Measuring Time and Risk Preferences in an Integrated Framework*

Mohammed Abdellaoui (abdellaoui@hec.fr)[1], Emmanuel Kemel† (kemel@hec.fr)[1], Amma Panin (amma.serwaah@gmail.com) [2] and Ferdinand M. Vieider (fvieider@gmail.com)[2,3]

[1] *HEC Paris and CNRS, France, , 1 rue de la Libération,, 78350 Jouy-en-Josas*
[2] *WZB Berlin Social Science Center, Germany,Reichpietschufer 50, 10785 Berlin*
[3] *University of Reading, UK, Whiteknights Campus, Reading RG6 6UR*

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Abstract

We present a novel method to elicit time preferences in the context of risk. The method builds on a multiple price list (*MPL*) design popular with economists, and consists in simply delaying some choice alternatives into the future. We also show how the same MPL can be used to estimate probability weighting in addition to utility curvature. We use the data obtained to estimate structural models of decision-making. The estimations yield several substantive insights. For one, we find present bias to persist under conditions of risk, contrary to some previous evidence from the psychology literature. We further confirm the robustness of inverse-S shaped probability weighting to the use of this particular type of MPL. This is important inasmuch as random choice may lead to the opposite choice pattern in our setup. Finally, we show that accounting for probability weighting impacts the assessment of discount rates, which may be systematically underestimated under more restrictive modeling assumptions under risk such as expected utility theory.

Keywords: time preferences; risk preferences; rank-dependent utility; present bias

JEL-classification: D81; D90

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†Corresponding author.

1 Introduction

Risk and time are fundamentally intertwined—the future is inherently risky. Yet time preferences have mostly been studied abstracting from risk under presumed certainty (see Frederick, Loewenstein and O'Donoghue, 2002, for a review of the literature). Indeed, it has been posited that deviations from the standard model of inter-temporal decision making, discounted utility with an exponentially decreasing discount function (DU; Samuelson, 1937), may be largely or entirely due to elicitation methods positing certainty of future outcomes (Keren and Roelofsma, 1995; Weber and Chapman, 2005; Halevy, 2008; Gerber and Rohde, 2010; Epper, Fehr-Duda and Bruhin, 2011). According to this intuition, (quasi-) hyperbolic preferences (Phelps and Pollak, 1968; Laibson, 1997; Rohde, 2010; Pan, Webb and Zank, 2015) are imputable to the absence of risk in the present, while risk is inherent in any future outcomes. A dislike of risk would then result in a choice of immediate outcomes over future ones, regardless of a respondent's true underlying discount rate.

In this paper we present a novel method to elicit time preferences that naturally integrates time and risk. The method consists of a variation on the multiple price lists (MPLs) popularized in economics by Holt and Laury (2002). We start by using standard MPLs to elicit risk preferences. That is, we compare two non-degenerate binary lotteries while changing the probabilities attached to the different outcomes in a choice list. By eliciting the switching probability between a (relatively) risky and a (relatively) safe lottery, we are able to clearly identify respondents' preferences over risk. In a second step, we elicit time preferences using the same choice setup. The only difference is that the payouts from one of the lotteries are deferred into the future (the resolution of uncertainty is always immediate). By always deferring the outcomes of the *safe* lottery we create a psychological tradeoff between preference for the present and risk aversion, since the price to pay for increased safety is a delay in the payout of the outcome. By administering appropriate delays of both lotteries to different future dates, we can identify quasi-hyperbolic and hyperbolic discounting, going beyond the exponential model.

In addition, we show how to use MPLs to elicit probability weighting jointly with utility curvature. Previous studies were generally not set up to do this (we will return to this point in the discussion). This serves as a stability check of the typical inverse-S shape of probability weighting (see van de Kuilen and Wakker, 2011, for an overview).

While different methods have been used to measure probability weighting (see e.g. Abdellaoui, 2000, and Bleichrodt and Pinto, 2000, for nonparametric measurements), many studies have employed certainty equivalents (*CEs*) to parametrically identify probability weighting functions (Tversky and Kahneman, 1992; Bruhin, Fehr-Duda and Epper, 2010; Abdellaoui, Baillon, Placido and Wakker, 2011; L'Haridon and Vieider, 2016). In these tasks, lotteries with a given probability of winning a prize are compared to a series of sure amounts of money in a choice list. While being eminently tractable, responses in such choice lists may be biased by systematic noise. Recent studies have emphasized how some people may switch systematically towards the middle of a list, or at random (Andersson, Tyran, Wengström and Holm, 2016; Vieider, 2017). Using CEs such random choices could result in inverse-S shaped probability weighting even if respondents were in reality expected utility maximizers. The MPLs employed here, however, would result in the opposite pattern based on the random choice explanation, thus providing a stability test for inverse-S shaped weighting functions.

Being able to estimate probability weighting in addition to utility curvature further allows us to examine the effect of the model adopted under risk on the estimated discount function. We start from the estimation of the standard model of inter-temporal decision making in the presence of risk, discounted expected utility (*DEU*), which results from the combination of DU over time with expected utility (*EU*) under risk. We then relax its most restrictive assumptions one by one, by allowing for non-constant discounting and non-linear probability weighting, both of which substantially improve the fit of the model to the data. Accounting for nonlinear probability weighting is also important inasmuch as the curvature of the utility function will influence estimated time discounting, and the latter is generally not the same if estimated under the linear probability assumption of EU or allowing for non-linear probability weighting (Bleichrodt, Abellan-Perpiñan, Pinto-Prades and Mendez-Martinez, 2007; Schmidt and Zank, 2008).

We find that probability weighting is indeed inverse-S shaped, thus confirming the stylized fact of probabilistic insensitivity and showing the robustness of this finding to the potential confound of random switching. We also reject constant discounting in favor of hyperbolic discounting. Estimating a DEU model with constant discounting and linear probabilities, we estimate a low yearly discount rate of around 6%. Once we allow for nonlinear probability weighting, however, the estimated discount rate more than doubles to 14%. This dramatic change is due to the fact that utility estimated in conjunction with probability weighting exhibits considerably less curvature than utility estimated under the expected utility assumption. This shows that correcting discount rates for utility measures obtained from risky choices under the assumption of expected utility maximization may lead to the systematic underestimation of discounting. We will further discuss these insights after presenting the results.

2 Experimental design and model estimation

Subjects. We recruited 100 subjects at the laboratory of the Technical University in Berlin, Germany. The students were from a variety of study majors, 41% were female, and the average age was approximately 22 years. The experiment was computerised and run in 20 small group sessions of five participants each (except for one session with four participants and one with six).

General choice setup. Each MPL presented subjects with two dated lotteries, shown in figure 1. The lotteries are constructed in such a way that $x_{r,t} > x_{s,t+\tau} > y_{s,t+\tau} > y_{r,t}$. This means that the lottery to the left of the figure exhibits a higher spread in outcomes than the lottery to the right, so that we refer to it as the *risky* lottery and subscript its outcomes by r. The lottery to the right will be referred to as the *safe* lottery, with its outcomes subscripted by s (neither of these terms were used in the experiment). The subscripts t and $t+\tau$ serve to indicate the date at which the outcomes of the lottery will be paid. In order to elicit risk preferences, we simply set $t = \tau = 0$, so that all payouts take place in the present. We subsequently introduce time delays from the present by introducing $\tau > 0$. We also introduce up-front delays, which will allow us to test for hyperbolic behavior, by introducing $t > 0$. The elicitation task consist in finding the probability for which subjects will switch from a preference for the safe lottery to a preference for the risky lottery. The exact procedures used will be described below.

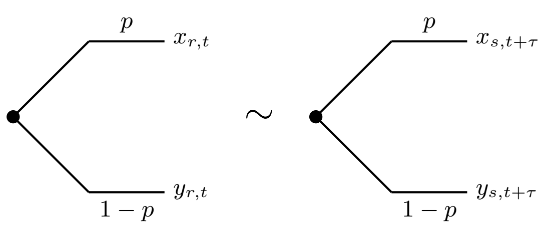


Figure 1: General choice setup

Decision model. We next describe our modeling assumptions. We start from a discounted expected utility (*DEU*) model, where a subject will choose the risky lottery whenever:

$$pD(t)u(x_r) + (1-p)D(t)u(y_r) \geq pD(t+\tau)u(x_s) + (1-p)D(t+\tau)u(y_s), \qquad (1)$$

where u indicates utility, and $D(t) = e^{-rt}$ the exponential discount function with constant discount rate r. We are furthermore interested in two extensions to this model. One is to replace the linear treatment of probabilities in equation 1 by nonlinear probability weighting, thus substituting $w(p)$ for p. The other is to allow for more general functional forms for discounting, $D(t)$, which can capture non-constant discount rates.

Functional forms. For utility, we employ a simple power function, $u(x) = x^{\rho}$. This function is the most commonly used, and we will show below that it provides a good fit for our data. For probability weighting, we use the 2-parameter function proposed by Prelec (1998), $w(p) = \exp(-\gamma(-log(p))^{\alpha})$. The latter fits the data significantly better than 1-parameter functions such as the one proposed by Tversky and Kahneman (1992) ($z = 16.4, p < 0.001$; Vuong, 1989, test), or the 1-parameter version of the same function obtained by imposing $\gamma = 1$ ($\chi^2(1) = 13.23, p < 0.001$; likelihood ratio test). Alternative 2-parameter functions, such as the one proposed by Goldstein and Einhorn (1987), provide a similar fit to the data, and using them instead does not affect our results. The two parameters of the weighting function have a specific interpretation, with α capturing mostly the curvature of the weighting function. Specifically, values of $\alpha < 1$ indicate inverse-S shaped probability weighting, $\alpha = 1$ linearity, and $\alpha > 1$ S-shaped weighting. The parameter γ indicates (mainly) the elevation of the weighting function, with $\gamma > 1$ capturing the typical case of probabilistic pessimism. Finally, we use the so-called $\beta\delta$ function to capture quasi-hyperbolic discounting, resulting in the following functional form for discounting:

$$D(t) = \begin{cases} 1, & \text{if } t = 0 \\ \beta e^{-rt} & \text{otherwise} \end{cases}$$

.

For $\beta = 1$, the function above reduces to the exponential discount function of DEU.

Values of $\beta < 1$ capture systematically lower valuations of future outcomes relative to present outcomes. In addition, we also fit a fully hyperbolic discounting function proposed by Loewenstein and Prelec (1992) to the data. The function takes the form $D(t) = (1 + \zeta t)^{\frac{-r}{\zeta}}$, where the ζ parameter captures the degree of deviation from exponential discounting. The limit of this specification as ζ tends to 0 is the exponential discounting function.

Stochastic specification and econometrics. We account for potential noise in the data by incorporating an error term, ϵ_i, into our model. Writing the valuation of the risky lottery as U_r and the corresponding valuation of the safe lottery as U_s, a subject will choose the *risky* lottery if $U_r \geq U_s + \epsilon_i$. We assume ϵ_i to be normally distributed (Hey and Orme, 1994), $\epsilon_i \sim N(0, \sigma_i^2)$. We further allow the error term to depend on characteristics of the specific MPL, indexed by i. In particular, we let the error term depend linearly on the outcome range in the risky prospect, $x_r - y_r$, which provides a good fit to our data (see also Bruhin et al., 2010). The decision problem can then be written as

$$P(\text{choose risky}) = P(\epsilon_i < U_r - U_s) = \Phi\left(\frac{U_r - U_s}{\sigma_i}\right), \tag{2}$$

where $P(\text{choose risky})$ indicates the probability of choosing the risky lottery, and Φ is the cumulative normal distribution function. The model can now be estimated by maximum likelihood. To obtain the overall log-likelihood function, we take the natural logarithm of the cumulative distribution function in equation 2 and aggregate it over prospects and decision makers as follows:

$$LL(\boldsymbol{\theta}) = \sum_{n=1}^{N}\sum_{i=1}^{43} \ln\left(\mathbb{1}_{\mathrm{r}}\Phi\left(\frac{U_r - U_s}{\sigma_i}\right) + (1 - \mathbb{1}_{\mathrm{r}})[1 - \Phi\left(\frac{U_r - U_s}{\sigma_i}\right)]\right) \tag{3}$$

where $\mathbb{1}_{\mathrm{r}}$ is an indicator variable that is equal to 1 if the risky prospect is chosen, and equal to 0 if the safe prospect is chosen, and $\boldsymbol{\theta}$ is the parameter vector to be estimated such as to maximize the log-likelihood function. The likelihood model is estimated using the Broyden-Fletcher-Goldfarb-Shanno optimization algorithm and errors are clustered at the subject level.

Identification of risk preferences. We identify risk preferences from choices amongst lotteries with payouts in the present ($t = \tau = 0$). Table 1 shows a list of the MPLs used for the elicitation. MPLs 1 to 5 in the list keep the expected value switching probability (i.e., the probability at which an expected value maximiser would switch from the safe lottery to the risky one) fixed at 0.44—the switching probability originally used by Holt and Laury (2002). These MPLs were constructed to systematically differ in terms of outcomes, allowing us to scan the outcome range and to thus identify utility curvature. On the other hand, we constructed prospect pairs 6 to 12 explicitly in such a way as to scan the probability interval in terms of expected value (EV) switching probabilities.[1] While other studies have tried to estimate probability weighting using MPLs, they usually presented too narrow a range of EV switching points to be able to cleanly separate utility curvature from probability weighting. For instance, Andersen, Harrison, Lau and Rutström (2014) used four MPLs with a range between 0.30 and 0.45, finding S-shaped probability weighting. The power to clearly identify probability weighting is likely to be lacking in their design, since it is well known that probability weighting functions tend to be relatively flat and close to linearity for the types of ranges of EV switching points used. This issue may be further confounded by noise in the data. By systematically introducing variation in EV switching probabilities, we solve this issue and augment the power to separately identify probability weighting and utility curvature.

Table 1: Prospect pairs to identify risk preferences

MPL nr.	outcomes in €	EV prob.
1	(250, 10) vs. (200, 50)	0.44
2	(300, 20) vs. (200, 100)	0.44
3	(500, 0) vs. (250, 200)	0.44
4	(500, 20) vs. (400, 100)	0.44
5	(500, 220) vs. (400, 300)	0.44
6	(500, 10) vs. (150 , 50)	0.10
7	(500, 220) vs. (300, 250)	0.13
8	(450, 150) vs. (250, 200)	0.20
9	(500, 10) vs. (450, 50)	0.44
10	(350, 50) vs. (250, 200)	0.60
11	(500, 0) vs. (350, 300)	0.67
12	(500, 0) vs. (400, 350)	0.78

Before moving on to time preferences, we quickly discuss the issue of random switching. Assume that some subjects switch at random points in a list (a tendency to switch

[1] This is done by systematically adjusting the outcome spread in the two prospects. Let $k = \frac{x_r - x_s}{y_s - y_r}$. Then we can solve the expected value of the choice probelm for $p(EV) = \frac{1}{1+k}$. It is now straightforward to manipulate k in such a way as to obtain EV switching probabilities $p(EV)$ that scan the probability interval.

towards the middle of a list results in the same prediction). On average, such subjects will exhibit a switching probability of 0.5. Now take MPL 6. Since a risk neutral respondent would switch to the risky lottery at $p = 0.1$, a risk seeker would switch to that lottery at an even lower probability. Since the choice list ranges over the whole probability interval, however, random switching behavior would result in an estimate of risk *averse* behavior. Conversely, for MPL 12, a risk averse subject would switch to the risky lottery only once the probability is above 0.78. That is, random choices would be counted towards risk *seeking*. We conclude from this that systematic noise in the form of random switching would result in an S-shaped probability weighting function in the current setup. This is exactly the opposite of what happens for CEs, where random choice is potentially confounded with inverse-S probability weighting, thus constituting an test for the importance of systematic noise in the identification of probability weighting.

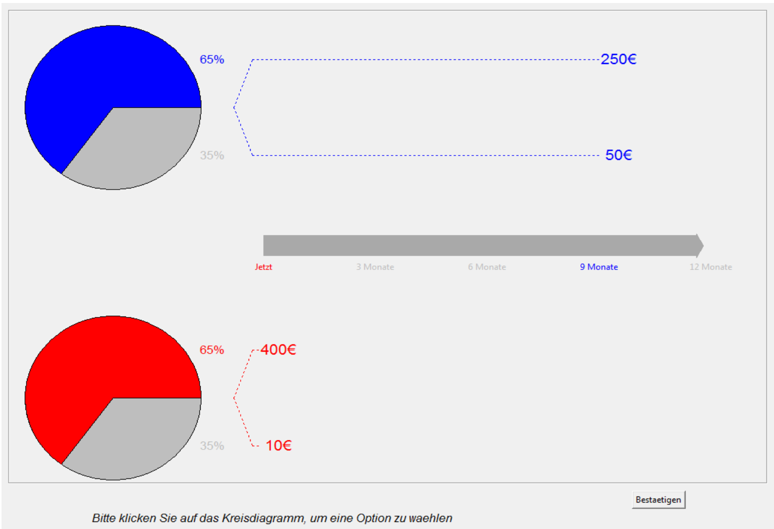
Identification of time preferences. Time preferences are identified by delaying the payouts of the lotteries into the future (the uncertainty is always resolved immediately after the experiment). Table 2 provides an overview of the choice tasks used to identify time preferences. The EV switching probability is now always fixed at 0.44. All the different MPLs are repeated for all time delays, which are fixed at $(t, t + \tau) = \{(0, 3); (0, 6); (0, 9); (0, 12); (6, 12); (9, 12)\}$ months. By comparing the lottery choice resulting from $t = 0, \tau > 0$ to the equivalent choice for $t = 0, \tau = 0$, we obtain an estimate of discounting. By further comparing choices in MPLs with constant delays, $(0, \tau)$ and $(t, t+\tau)$, we can determine whether the discount rate is constant, or whether discounting follows a hyperbolic pattern.

Table 2: Prospect pairs to identify time preferences

MPL nr.	outcomes in €	EV prob.
1	$(250_t,\ 10_t)$ vs. $(200_t + \tau,\ 50_t + \tau)$	0.44
2	$(300_t,\ 20_t)$ vs. $(200_t + \tau,\ 100_t + \tau)$	0.44
3	$(500_t,\ 0_t)$ vs. $(250_t + \tau,\ 200_t + \tau)$	0.44
4	$(500_t,\ 20_t)$ vs. $(400_t + \tau,\ 100_t + \tau)$	0.44
5	$(500_t,\ 220_t)$ vs. $(400_t + \tau,\ 300_t + \tau)$	0.44

Choice procedures. The experiment consisted of 42 distinct choice lists. Three of these lists were randomly selected for each subject and repeated during the experiment, so that subjects completed a total of 45 choice lists. The order of questions was randomised at the subject level. Within each choice list, the amounts were kept fixed but the probabilities varied across each row in steps of 5%. In order to focus subjects' attention, choices were presented one by one. A screenshot of a choice problem is shown in figure 2. The figure shows a choice between a risky lottery, offering either €400 with a probability of 0.65 or else €10, both to be paid now, against a safe lottery offering the same probability of €250 or else €50 in 9 months. The probability of winning was adjusted according to the choice using a bisection mechanism. It was, however, made clear to subjects that this mechanism served purely as a decision aid to quickly fill in the choice list. Once all the choices for a given list had been taken and the list was thus fully filled in, subjects were shown the complete choice list and explicitly encouraged to amend their choice in case they were not happy with it. Importantly, it was made clear to them that the full list would be used for the final extraction of the payout-relevant choice, with all probabilities equally likely to be selected.

Figure 2: Screenshot from time preference section of experiment



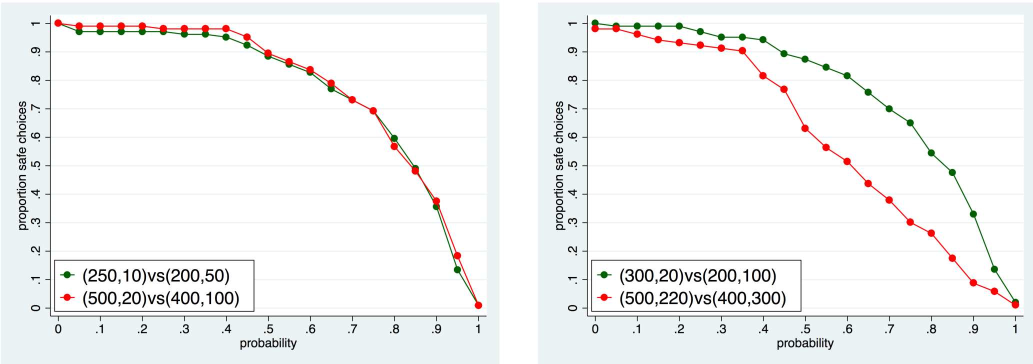
Incentives and randomisation. Subjects were paid a fixed amount of €15 for their participation. In addition, we used a random incentive mechanism whereby each subject had a 1 in 10 chance of receiving payment for their choices. This allowed us to use high monetary stakes ranging up to €500, which are important when estimating utility functions, as well as for the estimation of time discounting. Subjects were informed that if they were selected to play the tasks for real money, one of the choice lists would be selected at random. Within that choice list, one probability would then be selected, and the lottery of their choice would be played out for that probability.

Delayed payouts. The participation fee of €15 was paid directly after the experiment was over. All other payouts were made by bank transfer initiated at time t or $t + \tau$. This meant a fixed upfront delay of 3 days between the date indexed by t and the day the subject would have the money available for consumption, which for consistency was also kept for later dates. This serves to address worries that any present bias observed may be driven by the immediacy of the current payoff (Coller and Williams, 1999). All payments were guaranteed by the WZB Berlin Social Science Center, which was familiar to participants inasmuch as it is one of the institutions running the lab. Subjects were given a certificate indicating the amount won and the day on which the transfer would take place, which was signed by the experimenter. The certificate also contained the address, email address, and phone number of the person responsible of the payouts at the WZB. Subjects were explicitly encouraged to get in touch in case their bank details changed, or if they had any doubt about the payout procedure.

3 Results

3.1 Non-parametric results

We begin our analysis by presenting some nonparametric results that convey a feeling for our main findings. Figure 3 shows two plots, which together constitute a test of whether utility follows constant relative risk aversion (*CRRA*, i.e. a power function) or constant absolute risk aversion (*CARA*; i.e. an exponential function). If utility exhibits CRRA, the choice patterns for the two MPLs shown in panel 3(a), (500, 20) vs. (400, 100) and (250, 10) vs. (200, 50), ought to be identical. This is because the former MPL can be obtained from the latter by doubling all outcomes, so that the relative risk remains constant across MPLs. A similar test is shown for CARA in panel 3(b). Here one of the MPLs, (500, 220) vs. (400, 300), is obtained from the other, (300, 20) vs (200, 100), by adding a fixed amount of €200 to each outcome. Choice behavior ought to be the same in the two MPLs if subjects exhibit CARA utility due to the exponential form of the utility function. The distributions of choices in the CRRA comparison coincide almost perfectly ($z = 0.293, p = 0.770$, Mann-Whitney test on switching probabilities). In the CARA comparison, on the other hand, the proportion of safe choices is always lower and drops off more sharply for the second MPL ($z = 4.78, p < 0.001$).



(a) CRRA test

(b) CARA test

Figure 3: Nonparametric test of CRRA and CARA utility

We next examine choice behavior in the MPLs scanning the probability interval. Figure 4 plots choices for lotteries pairs 6 to 12 from table 1. We would expect the proportion of safe choices to drop off more quickly for MPLs with a lower expected value switching point. This is indeed mostly the case. More interestingly, we can use the choices to garner a first impression of whether risk preferences may change with the level of the EV switching point. For example, for the prospect pair (500 , 220) vs. (300 , 250), with an EV switching probability of $p = 0.13$, the proportion of safe choices drops quickly and by the EV probability, about 50% of participants have stopped choosing the safe option. This is an indication of risk neutral behavior. At the other extreme of the probability interval, for the prospect pair (500, 0) vs. (400, 350) with an EV switching probability of $p = 0.78$, close to 90% of subjects are still choosing the safe prospect by the EV probability—an indication of considerable risk aversion for large probabilities. At the same time, however, we also observe considerable heterogeneity in choice behavior between MPLs with relatively similar EV switching probabilities. This points at the importance of utility curvature in addition to probability weighting.

This leaves the effect of time delays to be discussed. Figure 6 focuses on one specific MPL, (500, 220) vs. (400, 300), and presents distributions of choices for this pair at the 5 different time delays from $t = 0$ (results for other MPLs are similar). The proportion of safe choices at different probabilities is highest in the present by some distance. As choices are delayed into the future, subjects choose the risky, sooner option more frequently, just as one would expect. For the longest delay of $\tau = 12$ months, 60% of subjects prefer to choose the risky, sooner lottery even when there is a 0% probability of obtaining the

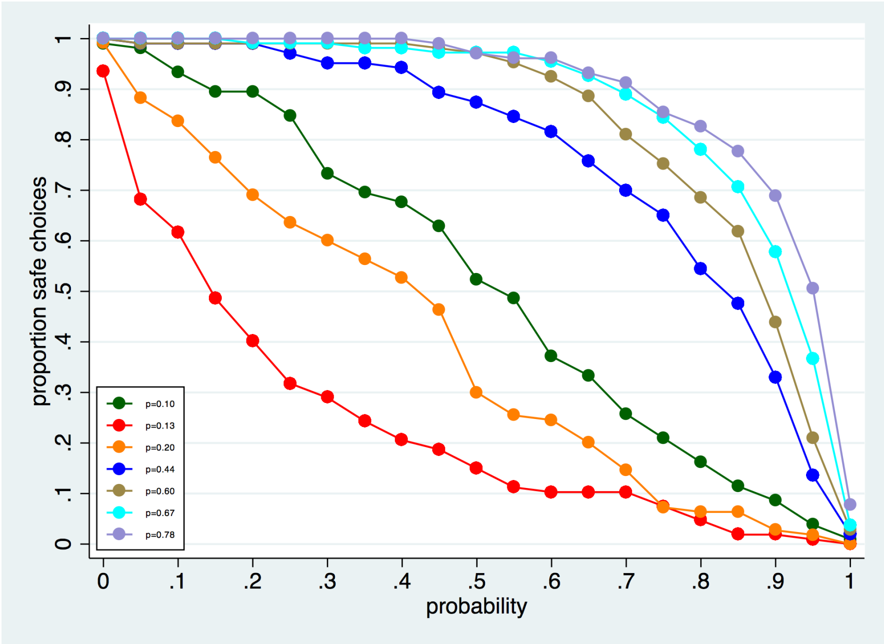


Figure 4: Choicelists in the present spanning a range of expected value switching points

high outcome. This indicates a preference for €220 now over €300 in 12 months' time, thus implying a yearly discount rate of 36% or greater under a linear utility assumption (which we will abandon in due time).

Finally, we take a look at whether discount rates are constant or whether there is an indication of (quasi-) hyperbolic behavior in our data. Figure 6 shows comparisons between choices in pairs of MPLs that can be used to identify such behavior. Panel 6(a) shows choices for the MPLs with a 3 months delay from the present versus a three months delay from 9 months, while panel 6(b) shows choices for the MPL with a 6 months delay from the present versus the MPL with a 6 months delay from 6 months. Under constant discount rates, we would expect these two pairs to show identical choice patterns. Present bias, on the other hand, would make the risky lottery more attractive when there is no upfront delay (i.e., when $t = 0$). This is indeed what we observe, providing a first indication of present bias in our data.

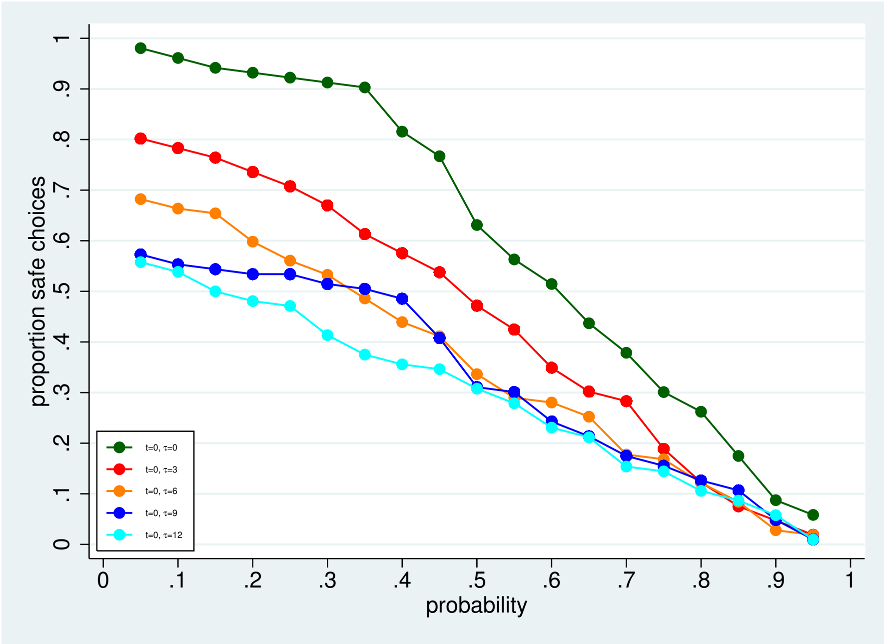
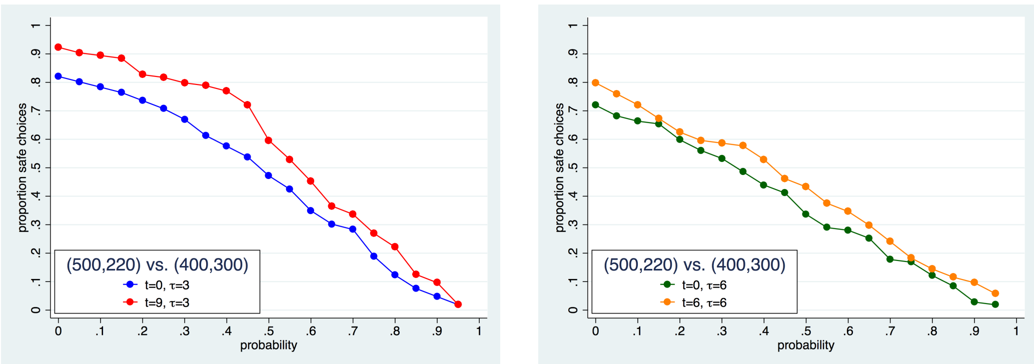


Figure 5: Choices for MPL (500, 220) vs (400, 300) with different delays from $t = 0$



(a) Choice patterns for 3 months delays

(b) Choice patterns for 6 months delays

Figure 6: Nonparametric test of (quasi-) hyperbolic behavior

3.2 Parametric estimations

Table 3 presents the results of our structural estimations. Column 1 presents the DEU model, assuming linear probabilities and constant discounting. We find a considerable degree of utility curvature, while the yearly discount rate is estimated to be quite low at 5.9%.

The second column reports parameters for what we call the discounted rank-dependent utility model ($DRDU$). This model combines constant discounting with a model under risk allowing for both utility curvature and nonlinear weighting of probabilities. The functional fit is improved considerably relative to the DEU model ($\chi^2(2) = 4094.83, p <$

0.001; likelihood ratio test). The sensitivity parameter α is clearly smaller than 1, indicating an inverse-S shaped probability weighting function. This shows that the estimation of such functions is robust to using a method in which systematic noise would work against inverse-S weighting. We also find a considerable degree of probabilistic pessimism, captured by $\gamma > 1$.

Table 3: Parameter estimates of structural models

parameter	DEU	DRDU	QHRDU	HRDU
ρ (utility curvature)	0.273	0.512	0.517	0.514
95% CI	(0.268, 0.279)	(0.499, 0.526)	(0.503, 0.531)	(0.5, 0.528)
r (discount rate)	0.059	0.141	0.111	0.239
95% CI	(0.056, 0.061)	(0.135, 0.148)	(0.103, 0.119)	(0.211, 0.268)
α (prob. sensitivity)		0.675	0.672	0.674
95% CI		(0.655, 0.694)	(0.652, 0.691)	(0.654, 0.693)
γ (prob. pessimism)		1.405	1.42	1.411
		(1.364, 1.447)	(1.378, 1.462)	(1.369, 1.452)
β (<1: present bias)			0.972	
			(0.967, 0.977)	
ζ (hyperbolicity)				1.788
				(1.201, 2.376)
σ (noise)	0.002	0.008	0.008	0.008
	(0.002, 0.002)	(0.007, 0.009)	(0.007, 0.009)	(0.007, 0.009)
max LL	-37348.93	-36130.75	-36073.05	-36066.97

Figure 7 depicts the probability weighting function estimated in the DRDU model (functions estimated in other models allowing for probability weighting are very similar). The function clearly exhibits an inverse-S shaped pattern, confirming previous results (Tversky and Kahneman, 1992; Wu and Gonzalez, 1996; Abdellaoui, 2000). At the same time, the inflection point falls relatively low, and the degree of probabilistic pessimism is quite high. This may be due to one of two possible factors. One, we used real incentives up to €500, which are higher than in most experiments. To the degree that relative risk aversion increases with stakes, this may be reflected in a lower probability weighting function (Fehr-Duda, Bruhin, Epper and Schubert, 2010; Bouchouicha and Vieider, 2017). Two, the type of MPL task used may result in systematically higher estimates of risk aversion than alternative measurement techniques. Given the setup of the MPLs, there is less space in most lists to detect risk seeking than risk aversion. This design element may well influence the overall estimate of risk aversion, although comparative data would be needed to clearly establish this.

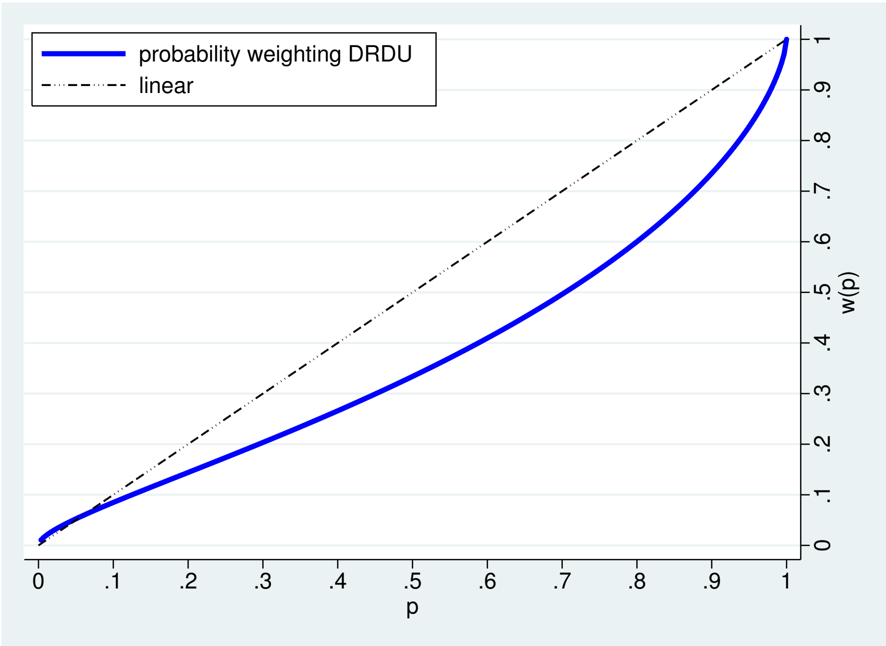


Figure 7: Probability weighting function estimated in RDRU model

The corollary of the high level of pessimism we find is a utility function that exhibits significantly less curvature in the DRDU model than the one estimated under DEU. This, in turn, also impacts the estimate of the discount rate, which at over 14% is now more than twice as high as the one estimated under DEU.

The model in column 3 relaxes the assumption of constant discounting, and instead allows discounting to be quasi-hyperbolic. This further increases model fit ($\chi^2(1) = 112.02, p < 0.001$; likelihood ratio test). The β parameter is significantly smaller than 1, indicating present bias. Finally, column 4 presents an RDU model combined with a fully flexible hyperbolic discount function. Compared to the RDU model with quasi-hyperbolic discounting, this model fits the data even better ($z = 1.90, p = 0.02$; Vuong test), providing some evidence for fully hyperbolic behavior.

3.3 Individual estimates

The results discussed up to this point are derived from aggregate estimates of the choice data. It is, however, well-known that there is considerable heterogeneity in individual preferences. Table 4 presents summary statistics of these estimates for our two best-fitting models, QHRDU and HRDU. The individual estimates of these models converged for 87 and 83 of our 100 subjects respectively. In addition to descriptive statistics of the distribution of estimates, the table reports the number of statistically significant parameter estimates. The significance is measured against appropriate benchmarks for the different parameters, i.e. against 1 for utility curvature, probabilistic sensitivity, probabilistic pessimism, and the present-bias parameter in the QHRDU model; and against 0 for the discount rate, noise, and the hyperbolicity parameter.

Table 4: Individual-level estimates of QHRDU and HRDU models

QHRDU model

Parameter	1stQ	Median	3rdQ	Mean	Nr. significant
ρ (utility curvature)	0.27	0.45	0.61	0.45	83
α (prob. sensitivity)	0.51	0.76	1.13	0.82	54
γ (prob. pessimism))	1.01	1.31	1.79	1.52	59
r (discount rate)	0.05	0.12	0.23	0.16	67
β (<1: present bias)	0.96	0.99	1.01	0.98	42
σ (noise)	0.00	0.00	0.01	0.01	68

Based on N=87 subjects; the model did not converge for 13 subjects.

HRDU model

Parameter	1stQ	Median	3rdQ	Mean	Nr. significant
ρ (utility curvature)	0.26	0.44	0.61	0.44	76
r (discount rate)	0.04	0.15	0.41	0.34	52
α (prob. sensitivity)	0.52	0.74	1.15	0.82	53
γ (prob. pessimism)	1.01	1.35	2.02	1.65	58
ζ (hyperbolicity)	0.73	2.24	4.17	4.26	33
σ (noise)	0.00	0.00	0.01	0.01	61

Based on N=83 subjects; the model did not converge for 17 subjects.

Some interesting features stand out. We found strong probabilistic insensitivity in the aggregate estimates, and 62% of subjects exhibit statistically significant probabilistic insensitivity. At the same time, close to 70% of subjects exhibit a pessimism parameter significantly different from 1. Overall, for 15% of subjects both sensitivity and pessimism were not significantly different from 1. This gives a rough estimate of the number of subjects for whom we cannot reject the expected utility decision model. The number of subjects following expected utility in our setup is indeed quite similar to the proportion of EU followers estimated by Bruhin et al. (2010) employing a finite mixture model. In terms of time preferences, we find that we can reject the null of non-hyperbolic preferences for approximately 50% of subjects according to the quasi-hyperbolic model and 40% of subjects under the fully-hyperbolic model.

4 Discussion and conclusion

In this paper, we presented results from a comprehensive multiple price list experiment to elicit risk and time preferences in an integrated framework. Using a variation on a popular multiple price list design, we were able to estimate time preferences in addition to risk preferences. We did so in a context of pervasive risk, which may be more realistic than the artificial certainty assumed by the majority of elicitation designs to date. In addition, we designed the choice lists with the explicit goal to allow us to separate utility curvature from probability weighting. Introducing orthogonality between stakes and probabilities, and scanning the probability interval, we were able to show that typical patterns of inverse-S shaped probability weighting are stable to the use of this method.

In the context of time preferences, we found clear evidence for present bias and hyperbolic behavior. This evidence is contrary to some previous studies that had shown present bias to disappear once risk was added to the elicitation mechanism (Keren and Roelofsma, 1995; Weber and Chapman, 2005). In terms of discount rates, we found the estimated yearly rate to be as low as 6% when adopting discounted expected utility. Adopting a rank-dependent formulation including probability weighting instead, however, more than doubled the estimated discount rate to 14%. This shows that using utility curvature obtained from risky decisions and estimated under the assumption of expected utility theory, as proposed by Andersen, Harrison, Lau and Rutström (2008), is problematic, and may lead to artificially low estimates of discounting. More generally, it points towards the importance of a careful treatment of utility in the assessment of discounting.

Finally, we showed that inverse-S shaped probability weighting is stable to the use of the particular form of multiple price list we used. This is important, inasmuch as systematic noise under the form of random switching (or switching towards the middle of a list) could potentially distort estimates of probability weighting. In the particular design used, however, this bias would work *against* inverse-S shaped probability weighting. The fact that we replicated the typical inverse-S shape thus shows the stability of the empirical phenomenon.

Some studies have reported different shapes of probability weighting, including the opposite pattern of S-shaped probability weighting. For instance, Harrison, Humphrey and Verschoor (2010) reported S-shaped probability weighting from four developing countries. Andersen et al. (2014) and Andersen, Harrison, Lau and Rutström (2017) reported S-shaped probability weighting estimated based on the same type of choice lists as used in this paper. The latter finding is likely due to poor discriminatory power between utility curvature and probability weighting, given a narrow range of expected value switching probabilities in the stimuli, and potentially to the presence of noise. The findings in the former study are likely to be driven by the restrictive assumption of a 1-parameter probability weighting function. Indeed, L'Haridon and Vieider (2016) showed that probabilistic sensitivity is one of the few universal behavioral patterns in student populations from 30 countries. Vieider, Beyene, Bluffstone, Dissanayake, Gebreegziabher, Martinsson and Mekonnen (2016) generalized this finding to a representative rural population sample from Ethiopia. We thus conclude that—notwithstanding some claims to the contrary—inverse-S shaped probability weighting is alive and in good health.

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A ONLINE APPENDIX: Full-lenght instructions (English)

Below we include the instructions in English, which have been translated from the original German. German instructions available upon request.

Instructions

Thank you for participating in this experiment in decision making! You will obtain a fixed payment of 15 Euros for your participation in this experiment—those 15 Euros are yours to keep independently of the outcomes in the experiment. In addition, you will be compensated with whatever you earn during the experiment according to the procedures described in these instructions.

You may consult these instructions at any time during the experiment. In case you should have any questions or doubts after these instructions are read to you (or at any point during the experiment), please raise your hand and an experimenter will come and assist you in private. We are only interested in your preferences: there are no right or wrong answers!

You will be asked to make a number of different choices. Please consider each decision carefully. Take a careful look at outcomes and the probabilities associated to them before taking a decision. Remember that your final payoffs from this experiment will depend on the decisions you take (and of course, on chance). There is no need to rush: the experiment has been designed to be easily completed in less than an hour, and the experiment will only end once everybody in the session is done with all the tasks.

Please remain seated when you are finished with the tasks. At the end of the experiment, you will be asked to fill out a questionnaire. The answer to the questionnaire as well as all your answers to the tasks will be private, and cannot be traced back to you personally. Once everybody is done filling in the questionnaire, an experimenter will call you up to proceed to the payout.

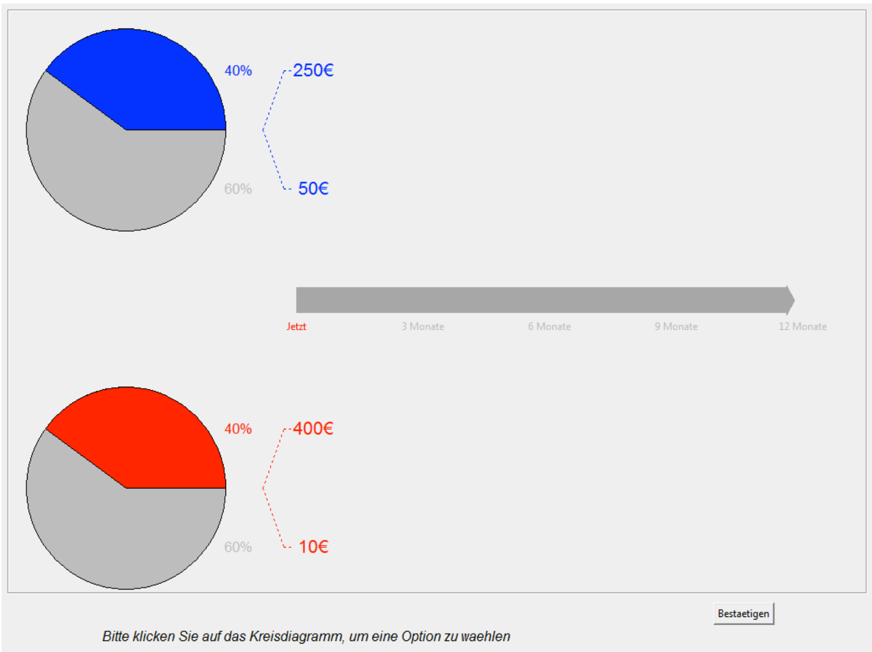
After this, you will be paid your participation fee, plus any additional amount you may have won, in private. At this point the experiment is over and you may leave.

Do not talk during the experiment, or you will be immediately excluded!

Good luck!

Decision Task

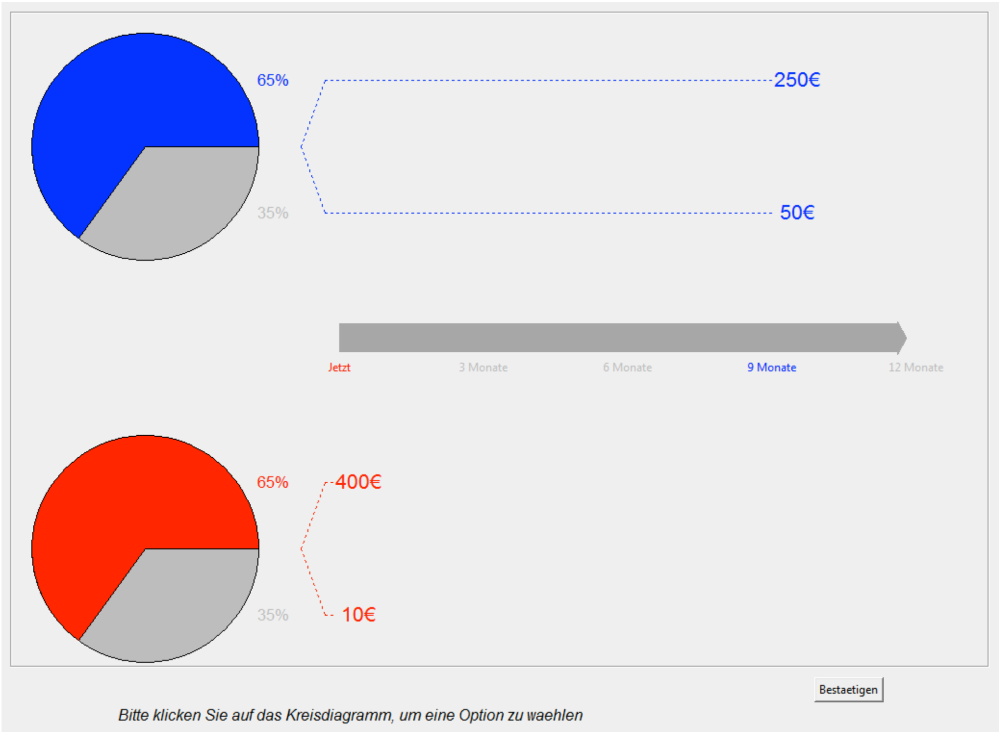
In this experiment, you are asked to indicate your preferences between lotteries involving both risk and time delays. A typical choice is depicted below:



The lottery at the top provides a 40% probability to obtain 250 €, and a complementary probability of 60% to obtain 50 €. The option at the bottom provides a probability of 40% to obtain 400 € and a complementary probability of 60% to obtain 10 €. Notice how the probabilities associated to the higher and lower amounts in the two options are the same. This is a general feature of the decision task, which will hold throughout the experiment.

In the example above, all payoffs obtain now, as indicated by the time arrow between the two lotteries. In other decision tasks, however, either one or both lotteries may offer a payout that obtains at some later point in the future. An example of this is depicted here below:

2



In this example, both the outcomes in the two lotteries and the probabilities with which they obtain are the same as in the first example above. However, the timing of the payment now differs across options. Should you be selected to play this lottery for real, the outcomes of the lottery at the top will be paid in 9 months. The outcomes of the lottery at the bottom, on the other hand, will be paid today. This is again indicated by the large time arrow between the two lotteries.

These two examples illustrate all the dimensions involved in the decision tasks: two different outcomes for each of two lotteries; a probability of winning the higher amount within the lottery, which is the same across lotteries; and the time at which the indicated amounts are to be paid out, which may or may not differ between the two lotteries (but which is always the same within the same lottery).

The choice lists

The choices are grouped within lists. Within a list, the outcomes and payment periods of the two options are fixed, while the probabilities range from a 0% chance to obtain the higher outcome in the lottery to a 100% of obtaining the higher outcome in the lottery, with a step of 5%. More precisely, for each, list you will have to make decisions for each probabilities 0%, 5%, 10%, 15%, 20%, 30%, 35%, 40%, 45%, 50%, 55%, 60%, 65%, 70%, 75%, 80%, 85%, 90%, 95%, 100%.

Take again a look at the first example above (all outcome obtaining now). You can see all the choices involving probabilities ranging from 0% to 100%. For a 0% chance of winning the higher outcome, you

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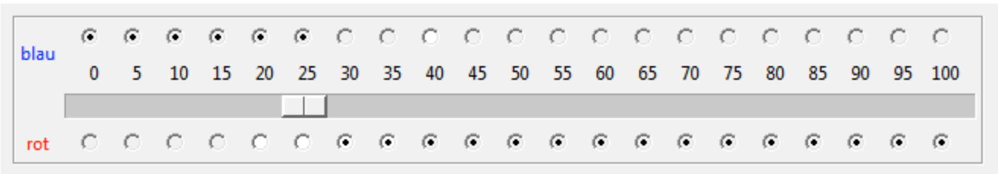
will want to choose the lottery at the top, which in this case offers 50 € for certain (as opposed to the 10 € for the lottery at the bottom). For a 100% chance of winning the higher outcome, you will want to choose the lottery at the bottom, which now offers 400 € for sure instead of the 250 € for the top lottery. Taken together, this indicates that you will want to switch from the top to the bottom lottery at some point as the probabilities increase. Where you switch depends entirely on your preferences—there are no right or wrong answers.

In order to help you save time in completing the choice list, the software will initially present you with some isolated choices from the list and then fill in the list according to your preferences. Looking again at the example, a preference for the bottom over the top lottery for a probability of 65% of winning the higher amount means that you would also prefer the top option for larger probabilities. In that case, the software would select the top lottery for a probability of 65%, and would also complete the choices, selecting the top lottery for probabilities 70%, 75%, 80%, 85%, 90%, 95%, 100%.

It is important to understand that this is merely an algorithm devised to speed up the choice process. Once the complete list has been filled in by the algorithm, you will be asked to double-check your choices by directly looking the list including all different probability levels, as shown below. At this point, you should check whether the indicated choice does indeed correspond to your preferences for each probability. If this is not the case, you can still change any decisions that do not correspond to your preferences by moving the ruler to the right of the screen. Once you are satisfied with your choices, you can confirm this and move on to the next decision task. Please notice that there will be no possibility to come back to a choice once you have confirmed the final choice list!

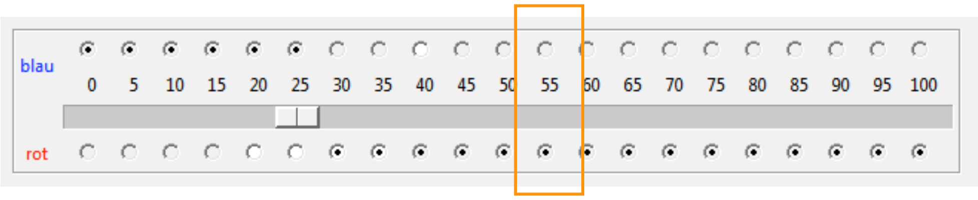


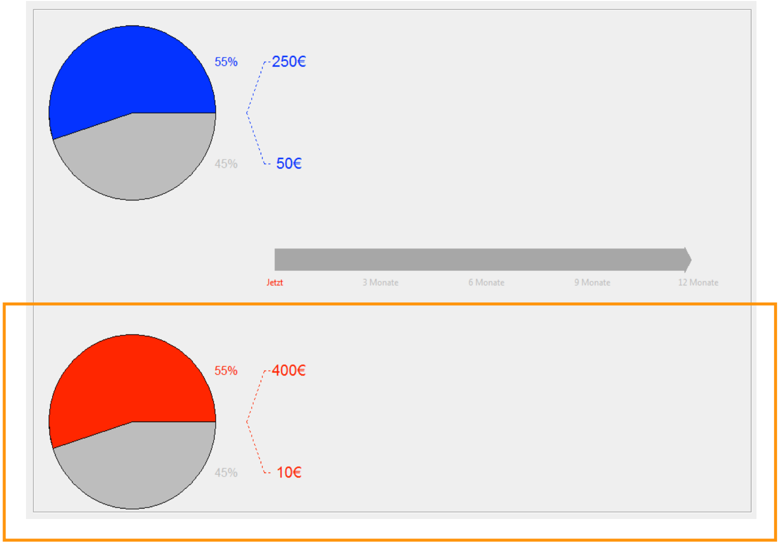
Payment mechanism

You will receive a flat payment of 15 € for your participation in the experiment. This payment is independent of your choices, and will be given to you as soon as you finish the experiment and respond to all choices. In addition, you may play out one of your choices in the task for real. It is thus important that you pay close attention to all the aspects in all decision tasks, as these may determine the level and timing of your additional compensation.

At the end of the session, once everybody has completed the experiment, every participant will draw a chip from a bag containing 10 chips in total, one red and nine black. Those who drew the red chip will get the chance to play some choice for real money. At this point, all the participants who drew a black chip will be paid their 15 € and will be allowed to leave, while the other participants will stay to play out one of his/her choices.

To do this, first one of the 45 choice lists in the experiment will be drawn at random by picking a numbered ball from a bag. For the selected list, one of the 21 choices (probabilities) will subsequently be randomly selected. For the selected choice, the option chosen by the subject during the experiment will then be played for real, again by drawing a numbered ball from a bag. You may check the contents of the bags at any time during the procedure should you desire to do so. The decision will be played out immediately after the experiment, no matter of the payout date of the selected lottery.





Notice that only one choice will be played for real and that the selected lottery will be played only once. Since every single choice has the same probability of being selected to be played for real, you should respond to every single choice as if it were the one you will ultimately play. In other words, there is no way in which you can increase your winnings or spread your risk by answering strategically. The optimal strategy is to fill out each single choice as if it were the one that will be selected for real play.

Procedures for delayed payout

Everybody will obtain the participation payment of 15 € immediately after the experiment. In case you should win any additional money, this amount will be paid to you via bank transfer. The bank transfer will be initiated on exactly the day indicated on the decision screens. This means that the amount will be on your bank account 3 days after the payment is initiated. This means that any outcomes that obtain now will in fact be on your account in 3 days. A payout that obtains in 6 months will be on your account 6months + 3 days from today.

To make the bank transfer possible, we will ask for your bank information if you are selected to play one of your choices for real. This information will be given to the administration of the Wissenschaftszentrum Berlin für Sozialforschung (WZB), so that the transfer can be effectuated on the date indicated. This information will in no way be linked to your decisions in the experiment, but only to the final amount you won. Also, it will be destroyed once the transaction has taken place.

The Bank transfer will be executed by the WZB through Commerzbank. Once the outcome has been determined, you will also be given an official certificate, stating that you are entitled to a given payout on a given date. This certificate constitutes a guarantee from the WZB that you will obtain that payout on the indicated date. The certificate also contains the contact details of the person responsible for the transfers at the WZB, whom you can contact in case you have any doubts about the procedures, or in case you banking details should change before the payment date.

Final remarks

Please take the time to read through the instructions again on your own. If you have any doubt, raise you hand and an experimenter will help you out. Once you understand how the choices work, you will have the opportunity to familiarize yourself with the software with a few practice questions. Only then will the real experiment start.