robustness checks. The main findings in terms of luck effects were robust to this modification. This implied that changes in risk-taking behavior due to luck could be explained by changes in the $w(p)$ function.

Risk preferences and expectations are hard to separate. When risk-taking behavior is modeled through the two-parameter $w(p)$ function rather than through the utility function, expectations are better integrated and made more explicit, and risk tolerance can vary with the probability of winning. We have also demonstrated that patience and probability weighting can vary with time horizon. We found subjects to be more patient and optimistic in the 12-month time horizon than in the 6-month time horizon.

References

Abdellaoui, M., Bleichrodt, H., l'Haridon, O., Paraschiv, C. (2013). Is there one unifying concept of utility? an experimental comparison of utility under risk and utility over time. *Management Science*, *59*(9), 2153–2169,

Abdellaoui, M., Diecidue, E., Öncüler, A. (2011). Risk preferences at different time periods: An experimental investigation. *Management Science*, *57*(5), 975–987,

Abdellaoui, M., Kemel, E., Panin, A., Vieider, F.M. (2019). Measuring time and risk preferences in an integrated framework. *Games and Economic Behavior*, *115*, 459–469,

Andreoni, J., Kuhn, M.A., Sprenger, C. (2015). Measuring time preferences: A comparison of experimental methods. *Journal of Economic Behavior & Organization*, *116*, 451–464,

Cheung, S.L. (2016). Recent developments in the experimental elicitation of time preference. *Journal of Behavioral and Experimental Finance*, *11*, 1–8,

Cheung, S.L. (2019). Eliciting utility curvature in time preference. *Experimental Economics*, 1–33,

Cohen, J., Ericson, K.M., Laibson, D., White, J.M. (2020). Measuring time preferences. *Journal of Economic Literature*, *58*(2), 299–347,

Enke, B., & Graeber, T. (2021). *Cognitive uncertainty in intertemporal choice* (Tech. Rep.). National Bureau of Economic Research.

Enke, B., & Graeber, T. (2023). Cognitive uncertainty. *The Quarterly Journal of Economics*, *138*(4), 2021–2067,

Enke, B., Graeber, T., Oprea, R. (2023). *Complexity and time* (Tech. Rep.). National Bureau of Economic Research.

Gneezy, U., Leonard, K.L., List, J.A. (2009). Gender differences in competition: Evidence from a matrilineal and a patriarchal society. *Econometrica*, *77*(5), 1637–1664,

Gneezy, U., & Potters, J. (1997). An experiment on risk taking and evaluation periods. *The Quarterly Journal of Economics*, *112*(2), 631–645,

Grijalva, T.C., Lusk, J.L., Rong, R., Shaw, W.D. (2018). Convex time budgets and individual discount rates in the long run. *Environmental and Resource Economics*, *71*(1), 259–277,

Grijalva, T.C., Lusk, J.L., Shaw, W.D. (2014). Discounting the distant future: An experimental investigation. *Environmental and Resource Economics*, *59*(1), 39–63,

Holden, S.T., & Quiggin, J. (2017). Bounded awareness and anomalies in intertemporal choice: Zooming in google earth as both metaphor and model. *Journal of Risk and Uncertainty*, *54*(1), 15–35,

Holden, S.T., & Tilahun, M. (2024). Can climate shocks make vulnerable subjects more willing to take risks? *Environmental and Resource Economics*, 1–41,

Holt, C.A., & Laury, S.K. (2002). Risk aversion and incentive effects. *American Economic Review*, *92*(5), 1644–1655,

l'Haridon, O., & Vieider, F.M. (2019). All over the map: A worldwide comparison of risk preferences. *Quantitative Economics*, *10*(1), 185–215,

Prelec, D. (1998). The probability weighting function. *Econometrica*, 497–527, Quiggin, J. (1982). A theory of anticipated utility. *Journal of Economic Behavior & Organization*, *3*(4), 323–343,

Rabin, M. (2000). Risk-aversion for small stakes: A calibration theorem. *Econometrica*, *68*, 1281–1292,

Tanaka, T., Camerer, C.F., Nguyen, Q. (2010). Risk and time preferences: Linking experimental and household survey data from vietnam. *American economic review*, *100*(1), 557–571,

Tversky, A., & Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and uncertainty*, *5*(4), 297–323,

Vieider, F.M., Martinsson, P., Nam, P.K., Truong, N. (2019). Risk preferences and development revisited. *Theory and Decision*, *86*(1), 1–21,

Yaari, M.E. (1987). The dual theory of choice under risk. *Econometrica: Journal of the Econometric Society*, 95–115,

Supplementary information. The experimental protocols are uploaded as separate files.

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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 available upon the paper's publication and can be made available for reviewers upon request.
- 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 Robustness test: Are the luck treatment effects sensitive to the utility curvature?

We have included structural models to test whether the estimated $w(p)$ function responses to the luck treatments are robust to the alternative assumptions about the utility curvature. We have, therefore, relaxed the linear utility assumption and tested whether weakly concave utility functions give close to similar results. We, therefore, find our key results to be robust to allowing the utility curvature to be weakly concave.

Table A1 Rubustness check of luck effects (T1): Models with concave utility functions

		Integrated time and risk preference models			
EQUATION	VARIABLES	(1) θ=0.1 6-month	(2) θ=0.1 12-month	(3) θ=0.2 6-month	(4) θ=0.2 12-month
Discount rate	stud	-0.133***	-0.096***	-0.133***	-0.096***
		(0.040)	(0.034)	(0.040)	(0.034)
	strow	0.008	0.011***	0.008	0.011***
		(0.005)	(0.004)	(0.005)	(0.004)
	Constant	0.993***	0.341***	0.878***	0.225***
		(0.047)	(0.034)	(0.047)	(0.034)
CEMU-θ	Constant	0.100	0.100	0.200	0.200
Prelec α	T1	0.113*	0.274***	0.114*	0.275***
		(0.068)	(0.082)	(0.068)	(0.083)
	stud	-0.152*	-0.066	-0.153**	-0.066
		(0.078)	(0.071)	(0.078)	(0.071)
	strow	0.014	-0.002	0.014	-0.002
		(0.010)	(0.014)	(0.010)	(0.014)
	Constant	0.613***	0.677***	0.615***	0.679***
		(0.106)	(0.110)	(0.107)	(0.110)
Prelec β	T1	-0.087	-0.238***	-0.077	-0.212***
		(0.064)	(0.068)	(0.057)	(0.061)
	stud	0.149**	0.027	0.133**	0.023
		(0.070)	(0.058)	(0.063)	(0.052)
	strow	0.001	0.002	0.001	0.002
		(0.010)	(0.010)	(0.009)	(0.009)
	Constant	0.808***	0.856***	0.719***	0.763***
		(0.099)	(0.083)	(0.089)	(0.074)
Luce error	probwin1	-1.295***	-1.020***	-1.164***	-0.917***
		(0.171)	(0.167)	(0.153)	(0.149)
	strow	-0.079***	-0.038**	-0.071***	-0.034**
		(0.017)	(0.016)	(0.015)	(0.014)
	CL-order FE	Yes	Yes	Yes	Yes
	Constant	4.521***	4.839***	4.040***	4.334***
		(0.393)	(0.537)	(0.351)	(0.482)
	Observations	13,102	17,606	13,102	17,606
	p	0.00120	0.000788	0.00120	0.000779
	chi2	13.45	14.29	13.45	14.31
	ll	-8805	-11821	-8805	-11821
	N_clust	1108	1110	1108	1110

Note: stud=student sample dummy, strow=starting row in CL, probwin1 is probability of winning in CL. Cluster-corrected standard errors in parentheses, clustering on subjects. Significance levels: *** p<0.01, ** p<0.05, * p<0.1

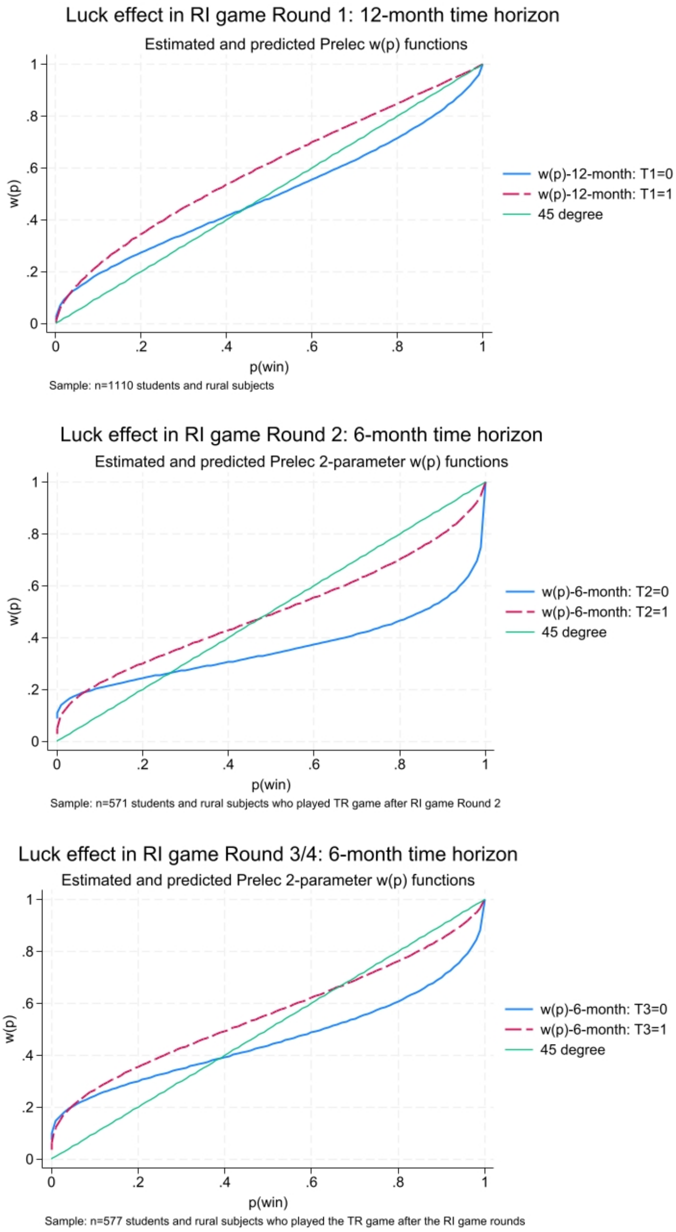

Fig. 5 Significant luck effects from RI games on Prelec w(p) functions by time horizon in TR game

Table A2 Robustness check of luck effects (T2): Models with concave utility functions

Integrated time and risk preference models

EQUATION	VARIABLES	(1) θ=0.1 6-month	(2) θ=0.1 12-month	(3) θ=0.2 6-month	(4) θ=0.2 12-month
Discount rate	stud	-0.111*	-0.046	-0.111*	-0.046
		(0.057)	(0.048)	(0.057)	(0.048)
	strow	0.023***	0.004	0.023***	0.004
		(0.008)	(0.006)	(0.008)	(0.006)
	Constant	0.854***	0.359***	0.737***	0.242***
		(0.066)	(0.043)	(0.066)	(0.043)
CEMU-θ	Constant	0.100	0.100	0.200	0.200
Prelec α	T2	0.255**	-0.002	0.256**	-0.003
		(0.109)	(0.137)	(0.110)	(0.138)
	stud	-0.090	0.142	-0.091	0.142
		(0.108)	(0.123)	(0.109)	(0.124)
	strow	0.039**	-0.063***	0.039**	-0.064***
		(0.018)	(0.024)	(0.018)	(0.024)
	Constant	0.408***	1.208***	0.409***	1.211***
		(0.157)	(0.183)	(0.158)	(0.184)
Prelec β	T2	-0.279***	-0.132	-0.249***	-0.118
		(0.086)	(0.090)	(0.077)	(0.081)
	stud	0.119	-0.001	0.106	-0.001
		(0.085)	(0.081)	(0.076)	(0.073)
	strow	-0.016	0.034**	-0.014	0.031**
		(0.014)	(0.014)	(0.013)	(0.012)
	Constant	1.025***	0.543***	0.912***	0.483***
		(0.130)	(0.102)	(0.116)	(0.091)
Luce error	probwin1	-1.439***	-1.224***	-1.293***	-1.101***
		(0.290)	(0.230)	(0.259)	(0.206)
	strow	-0.047*	-0.036*	-0.042*	-0.032*
		(0.025)	(0.019)	(0.022)	(0.017)
	CL-order FE	Yes	Yes	Yes	Yes
	Constant	4.328***	5.171***	3.870***	4.629***
		(0.450)	(0.611)	(0.402)	(0.548)
	Observations	6,582	8,786	6,582	8,786
	p	0.000977	0.570	0.000970	0.569
	chi2	13.86	1.126	13.88	1.126
	ll	-4428	-5894	-4428	-5893
	N_clusters	571	572	571	572

Note: stud=student sample dummy, strow=starting row in CL, probwin1 is probability of winning in CL. Cluster-corrected standard errors in parentheses, clustering on subjects. Significance levels: *** p<0.01, ** p<0.05, * p<0.1

Table A3 Robustness check of luck effects (T3): Models with concave utility functions

		Integrated time and risk preference models			
EQUATION	VARIABLES	(1) θ=0.1 6-month	(2) θ=0.1 12-month	(3) θ=0.2 6-month	(4) θ=0.2 12-month
Discount rate	stud	-0.126**	-0.073	-0.126**	-0.073
		(0.059)	(0.050)	(0.059)	(0.050)
	strow	0.015*	0.010	0.015*	0.010
		(0.008)	(0.006)	(0.008)	(0.006)
	Constant	0.917***	0.345***	0.801***	0.228***
		(0.072)	(0.044)	(0.072)	(0.044)
CEMU-θ	Constant	0.100	0.100	0.200	0.200
Prelec α	T3	0.232**	-0.032	0.234**	-0.033
		(0.115)	(0.173)	(0.116)	(0.174)
	stud	-0.064	0.055	-0.065	0.055
		(0.115)	(0.141)	(0.116)	(0.142)
	strow	0.024	-0.031	0.024	-0.031
		(0.019)	(0.034)	(0.019)	(0.034)
	Constant	0.473***	1.020***	0.474***	1.022***
		(0.179)	(0.258)	(0.180)	(0.260)
Prelec β	T3	-0.175*	-0.093	-0.156*	-0.083
		(0.093)	(0.110)	(0.083)	(0.098)
	stud	0.126	-0.005	0.112	-0.005
		(0.102)	(0.094)	(0.091)	(0.084)
	strow	0.005	0.017	0.004	0.015
		(0.015)	(0.020)	(0.014)	(0.018)
	Constant	0.819***	0.613***	0.728***	0.545***
		(0.149)	(0.146)	(0.133)	(0.131)
Luce error	probwin1	-1.237***	-0.970***	-1.111***	-0.875***
		(0.323)	(0.240)	(0.289)	(0.214)
	strow	-0.031	-0.032	-0.027	-0.028
		(0.029)	(0.020)	(0.026)	(0.018)
	CL-order FE	Yes	Yes	Yes	Yes
	Constant	4.041***	5.295***	3.611***	4.741***
		(0.504)	(0.664)	(0.451)	(0.595)
	Observations	6,664	8,874	6,664	8,874
	p	0.00495	0.173	0.00498	0.173
	chi2	10.61	3.513	10.61	3.507
	ll	-4482	-5950	-4482	-5950
	N_clust	577	578	577	578

Note: stud=student sample dummy, strow=starting row in CL, probwin1 is probability of winning in CL. Cluster-corrected standard errors in parentheses, clustering on subjects. Significance levels: *** p<0.01, ** p<0.05, * p<0.1