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Why Do People Discount? The Role of Impatience and Future Uncertainty

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Despite the intuition that risk preferences affect intertemporal choice because the future is uncertain, time discounting is commonly regarded as a reflection of impatience. This interpretation of time discounting rests on the assumption that risk preferences are fully controlled for in the estimation of time discounting and no longer act as a confounder. However, the evidence provided in this paper contradicts this standard interpretation. Through an experiment, we show that despite accounting for the utility curvature—the established approach to control for risk preferences—about 43% of the observed time discounting can be explained by an aversion against future uncertainty rather than impatience. Future uncertainty, although small, receives disproportional weight because subjects engage in subproportional probability weighting, an important characteristic of risk preferences that does not feature in the standard risk framework of most intertemporal choice models. Our finding implies that many people do not demand compensation for their waiting time but rather for an uncertain future.

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1 Introduction

The present is known, while the future is inherently uncertain. This fact has been recognized since the seminal work by Fisher (1930). It implies that intertemporal decisions are not only governed by people's attitudes toward delaying outcomes, but also depend on the uncertainty of the future and its evaluation (Azfar, 1999; Dasgupta & Maskin, 2005; Halevy, 2008; Sozou, 1998). Today, this insight about future uncertainty, defined as the probability that a future outcome fails to materialize, has led to the established notion that researchers need to account for both time and risk preferences to understand tradeoffs between present and future outcomes (Andersen et al., 2008; Andreoni & Sprenger, 2012; Wölbert & Riedl, 2013). Only by controlling for risk preferences can we understand pure time preferences and distinguish how much observed time discounting is due to impatience—the aversion to waiting for a future outcome—rather than aversion to an uncertain future.

Because uncertainty plays a prominent role in intertemporal choice, it is important to find a theoretical framework that can adequately explain a person's evaluation of future uncertainty. To date, much of the influential work in this regard (e.g., Andersen et al., 2008; Andreoni & Sprenger, 2012) builds on expected utility theory (EU), in which risk attitudes are captured by the curvature of the utility function.

However, EU does not feature deviations from a linear assessment of probabilities—notably, nonlinear probability weighting—which has been shown to be an important characteristic of risk preferences when a choice is atemporal (Quiggin, 1982; Tversky & Kahneman, 1992).

In this paper, we seek to disentangle impatience from future uncertainty within a framework that allows for both nonlinear utility and nonlinear probability weighting, as recent evidence suggests that models that incorporate both features perform better at predicting real-world outcomes (Lampe & Weber, 2021; Somasundaram & Eli, 2022). First, we provide empirical evidence which suggests that probability weighting plays an important role for the evaluation of future uncertainty. Second, we quantify future uncertainty and show how much of the observed time discounting it can explain. While the theoretical importance of future uncertainty is widely acknowledged, little is known about its empirical significance for intertemporal choice.

Our work builds on a model of intertemporal choice developed by Epper and Fehr-Duda (2021) (henceforth, the EFD model). The EFD model builds on the concept of *survival risk*, which is the risk that an outcome may not survive until its realization date. Thus, any allegedly sure future outcome is transformed into a lottery when the future is uncertain. In this lottery, the original outcome is realized with a given "survival probability", and the decision maker otherwise remains empty-handed. To define future uncertainty, we use the measure of *survival risk* that is employed in the EFD model, but extending its interpretation to also include the notion that decision makers may fail to derive utility from a realized future outcome. Importantly, the EFD model assumes rank-dependent utility (RDU), a popular generalization of EU (Quiggin, 1982; Tversky & Kahneman, 1992; Yaari, 1987) for the evaluation of risky lotteries. It incorporates subproportional preferences in a behaviorally appealing way to allow for Allais' common-ratio violations. Subproportionality implies that small probabilities are inflated while large probabilities are deflated (see, e.g., Camerer & Ho, 1994; Kahneman & Tversky, 1979; Tversky & Kahneman, 1992; Wu & Gonzalez, 1996). Moreover, it implies that adding future uncertainty—the small chance of an outcome realization failure—to an allegedly sure outcome has a different effect than adding future uncertainty to a lottery. That is, it leads to a stronger discounting of the sure future outcome than of the future lottery. Indeed, a series of experimental results provides empirical support for this hypothesis (Ahlbrecht & Weber, 1997; Coble & Lusk, 2010; Keren & Roelofsma, 1995).

We conduct a preregistered laboratory experiment (N=403) to test this model prediction and compare it to the standard intertemporal choice model that is based on EU. Moreover, we exploit the observable variation in the discounting of sure outcomes and lotteries that results from probability weighting in order to estimate future uncertainty. Our estimation procedure has two steps. First, we employ structural estimations to jointly estimate the utility curvature, probability weighting, and discount factors. Second, we estimate discount factors for three lotteries that have previously been used to elicit risk preferences and their corresponding certainty equivalents. Using these parameter estimates, we are able to measure future uncertainty and analyze the extent to which it explains time discounting.

We also analyze heterogeneity in future uncertainty regarding both its distribution and how it relates to individual characteristics such as ambiguity aversion and cognitive ability. Our hypothesis is that ambiguity aversion and cognitive ability both correlate with future uncertainty. More concretely, we predict that the extent to which the future is perceived as uncertain increases with ambiguity aversion but decreases with greater cognitive abilities.

Our experimental results suggest that lotteries are discounted less than their atemporal certainty equivalents. This observation is consistent with the prediction of the EFD model, but it contradicts prominent intertemporal choice models that account for risk attitudes through a standard EU framework, neglecting subjective probability weighting. We show that the stronger the subproportionality of the probability weighting function, the larger the difference in the discounting.

Moreover, our quantification of future uncertainty reveals further interesting insights. We find that the average (weighted) future uncertainty is sizable and statistically significant and that it does not seem to stem from a lack of trust in the experimenters. Amplified by the effect of subproportional probability weighting, future uncertainty explains about 43% of the time discounting observed in our experiment. This finding is important because our estimation of discount factors controls for the curvature of the utility function, which was previously deemed sufficient to account for risk attitudes. This finding implies that many decision makers prefer immediate gratification not because they are adverse to longer waiting times, but rather because they fear the risk that future outcomes will fail to generate utility.

Finally, our analysis provides meaningful insights about the predictors of individually perceived future uncertainty. Contrary to what has previously been hypothesized, we do not observe any significant correlations between ambiguity aversion and future uncertainty or between cognitive abilities and future uncertainty. However, we do find a striking gender gap in the perception of future uncertainty, with women assessing the risk of future adverse events as being smaller than men do.

Our paper makes three important contributions. First, it contributes to a discussion of how to separate time and risk preferences (Andreoni & Sprenger, 2012; Cheung, 2015; Epper & Fehr-Duda, 2015; Miao & Zhong, 2015). While it is widely agreed that future outcomes are subject to uncertainty and that risk preferences therefore need to be controlled for when estimating time preferences, recent influential work does this by accounting for the curvature of the utility function (e.g., Andersen et al., 2008; Andreoni & Sprenger, 2012). This has been responsible for significant methodological improvements and has advanced our understanding of how to correctly estimate time preferences. Nevertheless, the theoretical framework for that work appears inconsistent with our findings that reveal a systematic discounting difference between lotteries and certainty equivalents. The insights of our analysis suggest that EU does not adequately represent risk preferences in intertemporal choice models. Instead, our evidence highlights the role of probability weighting and supports theoretical models that capture risk aversion through both a concave utility function and subproportional probability weighting.

Second, our work provides a way to quantify future uncertainty and thus empirical support for an intuition that underlies much of modern intertemporal choice analysis. The result that time discounting is predominantly explained by future uncertainty supports the notion that time and risk preferences have a strong common factor. This connects to a line of theoretical work that has studied the effect of uncertainty on time discounting (Azfar, 1999; Dasgupta & Maskin, 2005; Halevy, 2008; Sozou, 1998). The common theme in this literature is the development of a theoretical foundation that explains intertemporal choice (including dynamic inconsistency) by the existence of uncertainty. One previous study has used the concept of future uncertainty similarly to our analysis: Epper et al. (2011) build on the same theoretical model that we use here to study hyperbolic discounting in an experimental setting.[1] These authors show that decreasing discount rates over time are strongly related to deviations from linear probability weighting. The authors argue that this result could be caused by future uncertainty, since individuals who weigh probabilities in a nonlinear way also weigh the uncertainty of the future in a nonlinear

[1] Andreoni and Sprenger (2012) also study the role of uncertainty in future outcomes to explore the role of present bias. However, unlike our approach, they induce uncertainty artificially by paying the larger-later payment with a given probability that is smaller than the probability of the smaller-sooner payment. In contrast, we believe that the uncertainty is already induced by the nature of the payoff delay.

way, resulting in hyperbolic discounting. While the results of Epper et al. (2011) are plausibly explained by future uncertainty,[2] their paper does not provide a way to quantify it.

Third, our paper contributes novel and important insights about the nature of time discounting that allow disentangling the effect of future uncertainty from impatience. To date, time discounting has commonly been interpreted as a reflection of impatience because it is believed that risk preferences are controlled for in the estimation (e.g., Anderson & Stafford, 2009; Echenique et al., 2020; Yoon, 2020). By allowing for probability weighting, our analysis highlights that for many people who face intertemporal tradeoffs, future uncertainty is indeed an important if not the main driver for their time discounting. They mind waiting not because they are impatient, but rather because they perceive the future as uncertain and fear the risk that future outcomes may not materialize or yield utility. This is an important insight for both practitioners and policy makers who have an interest in people investing in their future, for example, to save for their retirement. When relying on the interpretation of impatience, it is usually necessary to add a substantial "patience premium" to a future outcome to make it as attractive as an alternative that generates immediate utility. If, however, the source of the discounting is risk, such a premium may not be necessary. Instead of paying a risk premium, future investments could be made more attractive by reducing uncertainties about the future, for example, by providing guarantees.

The remainder of the paper is structured as follows: In Section 2, we recap the theoretical foundations of the EFD model and derive a directly testable implication and an expression that allows us to estimate future uncertainty. In Section 3, we detail our experimental setup. In Section 4, we present and discuss our results. In Section 5, we conclude.

2 Theoretical Background

The EFD model builds on RDU (Quiggin, 1982; Tversky & Kahneman, 1992; Yaari, 1987), the most popular generalization of the EU normative standard (Von Neumann & Morgenstern, 1944, 1947). The RDU representation for a generic lottery $(x_1 : p_1 \; ; \; \ldots \; ; \; x_n : p_n)$ assigning probability

[2] Epper et al. (2011) use the term *contract survival* for future certainty (future uncertainty = 1−contract survival).

p_i to outcome x_i, with complete ranking of the outcomes $x_1 \geq \ldots \geq x_n$, is:

$$(x_1 : p_1\, ;\ \ldots\ ;\ x_n : p_n) \quad \mapsto \quad \sum_{i=1}^{n} \left(\omega\Big(\sum_{j=1}^{i} p_j \Big) - \omega\Big(\sum_{j=1}^{i-1} p_j \Big) \right) u(x_i), \tag{1}$$

where the utility function $u(\cdot)$ maps outcomes to real numbers, and the probability weighting function $\omega(\cdot)$ is a mapping from the objective probability space $[0,1]$ to the weighted probability space $[0,1]$ that is assumed to satisfy $\omega(0) = 0$ and $\omega(1) = 1$ and to be nondecreasing in p. $\omega(\cdot)$ is assumed to satisfy $\omega(0) = 0$ and $\omega(1) = 1$ and to be nondecreasing in p. EU is a special case of RDU with linear probability when $\omega(p) = p$.

To map Allais' empirical observation of common-ratio violations, the EFD model further incorporates subproportional preferences (Kahneman & Tversky, 1979; Prelec, 1998). Subproportionality implies that the ratio of probability weights is closer to unity for two small probabilities than the ratio of probability weights for the same probabilities multiplied by a common factor.[3] Finally, the EFD model makes the important but credible assumption that in decisions over time, the realization of a future outcome is subject to uncertainty. That is, any allegedly sure future outcome is construed as a two-outcome lottery, where the outcome either materializes and yields utility with survival probability s or fails to materialize with probability $1 - s$. We refer to $1 - s$ as future uncertainty. In contrast, any present outcome is certain.

These two model characteristics have important implications. Since subproportionality implies that probabilities are transformed nonlinearly, the presence of future uncertainty can have different distortionary effects, depending on the nature of the outcome. Specifically, a small uncertainty revolving around an allegedly sure future outcome should receive larger weight than the same uncertainty revolving around a lottery, whose outcomes were probabilistic to begin with. The consequence of such probability weighting is that sure future outcomes are discounted more than future lotteries. Under standard parameter assumptions, this implication cannot be explained by EU.

To illustrate this point, we assume RDU with a utility function $u(x)$ and a probability

[3]Formally, subproportionality implies that $\frac{\omega(p)}{\omega(q)} < \frac{\omega(\lambda p)}{\omega(\lambda q)}$ for $1 \geq p > q > 0$ and $\lambda > 1$.

weighting function $\omega(p)$. When evaluating the lottery $L = (x_1 : p_1 ; ... ; x_m : p_m)$, where $x_1 > x_2 > ... > x_m$ and $\sum_{i=1}^{m} p_i = 1$, decision makers weigh outcomes depending on their relative ranks as follows:

$$\pi_i = \begin{cases} \omega\left(p_1\right) & \text{for } i = 1 \\ \omega\left(\sum_{k=1}^{i} p_k\right) - \omega\left(\sum_{k=1}^{i-1} p_k\right) & \text{for } 1 < i < m \\ 1 - \omega\left(1 - p_m\right) & \text{for } i = m, \end{cases} \tag{2}$$

where i is the relative rank of the outcome and $\pi_i \geq 0$ (Diecidue & Wakker, 2001). In the presence of future uncertainty, an allegedly sure future outcome can be expressed as the lottery $C_{future} = (c : s ; 0 : 1 - s)$, where the original outcome c occurs with survival probability s and the outcome 0 occurs with probability $1 - s$. Hence, the present value of C_{future} is

$$\begin{aligned} V_0(C_{future}) &= \left[u(c)\pi_1 + u(0)\pi_2\right]\rho \\ &= u(c)\omega(s)\rho, \end{aligned} \tag{3}$$

where ρ is the part of the time discounting that is independent of future uncertainty and captures a person's impatience. In the following, we refer to ρ as the "pure discount factor".[4] In contrast, the observed discount factor of the allegedly sure future outcome $\tilde{\rho}_C$ is obtained by dividing $V_0(C_{future})$ by the value of c evaluated today, $V_0(c) = u(c)$:

$$\tilde{\rho}_C = \frac{V_0(C_{future})}{V_0(c)} = \omega(s)\rho. \tag{4}$$

Note that the observed discount factor accounts for both the weighted survival probability $\omega(s)$ and the pure discount factor ρ.

Similarly, a two-outcome lottery in the future can be expressed as a three-outcome lottery under future uncertainty. The lottery $L = (x_1 : p ; x_2 : 1 - p)$ therefore becomes $L_{future} = (x_1 :$

[4] Naturally, any discount factor will be dependent on the time delay of an outcome, that is, the time until the outcome materializes. Unlike Epper and Fehr-Duda (2021), however, we ignore this dependency, as our focus is on a two-period model with constant delay.

$ps\ ;\ x_2 : (1-p)s\ ;\ 0 : 1-s)$. The present value of L_{future} is expressed as

$$\begin{aligned} V_0(L_{future}) &= [u(x_1)\pi_1 + u(x_2)\pi_2 + u(0)\pi_3]\,\rho \\ &= \big[u(x_1)\omega(ps) + u(x_2)[\omega(ps + (1-p)s) - \omega(ps)] + u(0)[1-\omega(s)]\big]\,\rho \\ &= \left[(u(x_1) - u(x_2))\frac{\omega(ps)}{\omega(s)} + u(x_2)\right]\omega(s)\rho, \end{aligned} \tag{5}$$

and the observed discount factor of the lottery is obtained by dividing $V_0(L_{future})$ by the value of L evaluated today, $V_0(L) = E(U(L))$:

$$\tilde{\rho}_L = \frac{V_0(L_{future})}{V_0(L)} = \frac{\left[(u(x_1) - u(x_2))\frac{\omega(ps)}{\omega(s)} + u(x_2)\right]\omega(s)\rho}{[u(x_1) - u(x_2)]\omega(p) + u(x_2)}. \tag{6}$$

As before, the observed discounting depends on both the weighted survival probability $\omega(s)$ and pure time preferences ρ, but the effect of both arguments is different than for the discounting of an allegedly sure future outcome. In fact, when probability weighting is subproportional, it follows that $\frac{\omega(ps)}{\omega(s)} > \omega(p)$. This implies that the observed discount factor of the lottery, $\tilde{\rho}_L$, should be larger than the observed discount factor of the sure outcome $\tilde{\rho}_C$. We test this prediction with the experiment presented in Section 3.

Finally, to quantify the future uncertainty $1-s$ and to disentangle its effect from the pure discount factor ρ, we can exploit the variation resulting from the fact that $\tilde{\rho}_L \neq \tilde{\rho}_C$. Dividing $\tilde{\rho}_L$ by $\tilde{\rho}_C$ and then rearranging yields

$$\frac{\omega(ps)}{\omega(s)} = \frac{\frac{\tilde{\rho}_L}{\tilde{\rho}_C}\left[(u(x_1) - u(x_2))\omega(p) + u(x_2)\right] - u(x_2)}{u(x_1) - u(x_2)}. \tag{7}$$

The goal for our empirical task is thus to collect data to structurally estimate the curvature of the utility function, the parameters of the probability weighting function and the discount factors $\tilde{\rho}_L$ for both lotteries, and their certainty equivalents $\tilde{\rho}_C$. Using these estimates, we can numerically solve equation (7) for the survival probability s and determine the future uncertainty $1-s$.

3 Experimental Methods and Econometric Estimations

We conducted our experiment in the spring of 2021 using the facilities of the INSEAD-Sorbonne behavioral lab in Paris, France. The experiment was preregistered at AsPredicted (registration number: 57554) and approved by the INSEAD ethical review committee (Protocol ID: 202025). It was programmed with the experimental software oTree (Chen et al., 2016). In total, 403 subjects participated in our study. The average age of the participants was 23.7 years, and 66% of the participants were women. Due to Covid-19 restrictions in France, the lab was partly closed, which entailed that only 234 subjects could be invited to the lab. The remaining 169 subjects from the same subject pool participated online from home, using their own computer. To keep the atmosphere of the online setup similar to the setup in the lab, the subjects who participated remotely joined a *Zoom* meeting attended by the experimenters. This allowed the experimenters to supervise the subjects' activities and to respond to possible questions that came up during the experiment. The interface and the procedure of the experiment were identical for both setups. Table A3 in the Online Appendix presents the summary statistics of variables capturing the socioeconomic backgrounds of the subjects and other individual characteristics. The summary statistics are presented separately for subjects who participated in the lab and subjects who participated online. The experiment consisted of three parts and a survey questionnaire.

3.1 Risk Preference Elicitation

In part one of the experiment, we elicited risk preferences, i.e., parameters for the power utility function and the probability weighting function, via 12 choice lists (see Figure B4 in the Online Appendix). Each list consisted of 16 rows with choices between two options: a sure option with a guaranteed payment, and a lottery option with two probabilistic and mutually exclusive outcomes. The lottery option remained identical across the 16 choices of a single list. The sure option, however, varied across the choices, with its value decreasing from row to row. Among the 12 choice lists, 11 were designed in such a way that for the first few choices the sure option was relatively attractive compared to the lottery, but since the payment of the sure option decreased over the 16 rows, subjects were likely to prefer the lottery option at some point in the list. In each list, it was only possible to switch once from the sure option to the lottery. Once a subject decided to switch, the computer marked all remaining choices with less attractive sure options as lottery choices.[5] The midpoint between the switching choice and the choice of the sure option prior to the switch identifies the certainty equivalent of the lottery.

The 12$^{\text{th}}$ choice list was included as an attention check, to test the quality of our collected data. In this list the lottery option dominated the sure option for all 16 choices because all potential lottery payments were larger than the payment of the sure option. The order of the choice lists was randomized.

3.2 Time Preference Elicitation

In part two of the experiment, we elicited the discount factors for the lotteries and their certainty equivalents. This part built directly on its predecessor in that we used the estimated certainty equivalents from three of the 12 lotteries employed in part one.[6] Thus, although the three lotteries were identical for all subjects, the three corresponding certainty equivalents presented as sure outcomes were individually tailored and therefore differed between subjects. Since the estimation of future uncertainty builds on a comparison of the two types of discount factors, it was important to ensure that the magnitude of the sure outcomes and the lotteries used to elicit the discount factors were comparable. This feature of our experiment is novel. Previous studies that have compared the discounting of lotteries and sure outcomes employ a sure outcome with the expected value of the lottery (e.g., Anderson & Stafford, 2009). While this feature has the benefit of keeping both the lotteries and the sure options identical across subjects, a valid comparison of the two rests on the assumption that all subjects were risk neutral. If subjects were risk averse, the lotteries would be perceived as less attractive than their expected value, which could in turn

[5] The enforcement of a single switching point imposes strict monotonicity on revealed preferences and enforces transitivity. Although this procedure is common for risk preference elicitation (see Andersen et al., 2006; Tanaka et al., 2010), Charness et al. (2013) argue that it could force noise into the data because confused subjects who might violate those assumptions are not identified. We acknowledge this concern, but believe that our additional questions that serve to capture noise and ensure data quality alleviate them to a large extent.

[6] The lotteries used were $(18 : 0.5\ ;\ 6)$, $(10.5 : 0.5\ ;\ 3.5)$, and $(12 : 0.5\ ;\ 0)$.

systematically affect the discounting (Andersen et al., 2011; Noor, 2011; Sun & Potters, 2021; Thaler, 1981). However, our comparison of the lotteries and certainty equivalents, as conducted in this study, overcomes this issue because it is independent of risk preferences.

To elicit discount factors, we employed a dynamic staircase method, that is, a different elicitation technique than in part one. The reason we adopted a new procedure was to retain the students' attention after the 12 choice lists in part one and to stimulate them with a new and intuitive interface. Part two consisted of two sequences with three rounds each: in one of the sequences we elicited the time discounting for three sure outcomes, and in the other sequence we elicited the time discounting for three lotteries. In each round, the subjects had to make five decisions, choosing between a smaller earlier outcome and a larger later outcome (see Figure B7 and Figure B8 in the Online Appendix). The earlier outcome would be paid after a delay of one day, while the later outcome would be paid after a delay of four weeks. The reason why the earlier outcome was not paid immediately was to guarantee that payments for the time preference elicitation task were separated from the payments of other tasks in this study. This was important to control for transaction costs and to avoid having subjects choose the earlier option simply because they preferred a single payment. Moreover, a delay of one day has the benefit of eliminating a large share of a potential present bias effect in the discounting (Balakrishnan et al., 2020). This increased the credibility of our parameter identification, as it allowed us to control for discounting differences between lotteries and their certainty equivalents being driven by potential differences in the present bias.

For the dynamic staircase method, the five decisions of each round were not displayed on a single page but rather on six different pages, so that the choice option for the larger later outcome could adjust dynamically. If a subject preferred a smaller earlier outcome, the larger later outcome on the next page would increase. In contrast, if a subject preferred a larger later outcome, the larger later outcome on the next page would decrease. By iterating this process over five choices, we could determine an accurate discount factor for each of the six rounds. In addition, we added a sixth choice at the end of each round. Intended as an attention check to verify data quality, this choice was either a direct duplicate of one of the five choices the subject had already seen, or it included a later outcome that paid less than the alternative early outcome. The order in which the sequences of lotteries and the sure outcomes were presented was randomized, and the order of lotteries and certainty equivalents within a sequence was also randomized.

Although the dynamic staircase method has been used in several influential studies (e.g., Abdellaoui, 2000; Van De Kuilen & Wakker, 2011), one potential concern is its adaptive nature, which subjects could exploit to "strategize". That is, during a chain of 5 adaptive choices, subjects could make sub-optimal early choices to strategically increase the payoffs of their late choices. Such a misrepresentation of preferences would seem beneficial if i) a subject understood the adaptive nature of the task, ii) a subject could credibly determine how best to manipulate her early choices to increase utility from later choices, and iii) the expected utility gain from increased payoffs in late choices outweighed the utility loss from early misrepresentation. Since our instructions did not reveal information about the adaptive nature of the task, we believe that such a degree of sophistication was rather unlikely. Indeed, Imai and Camerer (2018) provide evidence that time preference parameters estimated by means of a dynamic staircase method do not differ from those estimated through non-adaptive techniques such as choice lists or convex time budgets. Moreover, the task is easy to understand and less time-consuming than alternative tasks, and, especially in light of the cognitively more demanding trade-offs between two lotteries at two different points in time, we considered this ease valuable.

3.3 Ambiguity Attitudes

In the third part of our experiment, we elicited attitudes regarding ambiguity. Given the length of our experiment, we used a simple and time-efficient technique to elicit ambiguity attitudes as presented in Gneezy et al. (2015) (see Figure B10 in the Online Appendix). Subjects were presented with an urn filled with balls that were either blue or green. First, they had to choose their "winning color" of either green and blue. Next, they filled in a choice list with 16 choices. Each choice consisted of two alternatives: *a*) A random draw of one ball from an urn for which the distribution of green and blue balls was known (50/50) and *b*) a random draw of one ball from an urn for which the distribution of green and blue balls was unknown. Independent of the choice, the subject could only win money in this task if the drawn ball had the selected winning color. The payment corresponding with alternative a was constant throughout the choice list. The payment corresponding with alternative b, on the other hand, decreased from row to row. Following the logic of choice lists, our ambiguity list was designed such that many subjects would prefer alternative b at the outset but switch to alternative a at some point along the list. As in part one, we only allowed subjects to switch once, and the point at which subjects switched was used as a measure of their attitudes regarding ambiguity.

3.4 Survey

The fourth and final part of the experiment was a survey that included a series of three cognitive reflection test questions, as well as questions about the subjects' socioeconomic backgrounds, their preferences, and their attitudes. The cognitive reflection test questions were adapted from Frederick (2005). Performance on those questions has been shown to correlate with preferences, economic choices, and life outcomes, and is frequently used in the economic literature as a proxy for cognitive ability (Frederick, 2005; Toplak et al., 2011).

3.5 Payment

To ensure incentive compatibility, subjects could earn substantial amounts of money in each of the first three parts of the experiment. However, to account for the importance of each task and for budget constraints, we applied different payment procedures. In part one (i.e., the risk preference task), we realized one decision for each subject. We randomly drew one choice from the 12 choice lists and paid it after all tasks of the experiment were completed. Importantly, however, we only informed the subject at the end of the experiment about which choice would be realized. If the selected choice was the lottery option, we resolved the lottery at the end of the study and paid out the realized outcome. This is a widely established procedure in studies of individual choice (Hey & Lee, 2005; Starmer & Sugden, 1991).

In part two (i.e., the time preference task), we randomly drew one choice from the six rounds for each subject and paid it on the respective day. If the subject chose the late outcome, the payment was made four weeks after the experiment. If the subject chose the early outcome, the payment was made one day after the experiment.

In part three (i.e., the ambiguity task), we realized a randomly drawn decision for 10% of our subjects. For the selected participants, we randomly chose one of the 16 decisions on the choice list and resolved the corresponding lottery. If the drawn ball matched the participant's selected winning color, she received the respective payment immediately after the experiment, together with her payments from part one.

All payments for this experiment were made electronically through *PayPal* to ensure that they would arrive on the designated day. The average total payment was €18.90 (approx USD 22.80).

3.6 Noise and Data Quality

One potential problem with choice lists is that subjects who answer randomly will, on average, switch in the middle of a list (Andersson et al., 2016). Unless the true switching point of a list happens to be in the middle, such noisy responses could systematically bias the parameter estimates. To guard against such a bias, we calibrated our choice lists in part one of the experiment such that the average subject from a related study by Epper et al. (2011) (a study that used the same choice lists as we did) would switch in the middle of our lists. That is, if the true preferences of our sample are similar to those observed by Epper et al. (2011), noise induced by random switching should not bias our parameter estimates since up- and downward errors should be equally likely.

To ensure the quality of our data, we also included a number of measures that allowed us to understand subjects' comprehension and attention. First, before the risk and the time preference tasks, subjects had to participate in a short pre-experimental questionnaire, as suggested by Jacquemet and l'Haridon (2018), which tested their comprehension of the respective instructions. We only allowed subjects to proceed to the actual tasks if they were able to answer all questions correctly. Moreover, we recorded the number of attempts to proceed with incorrect quiz responses and use this information as an indicator for inattention. Second, as described in Sections 3.1 and

3.2, we included consistency and inattention checks in the risk and time preference elicitations. In the risk preference elicitation, we included a choice list for which the lottery dominated the sure outcome because even the lowest potential payment of the lottery exceeded the payment of the sure outcome. We interpret choices in favor of the sure outcome in that list as a sign of inattention. In the time preference task, we included in each round either a consistency question or a choice for which the early payment exceeded the late payment. Again, both measures serve as indicators for inattention.

3.7 Econometric Estimations

To estimate preference parameters, we need to make functional form assumptions for our rank-dependent utility function $u(x)$ and the probability weighting function $\omega(p)$. Following Wakker (2008), we assume that the utility of decision makers is represented by a power function

$$u(x) = \begin{cases} x^{\eta} & \text{for } \eta > 0 \\ \ln(x) & \text{for } \eta = 0 \\ -x^{\eta} & \text{for } \eta < 0, \end{cases} \tag{8}$$

where η describes the curvature of the utility function. Note that $u(x)$ is not defined for $x = 0$ when $\eta \leq 0$. As subjects do encounter outcomes equal to zero in the experiment, we add the smallest possible monetary increment of 0.01€ to all outcomes before estimating the parameters to avoid an undefined utility function. This procedure is consistent with Wakker (2008) and Epper et al. (2011). Further, we assume that decision makers transform probabilities with the (two-parameter) probability weighting function $\omega(p) = exp(-\beta(-lnp)^{\alpha})$, where $\alpha > 0$ and $\beta > 0$ (Prelec, 1998). The parameter α captures the curvature of the weighting function, that is, its degree of subproportionality and departure from linearity. The parameter β determines the range of convexity. The function satisfies the requirement of subproportionality and generates a curve that is inverse-S-shaped when $0 < \alpha < 1$. When $\alpha > 1$, the function is supraproportional and instead generates a curve that is S-shaped. Supraproportionality constitutes an alternative form of nonlinearity and implies that $\frac{\omega(ps)}{\omega(s)} < \omega(p)$. While it would reverse the prediction of the EFD model, suggesting that $\tilde{\rho}_L < \tilde{\rho}_C$ (see equations 4 and 6), it would not pose a problem for our identification of future uncertainty. For our estimations, we therefore remain agnostic about the shape of the probability weighting function and do not impose any explicit restrictions on the parameters other than requiring that $\alpha > 0$ and $\beta > 0$. The certainty equivalent of each lottery is elicited from the switching point within the choice list, and the risk preference parameters are obtained by solving the following equation:

$$CE_{i,l} = u_i^{-1}\Bigg(\omega_i(p_l)u_i(x_{l,1}) + \omega_i(1-p_l)u_i(x_{l,2})\Bigg) + \varepsilon_{i,l}, \tag{9}$$

where $\varepsilon_{i,l}$ is a normally distributed error term. As we simultaneously estimate equation 9 for each of the 11 choice lists, the standard deviation of $\varepsilon_{i,l}$ is dependent on the range of the sure outcomes in the lottery choice lists. This range is the difference between the highest sure outcome presented in the first row and the lowest sure outcome presented in the last row of the choice list, and it varies from three (lotteries 5, 6, and 12) to nine (lotteries 8,9, and 10). To account for this source of heteroskedasticity in the estimation, we standardize the standard deviation of the error term.

To estimate discount factors, we identify indifference points between an early outcome and a late outcome for each of the three lotteries and their certainty equivalents:

$$u_i(CE_{early,i}) = \tilde{\rho}_{iCE}u_i(CE_{late,i}) + \nu_{CE,i}, \tag{10}$$

$$\omega_i(p)u_i(L^{high}_{early}) + \omega_i(1-p)u_i(L^{low}_{early}) = \tilde{\rho}_{iL}\Big[\omega_i(p)u_i(L^{high}_{late}) + \omega_i(1-p)u_i(L^{low}_{late})\Big] + \nu_{L,i}, \tag{11}$$

where CE_{early} is the estimated certainty equivalent paid out the next day, CE_{late} is the certainty equivalent paid out in four weeks (where $CE_{early} \sim CE_{late}$), L^{high}_{early} is the high outcome of the lottery paid out the next day, L^{low}_{early} is the low outcome of the lottery paid out the next day, L^{high}_{late} is the high outcome of the lottery paid out in four weeks, and L^{low}_{late} is the low outcome of the lottery paid out in four weeks (where $L_{early} \sim L_{late}$), $\tilde{\rho}_{CE}$ is the discount factor for the

Table 1: Risk Preference Parameters on the Individual Level

		Full sample		Excl. top/ bottom 1%	
Model	**Parameter**	**Mean**	**SD**	**Mean**	**SD**
DEU	η	0.65	0.66	0.67	0.35
EFD	η	1.01	2.25	0.89	0.43
	α	0.59	0.38	0.58	0.34
	β	1.12	1.07	1.06	0.31

Notes: The table shows averages of risk preference parameters estimated at the individual level under the DEU and EFD models. Under DEU, risk attitudes are fully captured by η, which indicates the curvature of the utility function. Under EFD, risk attitudes are captured by the curvature of the utility function and by a two-parameter probability weighting function (Prelec, 1998), where α captures the degree of subproportionality and β captures the range for which the weighting function is convex.

certainty equivalents and $\tilde{\rho}_L$ is the discount factor for the lotteries, and $\nu_{CE,i}$ and $\nu_{L,i}$ are normally distributed error terms.

When estimating the survival probability s at the aggregate level, we simultaneously estimate equations 9, 10, and 11 using maximum likelihood. For individual-level estimations of s, we first estimate risk preference parameters from equation 9 using maximum likelihood, and then calculate discount factors from equations 10 and 11 using the individually estimated values for α, β, and η. For both the aggregate and the individual-level estimations, we numerically calculate the survival probability in Matlab by solving equation (7) with the nonlinear system solver *fsolve*. We do this for each of the three pairs of lotteries and certainty equivalents, resulting in a total of three estimates of s. The standard error of the aggregate estimate is estimated using bootstrapping techniques.

4 Results

4.1 Discounted Expected Utility Theory vs. the EFD Model

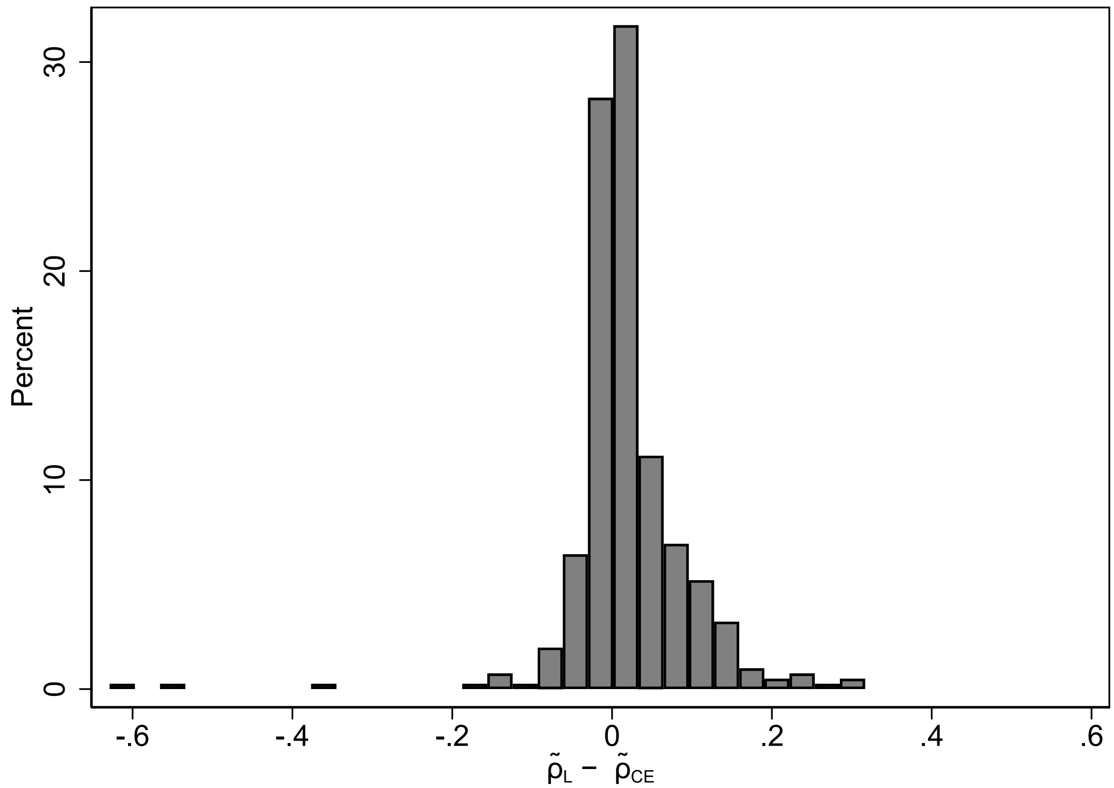
Discounted expected utility models (DEUs; i.e., intertemporal choice models that build on expected utility theory) predict that the time discounting of sure outcomes and lotteries should be the same. In contrast, models that handle risk aversion by means of a concave utility function and subproportional probability weighting, such as the EFD, imply that discount factors for lotteries are larger than for their certainty equivalents. That is, decision makers appear to be more patient for probabilistic than for sure outcomes as a result of different perceptions of future uncertainty. The data collected in our experiment allows us to conduct a direct test of this prediction by comparing the discount factors of lotteries and certainty equivalents at the individual level.

We start by estimating equation 9 under expected utility (i.e., $\omega(p) = p$) to obtain the risk aversion parameter η of the utility function $u(x) = x^{\eta}$. Here η captures the curvature of the utility function, where a concave utility function implies risk aversion. We present the summary statistics of the estimated η together with estimates of risk preference parameters from the EFD model in Table 1. Next, we enter η into equation 11 to calculate the lottery discount factor $\tilde{\rho}_L$ and into equation 10 to calculate the discount factor of the corresponding certainty equivalent $\tilde{\rho}_{CE}$.

Figure 1 illustrates the distribution of the differences between the estimated lottery discount factors $\tilde{\rho}_L$ and the estimated discount factors for their certainty equivalents $\tilde{\rho}_{CE}$. The discount factors are averages from the three lotteries and their three certainty equivalents, respectively. While the average difference is close to zero ($-0.03 \leq \tilde{\rho}_L - \tilde{\rho}_{CE} \leq 0.03$) for about 60% of our sample, as predicted by DEU, the figure also shows that the distribution is right-skewed. The share of observations with a positive difference is considerably larger than the share of observations with a negative difference. The average difference is 0.021 and significantly larger than 0 ($p < 0.001$). Thus, inconsistent with DEU, our data suggest that the lotteries were discounted less than their certainty equivalents. However, this finding is not specific to DEU. In Figure A2 in the Online Appendix, we present a similar histogram in which we assume that the probabilities are weighted with a Prelec probability weighting function, but the utility is linear (Yaari, 1987). The figure also shows a distribution that is right-skewed and conveys the same message: Lotteries are discounted less than their certainty equivalents.

To better understand this discrepancy in discount factors, we build on the EFD model assuming power utility and a Prelec probability weighting function when estimating the risk parameters

Figure 1: Differences in Discount Factors using an EU framework.



Notes: The figure shows the difference between observed discount factors of lotteries and their certainty equivalent outcomes, with risk preferences estimated in an EU framework.

and the discount factors from equations 9 and 10.[7] This allows us to study whether the difference between the discounting of lotteries and their certainty equivalents depends on the curvature of the weighting function (captured by the parameter α). Under intertemporal choice, both allegedly sure outcomes and lotteries are encompassed by an extra layer of (future) uncertainty—a subjective probability that the payoff won't materialize. In the EFD model, this probability is weighted subproportionally with the implication that, ceteris paribus, more subproportionality (a smaller α) increases the difference between $\tilde{\rho}_L$ and $\tilde{\rho}_{CE}$.

In Table 2, we show regression results that illustrate the discounting effect of the lottery and how this effect is mediated by the level of subproportionality. Unsurprisingly, our regression

[7] We present the distribution of the estimated preference parameters and discount factors in Figure A3 in the Online Appendix.

Table 2: **OLS Regression Results for Discount Factors**

	Dependent Variable: Discount Factor		
	(1)	(2)	(3)
1 if Lottery	0.031***	0.030***	0.054***
	(0.006)	(0.004)	(0.012)
α		0.049**	0.064***
		(0.020)	(0.024)
β		-0.085	-0.089*
		(0.053)	(0.053)
η		0.007	0.009
		(0.026)	(0.026)
1 if α in 2nd quartile & Lottery			-0.021
			(0.018)
1 if α in 3rd quartile & Lottery			-0.042**
			(0.019)
1 if α in 4th quartile & Lottery			-0.032*
			(0.018)
Constant	0.849***	0.906***	0.900***
	(0.003)	(0.030)	(0.029)
Observations	2,415	2,415	2,415
R-squared	0.89	0.14	0.14
Pair FE	✓	✓	✓
Individual FE	✓		

Notes: Robust standard errors are clustered on the individual level. α in 1st quartile: $\alpha < 0.33$, α in 2nd quartile: $0.33 \leq \alpha < 0.56$, α in 3rd quartile: $0.56 \leq \alpha < 0.81$, α in 4th quartile: $\alpha \geq 0.81$. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

results reveal a statistically significant, within-person discounting difference of 0.03 (regression 1), supporting the hypothesis that lotteries are discounted less than their certainty equivalents. In regressions (2) and (3), we further study whether the difference in discounting systematically varies with the level of α by including a dummy variable that captures the interaction of the α-quartile (where the first quartile represents the 25% lowest and the fourth quartile the 25% highest α values) and the lottery. Simultaneously, we control for the weighting function's range of convexity (β) and for the curvature of the utility function (η). The regression results show that for subjects who exhibit strong subproportional probability weighting (i.e., α values in the lowest quartile), the coefficient of the lottery dummy (0.054) is almost twice as large as the coefficient for the sample as a whole (0.030). At the same time, the discrepancy in discounting appears considerably smaller for participants who exhibit lower levels of subproportionality, as captured by the coefficients of the interaction dummies in regression (3). This suggests that the observed difference between $\tilde{\rho}_L$ and $\tilde{\rho}_{CE}$ is driven by subjects who weigh probabilities subproportionally, as predicted by the EDF model. For completeness, Table A1 in the Online Appendix presents the same estimations as Table 2, but for each of the three pairs separately.

Our finding that lotteries are discounted less than certain outcomes is consistent with the results of Keren and Roelofsma (1995) and Ahlbrecht and Weber (1997). Their findings deviate, however, from the findings of Anderson and Stafford (2009), which suggest the opposite. One important difference between our study and Anderson and Stafford (2009) is that we compare our lotteries with the lotteries' certainty equivalents, while Anderson and Stafford (2009) compare their lotteries with the lotteries' expected values. As discussed in Section 3.2, this could explain the difference between our results (Andersen et al., 2011; Noor, 2011; Sun & Potters, 2021; Thaler, 1981).

4.2 Estimating Future Uncertainty

So far, our analysis in this section has shown that our experimental data are consistent with the implications of the EFD model. In a second step, we now estimate preference parameters at the aggregate level for each lottery–certainty-equivalent pair and use these to identify future uncertainty. Such an analysis is useful because it simultaneously accounts for all data and thus allows for a more precise estimation.

Table 3 presents the estimated parameters and the corresponding calculated survival probabilities. Recall that the survival probability s is the complement of the future uncertainty $1 - s$. The table is divided into two panels: Panel A displays the risk preference parameters, while panel B shows the discount factors and the calculated survival probabilities. Figure 2 illustrates the resulting utility and probability weighting functions.

Our estimated risk preference parameters are consistent with the findings on probability weighting and utility curvature in related studies (e.g., Abdellaoui, 2000; Epper et al., 2011; Gonzalez & Wu, 1999; Tversky & Kahneman, 1992). The estimate for α is 0.488, indicating

Table 3: Parameter Estimates

	A. Risk Preference Parameters			
α (Subproportionality)	0.488 (0.016)			
β (Range of convexity)	1.005 (0.013)			
η (Utility curvature)	0.890 (0.020)			
	B. Time Preference Parameters			
	Average	Pair 1	Pair 2	Pair 3
$\tilde{\rho}_{CE}$	**0.777 (0.011)**	0.834 (0.010)	0.743 (0.014)	0.753 (0.013)
$\tilde{\rho}_{L}$	**0.824 (0.010)**	0.855 (0.009)	0.798 (0.013)	0.819 (0.011)
s (Survival probability)	**0.987 (0.005)**	0.997 (0.003)	0.970 (0.011)	0.993 (0.003)
$\omega(s)$	**0.897 (0.015)**	0.943 (0.020)	0.833 (0.025)	0.915 (0.014)

Notes: Pair 1 includes the lottery (18 : 0.5 ; 6). Pair 2 includes the lottery (10.5 : 0.5 ; 3.5). Pair 3 includes the lottery (12 : 0.5 ; 0). Standard errors clustered at the individual level in parenthesis, bootstrapped standard errors for s and $\omega(s)$.

a substantial degree of subproportionality and a considerable deviation from linear probability weighting. The estimate for β is 1.005. This implies that the probability weighting function is concave for approximately $p < 0.37$ and convex otherwise. Together, the estimates suggest a probability weighting function that is inverse-S-shaped, which implies that individuals overestimate low probabilities and underestimate high probabilities. The curvature of the utility function η is estimated to be 0.890 and implies a moderate degree of concavity.

For time discounting, we estimate the discount factors $\tilde{\rho}_{CE}$ and $\tilde{\rho}_{L}$ for three different pairs, each comprising a lottery and its certainty equivalent. For all three pairs, the certainty equivalent is discounted more strongly than the corresponding lottery ($\tilde{\rho}_{CE} < \tilde{\rho}_{L}$).[8] Finally, we calculate both the unweighted survival probability s and the weighted probability $\omega(s)$ for each of the three pairs. Consistent with probability theory, we restrict s to $s \leq 1$, and we assume that $s = 1$ (i.e., no future uncertainty) when one of the following conditions holds: (i) the probability weighting is proportional ($\alpha = 1$), (ii) the probability weighting is subproportional ($\alpha < 1$) and $\tilde{\rho}_{L} < \tilde{\rho}_{CE}$, or (iii) the probability weighting is supraproportional ($\alpha > 1$) and $\tilde{\rho}_{L} > \tilde{\rho}_{CE}$.

[8] Although our time preference estimates are similar to those of previous studies, we note that they may be subject to magnitude effects, as pointed out by Andersen et al. (2013). For our main analysis, however, potential magnitude effects should not raise critical concerns. To identify the survival probability s, we use the ratio of the lottery discount factor $\tilde{\rho}_{L}$ and the CE discount factor $\tilde{\rho}_{CE}$. Arguably, this ratio is independent of the level of the discount factors, suggesting that any magnitude effects in the estimation of the discount factors should not have any impact on our estimate of future uncertainty.

We find that there exists significant and economically sizable future uncertainty. We calculate an average survival probability of 0.987, which is significantly smaller than 1 ($p < 0.01$). Amplified by nonlinear probability weighting ($\omega(s) = 0.897$), this amounts to a substantial part of the observed time discounting of a future outcome—a result that is consistent across different combinations of lotteries and certainty equivalents. For all included pairs, we observe that the estimated weighted survival probability is significantly smaller than 1. The discounting that results from future uncertainty explains approximately 43% of the observed total discounting in our study.[9] The remainder of the total discounting is explained by the pure discount factor $\rho = 0.866$, which captures impatience.[10] This result is consistent with the feasible combinations of the survival risk and a pure discount factor in Epper et al. (2011). Given the authors' estimated risk and time preference parameters, a pure discount factor of 0.866 implies a survival probability of around 0.995, which is a only slightly larger than the value we estimate here ($s = 0.987$).[11]

4.3 Individual Heterogeneity of Future Uncertainty

Our within-subject design allows us to also estimate future uncertainty at the individual level. That is, we are able to study the heterogeneity of our results. We present the distribution of the estimated preference parameters and discount factors in Figure A3 in the Online Appendix.[12] For 72% of our subjects with an estimated survival probability s, we find that the weighted survival probability $\omega(s)$ is less than 0.95. These estimates underline that for a substantial share of people, future uncertainty plays an important role in their intertemporal choices.

Figure 3 illustrates the heterogeneity in the estimated $\omega(s)$ across subjects, as well as the

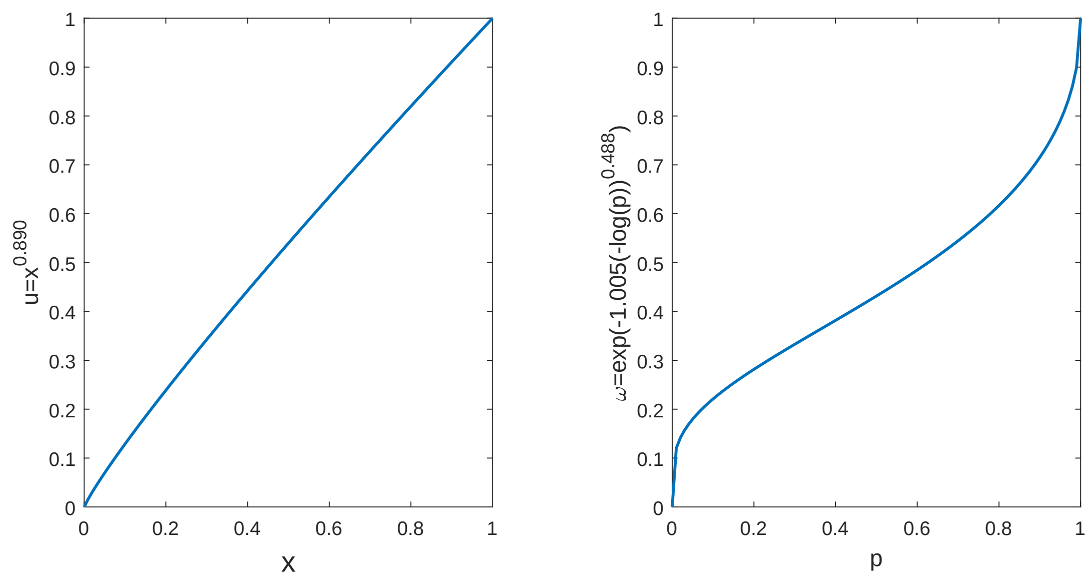
[9]The share is defined by the ratio $ln(\omega(s))/ln(\tilde{\rho}_{CE})$. We wish to point out, however, that, unlike our identification of future uncertainty, this share depends on the level of the estimated discount factor $\tilde{\rho}_{CE}$. As pointed out by Andersen et al. (2013), the estimation of discount factors can be prone to magnitude effects, as it depends on the stakes employed in the experimental task.

[10]Recall that the pure discount factor is calculated as $\rho = \tilde{\rho}_{CE}/\omega(s)$.

[11]In an analysis focusing on risk and time interaction, Somasundaram and Eli (2022) obtain, as a byproduct of their analysis, an estimate of mortality risk for the model by Halevy (2008). Their estimate at the aggregate level has the value 0.02 and is thus similar to the estimate of future uncertainty we find in our study.

[12]As in the aggregate estimation, the estimated individual survival probability s is the average over the three lottery pairs. We could not solve equation 7 for any of the three lottery–certainty-equivalent pairs for 14 subjects. These subjects are therefore excluded from the individual-level analysis. For 14 subjects, we were only able to estimate s for one of the three pairs, and for 48 subjects we were able to estimate s for two out of the three pairs. For the subjects with missing s values, the estimated s is the average of the existing s values.

Figure 2: Risk preferences parameters: Estimated utility function (left) and estimated probability weighting function (right)



Note: The figures use the estimated average values of the risk preference parameters, $\eta = 0.890$, $\beta = 1.005$, and $\alpha = 0.488$.

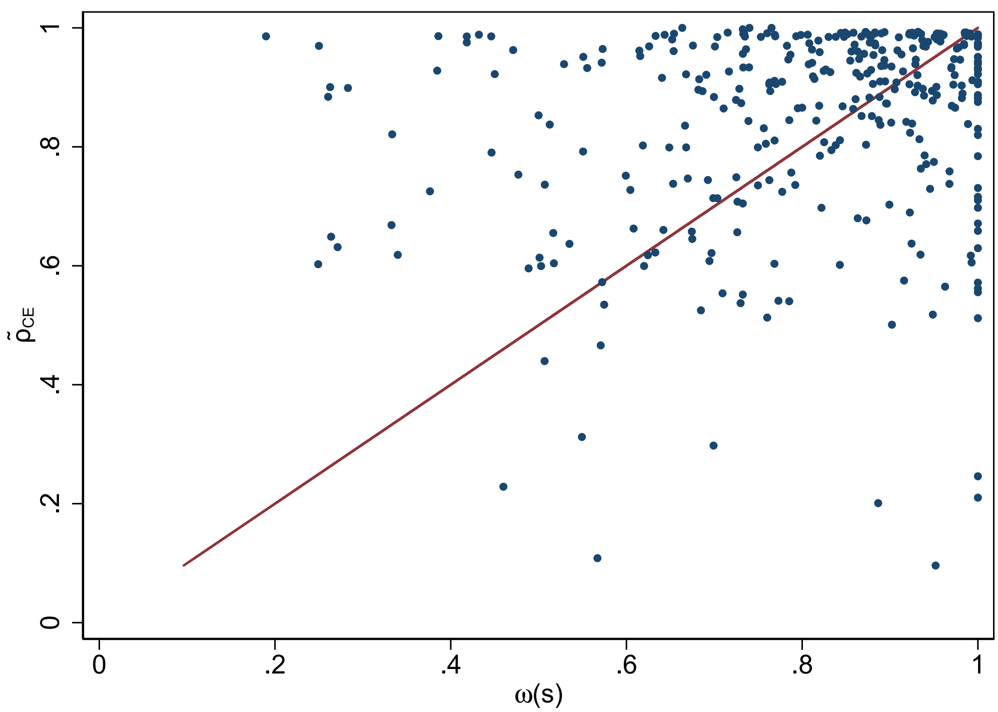
relationship between $\omega(s)$ and the observed time discounting $\tilde{\rho}$. For the purpose of categorization, Figure 3 also includes a 45-degree diagonal line: Observations that lie below the diagonal exhibit time discounting that is explained by both future uncertainty and impatience since $\omega(s) \leq 1$ and $\rho < 1$. For observations on and above the diagonal, the observed discounting is fully explained by future uncertainty because $\omega(s) < 1$ but $\rho \geq 1$.[13] Those subjects do not show any sign of impatience but instead discount because they fear that future outcomes may not materialize.

4.4 Future Uncertainty and Individual Characteristics

Is it possible to predict future uncertainty by means of individual characteristics? To answer this question, we exploit data from our ambiguity task and cognitive reflection test as well as information on gender and age. Figure 4 presents regression results in which the dependent variable is survival probability. The explanatory variables are ambiguity aversion, cognitive ability—

[13] We do not restrict the pure discount parameter ρ to be smaller or equal to 1 because we do not expect that all people are inherently impatient. Since the later payments in our experiment are always larger than the early payments (with the exception of our additional question that served as an attention check), we do, however restrict the observed discount factor $\tilde{\rho}$ to be smaller or equal to 1 by design. This is consistent with previous literature.

Figure 3: Discounting as a function of weighted survival probability at the individual level

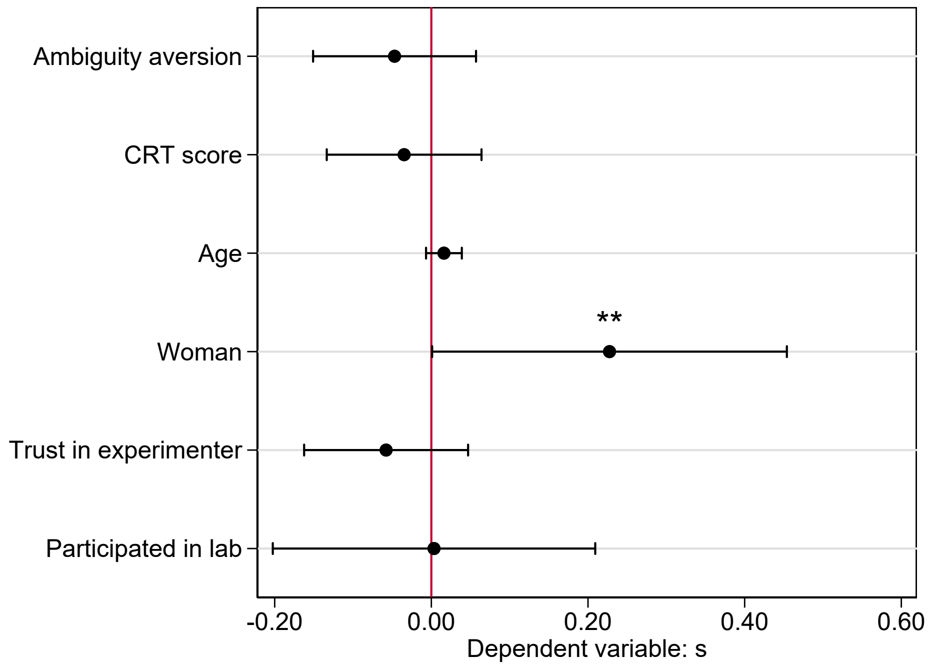


measured as the number of correctly answered cognitive reflection test questions, age, gender, trust in the experimenter—and a control dummy for participation in the lab (as opposed to participation from home administered through the communication platform *Zoom*). The survival probability, ambiguity aversion, cognitive ability, and trust in the experimenter are standardized for ease of interpretation. The complete regression results underlying Figure 4 are presented in Table A2 in the Online Appendix.

Contrary to our hypotheses, we find no significant correlations between ambiguity aversion and survival probability or between the subjects' cognitive abilities and survival probability. However, our results do reveal a substantial gender effect. We find that the estimated survival probability is 0.23 standard deviations larger for females than for males. We do not detect any significant age differences, but we point out that our sample of university students included mainly young adults, which implies that the variation in age was low to begin with.

Finally, Figure 4 reveals no significant relations between survival probability and perceived

Figure 4: Survival probability regressed on individual characteristics



Notes: N=385; 15 subjects for whom we could not estimate any s, two subjects who did not want to disclose their gender or did not identify as man/woman, and one subject with a missing value in the trust question are excluded from the analysis. CRT score is the number of correctly answered cognitive reflection test questions. Ambiguity aversion, CRT score, and s are standardized. Error bars represent 95% confidence intervals. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

trust in the experimenter, or between survival probability and participation in the lab. These findings are important because they suggest that our estimate of future uncertainty is unlikely to be an artefact of our experimental setup or of heterogeneity in the belief that promised payments would be transferred by the experimenters.

4.5 Robustness

A potential issue with running the experiment partly online and partly in a controlled lab environment is the risk that subjects who participated remotely would be more prone to inattention. To address this concern, our experiment included several consistency checks, both during the risk task and during the time preference task. We also recorded the incorrect attempts to answer quiz questions before the risk and time preference tasks. In Table A3 in the Online Appendix. we present statistics for the performance of lab participants and of participants who attended online, from home. The results indicate that online participants were less attentive to the comprehension questions than participants in the lab, but the difference between the two groups is small and not statistically significant. However, there is no difference between the two groups on the dominance test in the risk task or in consistent choices in the time task.

Although we find no alarming differences between our online and lab samples, it is important to investigate whether our results could be driven by subjects who answered inattentively. To do this, we replicated all of our analyses with a subsample of 314 subjects who passed our ambitious attentiveness criteria.[14] Figure A1 and Tables A4-A6 in the Online Appendix show the results of the robustness analyses. All robustness analyses provide support for our initial findings: Lotteries are discounted less than their certainty equivalents, the estimated future uncertainty is both sizable and statistically significant, and the estimated survival probability is significantly larger (future uncertainty is smaller) for women than for men.

Finally, we investigate the sensitivity of our estimation to the underlying functional form of the utility function. Instead of a power function, we assume that subjects are represented by an exponential utility function, $u(x) = (1-e^{-ax})/(1-e^{-a})$. This is similar to the procedure applied in Abdellaoui et al. (2022). The results of that robustness analysis are reported in Table A7 in the Online Appendix. Again, the results reinforce our main finding that future uncertainty is economically sizable and explains a large share of the observed total discounting.

5 Conclusion

We conduct a controlled experiment to provide empirical support for the intuition that time discounting depends on the inherent uncertainty of the future. Using the rank-dependent utility framework of the intertemporal choice model presented in Epper and Fehr-Duda (2021) (the EFD model), we estimate the effect of future uncertainty on time discounting and disentangle

[14]The attentiveness criteria are: (i) did not choose the dominated lottery in the 12th risk choice list, (ii) had an average of 4 or fewer attempts to answer the comprehension questions, and (iii) was consistent in at least 3 out of 4 time-discounting checks (providing the same answer when a question is repeated).

it from the effect of impatience. To achieve this, we exploit systematic discounting differences between lotteries and their certainty equivalents. Following the interpretation of the EFD model, these differences are an implication of nonlinear probability weighting in the presence of future uncertainty.

Our results suggest that future uncertainty is both statistically and economically significant and explains about 43% of the observed time discounting in our experiment. This finding implies that many people discount future outcomes not because they mind the wait, but because they perceive the future as uncertain and fear that future outcomes may not materialize or yield utility.

The insight that time discounting is highly dependent on future uncertainty provides a possible explanation for previous evidence about the dependence of time discounting and the environment of decision makers. For example, Falk et al. (2018) found that people from less developed countries discount more strongly than people from industrialized countries, but this difference could be driven by differences in future uncertainty between less developed countries and industrialized countries. Also, the importance of future uncertainty for time discounting might explain why people affected by extreme events exhibit smaller discount factors (Beine et al., 2020; Cassar et al., 2017).

Finally, our results provide important practical insights. Understanding the importance of future uncertainty for intertemporal choice is useful for practitioners and policy makers who would like people to be forward-looking, e.g., in saving for their retirement. Most often, it is necessary to add a substantial premium to a future outcome in order to make it as attractive as an alternative that generates immediate utility. The question is to what extent this premium compensates for the wait, and to what extent it compensates for the risk that results from an uncertain future. Our findings suggest that by reducing future uncertainties (e.g., by improving the social security system), policy makers could induce people to become more forward-looking. Such an option might be preferable to adding large premiums to future outcomes.

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Online Appendix A - Additional Figures and Tables (to be separated from main file)

Figure A1: The difference between observed discounting over lotteries and sure outcomes assuming DEU for subjects who passed our attentiveness checks (N=314).

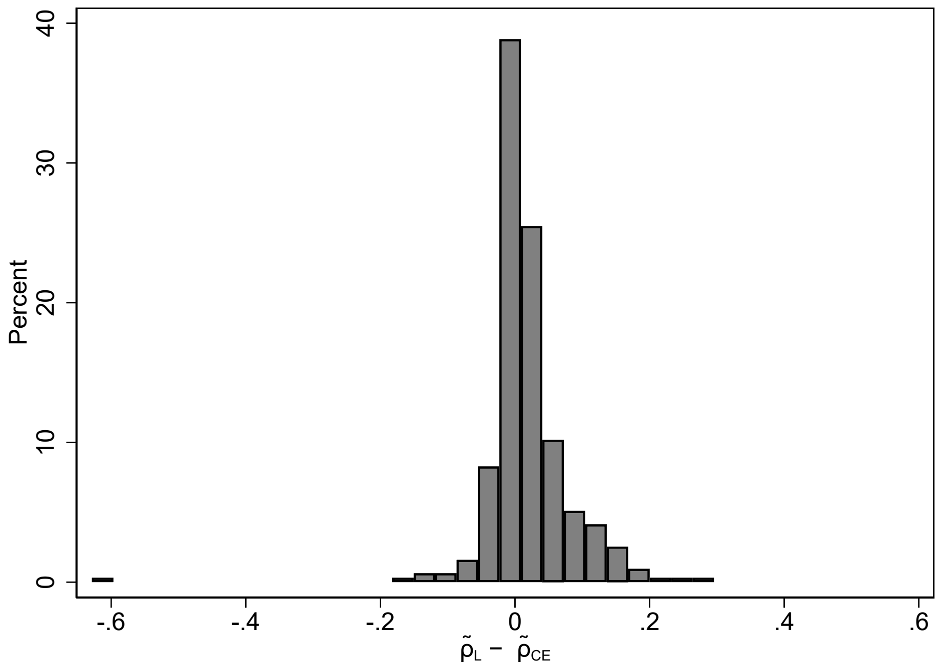


Figure A2: The difference between observed discounting over lotteries and sure outcomes assuming linear utility and a Prelec probability weighting function.

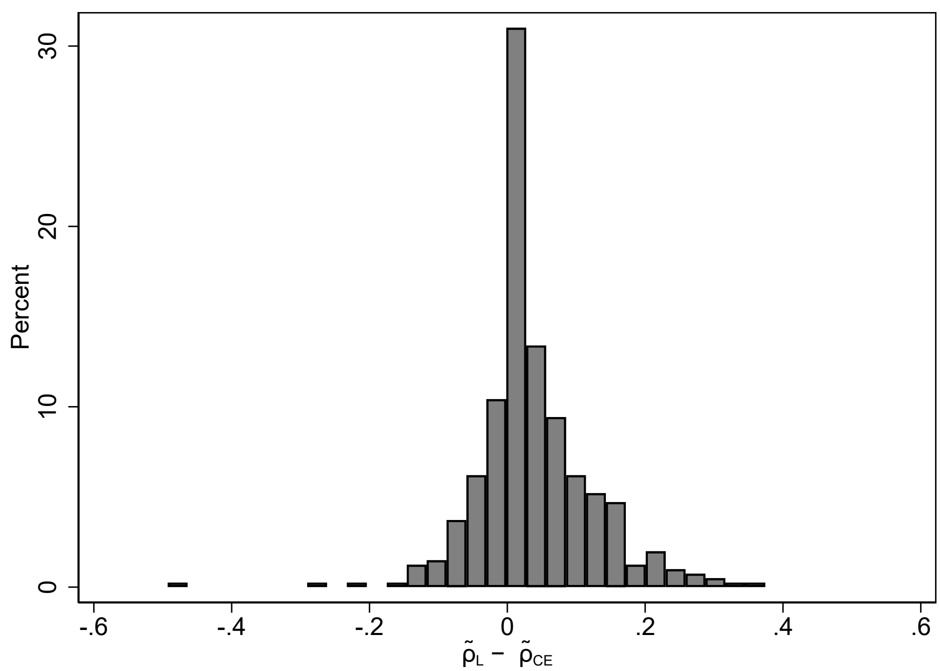
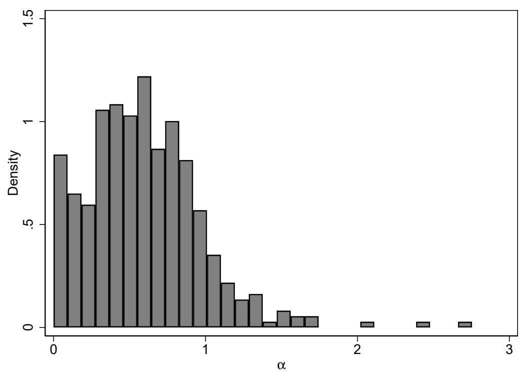
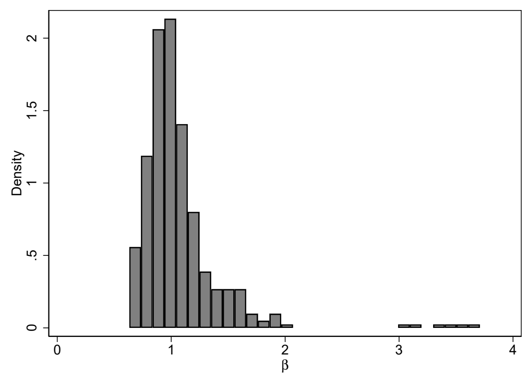


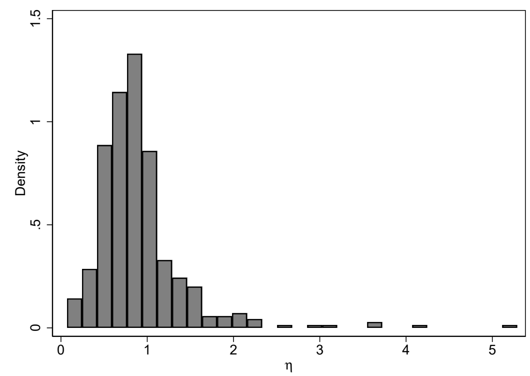
Figure A3: Distribution of risk preferences parameters, time discounting and survival probability measured at the individual level



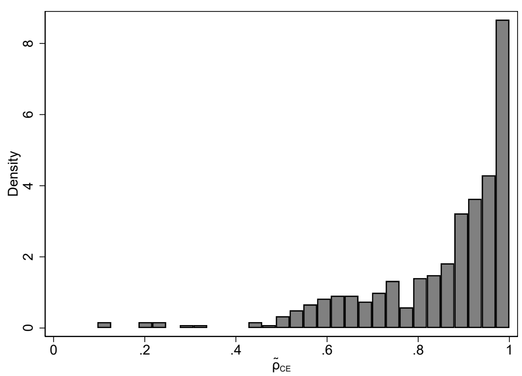
(a) α



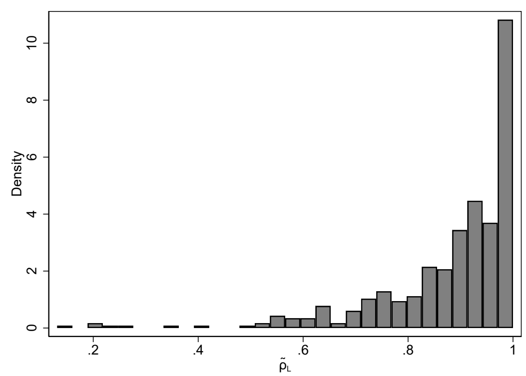
(b) β



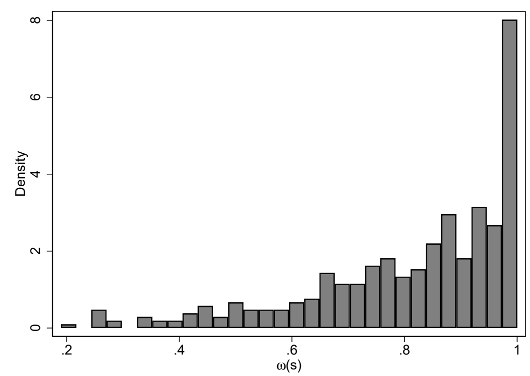
(c) η



(d) $\tilde{\rho}_{CE}$ **- average**



(e) $\tilde{\rho}_{L}$ **- average**



(f) $\omega(s)$ **- average**

Notes: N=402. We drop one observation where the subject was estimated with $\eta = 44$, $\beta = 21$ and $\alpha = 1.3$

Table A1: OLS Regression Results for Discount Factors, For Each Pair Separately

	Dependent Variable: Discount Factor					
	Pair 1		Pair 2		Pair 3	
	(1)	(2)	(3)	(4)	(5)	(6)
1 if Lottery	0.016***	0.033***	0.030***	0.066***	0.044***	0.063***
	(0.005)	(0.013)	(0.006)	(0.015)	(0.006)	(0.014)
α	0.048**	0.061***	0.054**	0.076***	0.044**	0.054**
	(0.020)	(0.023)	(0.023)	(0.027)	(0.021)	(0.025)
β	-0.100*	-0.103*	-0.085	-0.091	-0.069	-0.073
	(0.052)	(0.052)	(0.058)	(0.058)	(0.055)	(0.055)
η	0.014	0.016	0.006	0.009	0.001	0.003
	(0.025)	(0.025)	(0.028)	(0.028)	(0.026)	(0.026)
1 if α in 2nd quartile & Lottery		-0.014		-0.035*		-0.015
		(0.018)		(0.020)		(0.020)
1 if α in 3rd quartile & Lottery		-0.025		-0.059***		-0.041*
		(0.019)		(0.022)		(0.022)
1 if α in 4th quartile & Lottery		-0.029		-0.050**		-0.018
		(0.018)		(0.021)		(0.020)
Constant	0.943***	0.937***	0.893***	0.884***	0.883***	0.880***
	(0.029)	(0.027)	(0.033)	(0.031)	(0.032)	(0.030)
Observations	805	805	805	805	805	805
R-squared	0.15	0.16	0.12	0.13	0.12	0.13

Notes: Robust standard errors are clustered on the individual level. α in 1st quartile: $\alpha < 0.33$, α in 2nd quartile: $0.33 \leq \alpha < 0.56$, α in 3rd quartile: $0.56 \leq \alpha < 0.81$, α in 4th quartile: $\alpha \geq 0.81$. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Pair 1 includes the lottery (18 : 0.5 ; 6) and its certainty equivalent. Pair 2 includes the lottery (10.5 : 0.5 ; 3.5) and its certainty equivalent. Pair 3 includes the lottery (12 : 0.5 ; 0) and its certainty equivalent.

Table A2: Survival Probability Regressed on Individual Characteristics. Regression Results Behind Figure 4

	$s_{average}$
Ambiguity aversion	-0.047
	(0.053)
CRT score	-0.035
	(0.050)
Age	0.016
	(0.012)
Woman	0.227**
	(0.115)
Participated in lab	0.003
	(0.105)
Trust in experimenter	-0.058
	(0.053)
Constant	-0.532*
	(0.305)
Observations	385
R-squared	0.02

Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. 15 subjects for whom we could not estimate any s, two subjects who did not want to disclose their gender or did not identify as man/woman, and one subject with a missing value in the trust question are excluded from the analysis. CRT score is the number of correctly answered cognitive reflection test questions. Ambiguity aversion, CRT score, and s are standardized.

Table A3: Summary Statistics

	Lab					Online						
	N	Mean	SD	Min	Max	N	Mean	SD	Min	Max	Mean Diff	p-value
Female	234	.688	.464	0	1	169	.609	.489	0	1	.079	.102
Age	234	23.868	4.390	18	41	169	23.431	4.139	18	36	.437	.315
French	234	.889	.315	0	1	169	.864	.344	0	1	.025	.450
Student	234	.718	.451	0	1	169	.757	.430	0	1	−0.039	.378
Current Monthly Income (in Euro)	234	709.50	2,156.45	0	22,000	169	897.86	3,022.53	0	28,500	−188.36	.492
Patience	234	7.316	2.209	0	10	169	6.970	2.083	0	10	.346	.113
Risk	234	7.342	2.207	0	10	169	7.036	2.104	0	10	.306	.161
Health	234	7.598	2.042	0	10	169	7.254	2.116	0	10	.344	.101
Alcohol Consump.(Days per Week)	234	.790	1.212	0	7	169	.756	1.201	0	7	.034	.783
Smoker	234	.218	.414	0	1	169	.142	.350	0	1	.076	0.053
Exercise (Days per Week)	234	2.222	1.851	0	7	169	2.251	1.759	0	7	−0.029	.8735
Experienced Severe Loss	234	.709	.455	0	1	169	.734	.443	0	1	−0.025	.5927
Neighborhood Safety	234	7.542	2.114	0	10	169	7.296	2.078	0	10	.246	.245
Cancellation Insurance	234	.150	.357	0	1	169	.183	.388	0	1	−0.033	.366
Certainty about Near Future	234	7.346	2.199	0	10	169	7.047	2.106	0	10	.299	.172
Certinty about Medium Future	234	7.338	2.212	0	10	169	6.964	2.076	0	10	.374	0.087
Certainty about Distant Future	234	7.324	2.209	0	10	169	6.959	2.068	0	10	.365	0.093
CRT Score	234	1.197	1.166	0	3	169	.988	1.091	0	3	.209	0.070
Passed dominance test	234	.846	.362	0	1	169	.822	.383	0	1	.024	0.264
Incorrect attempts	234	.858	1.432	0	17	169	1.128	1.450	0	9.333	−0.270	0.03
Consistent answers	234	3.590	.704	0	4	169	3.615	.673	1	4	.026	.523

Notes: CRT Score is the number of correctly answered questions on a cognitive reflection test, Passed dominance test = 1 if a does not choose a dominated outcome in a risk price list, 0 otherwise, Incorrect attempts = the average number of times a subject answered incorrectly to comprehension questions about the experimental setup. The phrasing of the survey questions used to elicit preferences and attitudes can be found in Figure B11 in the Online Appendix. The last column contains p-values of a two sided t-test that compares the means between the lab group and the online group.

Table A4: OLS Regression Results for Discount Factors - Robustness Analysis

	Dependent Variable: Discount Factor		
	(1)	(2)	(3)
1 if Lottery	0.028***	0.028***	0.037***
	(0.006)	(0.004)	(0.013)
α		0.037*	0.039*
		(0.021)	(0.023)
β		-0.037	-0.038
		(0.039)	(0.040)
η		-0.126***	-0.124***
		(0.027)	(0.027)
1 if α in 2nd quartile & Lottery			-0.007
			(0.018)
1 if α in 3rd quartile & Lottery			-0.028
			(0.020)
1 if α in 4th quartile & Lottery			-0.001
			(0.016)
Constant	0.863***	0.990***	0.987***
	(0.003)	(0.033)	(0.033)
Observations	1,884	1,884	1,884
R-squared	0.88	0.17	0.17
Pair FE	✓	✓	✓
Individual FE	✓		

Notes: The table includes observations of 314 subjects who passed all of our three inattentive checks. Pair 1 includes the lottery (18 : 0.5 ; 6) and its certainty equivalent. Pair 2 includes the lottery (10.5 : 0.5 ; 3.5) and its certainty equivalent. Pair 3 includes the lottery (12 : 0.5 ; 0) and its certainty equivalent. Robust standard errors are clustered at the individual level. α in 1st quartile: $\alpha < 0.34$, α in 2nd quartile: $0.36 \leq \alpha < 0.57$, α in 3rd quartile: $0.57 \leq \alpha < 0.78$, α in 4th quartile: $\alpha \geq 0.81$.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Parameter Estimates - Robustness analysis

	A. Risk Preference Parameters			
α (Subproportionality)	0.500 (0.017)			
β (Range of convexity)	0.999 (0.013)			
η (Utility curvature)	0.881 (0.021)			
	B. Time Preference Parameters			
	Average	Pair 1	Pair 2	Pair 3
$\tilde{\rho}_{CE}$	**0.793 (0.013)**	0.846 (0.011)	0.765 (0.015)	0.768 (0.014)
$\tilde{\rho}_{L}$	**0.837 (0.011)**	0.866 (0.009)	0.813 (0.014)	0.830 (0.013)
s (Survival probability)	**0.988 (0.005)**	0.997 (0.003)	0.975 (0.012)	0.993 (0.003)
$\omega(s)$	**0.906 (0.016)**	0.943 (0.021)	0.854 (0.030)	0.920 (0.014)

Notes: The table includes observations of 314 subjects that passed our consistency checks. Pair 1 includes the lottery (18 : 0.5 ; 6). Pair 2 includes the lottery (10.5 : 0.5 ; 3.5). Pair 3 includes the lottery (12 : 0.5 ; 0). Standard errors clustered at the individual level in parenthesis, bootstrapped standard errors for s and $\omega(s)$.

Table A6: Survival Probability Regressed on Individual Characteristics. Robustness Analysis of the Results Presented in Figure 4.

	s
Ambiguity aversion	-0.086
	(0.065)
CRT score	-0.047
	(0.055)
Age	0.005
	(0.014)
Woman	0.227*
	(0.134)
Participated in lab	0.047
	(0.119)
Trust in experimenter	-0.087*
	(0.053)
Constant	-0.312
	(0.367)
Observations	302
R-squared	0.03

Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. In addition to 15 subjects for whom we could not estimate any s, two subjects who did not want to disclose their gender or did not identify as man/woman, and one subject with a missing value in the trust question are excluded from the analysis, subjects who did not pass our attentiveness criteria (described in Section 4.5) were dropped from the analysis. CRT score is the number of correctly answered cognitive reflection test questions. Ambiguity aversion, CRT score, and s are standardized.

Table A7: Parameter Estimates when Utility is Exponential

	A. Risk Preference Parameters			
α (Subproportionality)	0.596 (0.018)			
β (Range of convexity)	0.902 (0.010)			
η (Utility curvature)	0.081 (0.006)			
	B. Time Preference Parameters			
	Average	Pair 1	Pair 2	Pair 3
$\tilde{\rho}_{CE}$	**0.841 (0.007)**	0.902 (0.005)	0.815 (0.007)	0.805 (0.007)
$\tilde{\rho}_{L}$	**0.902 (0.005)**	0.927 (0.004)	0.871 (0.006)	0.909 (0.004)
s (Survival probability)	**0.946 (0.011)**	0.977 (0.008)	0.911 (0.019)	0.950 (0.011)
$\omega(s)$	**0.857 (0.012)**	0.909 (0.014)	0.803 (0.020)	0.858 (0.012)

Notes: Pair 1 includes the lottery (18 : 0.5 ; 6). Pair 2 includes the lottery (10.5 : 0.5 ; 3.5). Pair 3 includes the lottery (12 : 0.5 ; 0). Standard errors in parenthesis clustered at the individual level, bootstrapped standard errors for s and $\omega(s)$.

Online Appendix B - Experiment Instructions

Figure B1: Consent Form

LUND UNIVERSITY

Consent for participation

INSEAD The Business School for the World®

Welcome to our study and thank you for participating!

Background
We are a group of researchers from Lund University in Sweden and INSEAD in France. We are conducting a study on decision-making that allows you to earn money. By participating you contribute to research in this area. No special knowledge is required for participation. None of the questions that will be asked are designed to test you and there exists no "right" and "wrong" answers. However, it is required that you use a computer to participate in this study. It is not possible to participate with a tablet or smartphone.

The study will last approximately 1 hour. It will consist of three parts and a final questionnaire. For your participation, you are guaranteed to earn €10 but depending on you choices and your luck you can earn up to €X. Please note that all our tasks are designed such that your earnings depend on the decisions you make. Therefore, it is important that you think carefully, since every decision can affect your earnings.

Important: All your earnings from this study will be paid via PayPal. Moreover, they will be paid to you at two points in time; One part of the earnings will be paid to your PayPal account today, and another part of the earnings will be paid at some future date. We will specify the exact date later on. How much you will receive in total, as well as the share you receive today and the share you receive in the future, depends on the choices you make during the study. Note, however, that you are guaranteed to receive a total payment of at least €10.

Management of data and confidentiality
The project will collect and record information about you and your choices. However, all information will be confidential and anonymous. All responses will be protected so that unauthorized persons will not be able to access them. This is ensured by an encrypted link between your personal data and the responses collected in the study. The results of the project will be presented in research reports and scientific articles.

How do I get information about the project's results?
Research reports can be ordered from the researcher (see below). It usually takes time (more than a year) before a full report is available. Aggregated information on other participants' decisions can be obtained upon request.

Participation
Your participation is voluntary and you can choose to withdraw the participation at any time by pressing a button that cancels the questionnaire. If you choose not to participate or want to withdraw your participation, you do not need to state why.

Responsible researcher
Marco Islam
marco.islam@nek.lu.se
Department of Economics
Lund University, Sweden

I have been given information about the study, the purpose of the study and the handling of data.

Figure B2: Instructions Part 1 – Elicitation of Risk Preferences

Part 1 - Instructions

Task
In our first task you will have to choose between a lottery and a guaranteed payoff. While the guaranteed payoff is certain, the lottery consists of two possible payoffs: a high and a low payoff. For each lottery, we will specify the two payoffs (low and high) together with the corresponding probabilities as illustrated in the example below. Note that only one of the two payoffs will materialize if you choose the lottery option. The probabilities indicate the chance of receiving the respective payoff. Sometimes it is more likely to win the high payoff, sometimes it is more likely to win the low payoff and sometimes both payoffs are equally likely (as in the example below).

Lottery Example:
Receive either €12 with a probability of 50%
or €4 with a probability 50%.

You will be presented with 12 choice tables, all of which contain multiple rows. For each row, choose one of two alternatives: either the lottery (Option A) or the guaranteed payoff (Option B).
As you can see in Figure 1, the lottery option (Option A) will be constant throughout the entire list. However, the guaranteed payoff will decrease from row to row. It starts out being relatively attractive, but then decreases in attractiveness as you move down the list. Therefore, people usually prefer the guaranteed payoff (Option B) in the first row, but then switch to the lottery (Option A) at some row further down in the table. Please note, however, that our questions are not designed to test you. There exist no incorrect answers or incorrect switching points. For some tables it might feel more natural to switch rather early, while for other tables you may want to switch rather late. You might even feel that you don't want to switch at all. For every row in the choice table, simply choose the option that you prefer more.
Our computer is programmed such that once you switch from he guaranteed payoff (Option B) to the lottery (Option A), it will automatically mark all remaining rows as lottery choices. This implies that you can switch at most one time per table.

Option A	Your Choice		Option B
	A	B	
€12 with a probability of 50% or €4 with a probability of 50%.	○	◉	€12 guaranteed
	○	◉	€9 guaranteed
	◉	○	€6 guaranteed

Figure 1 – Example of choice table.

As mentioned above, you will walk through 12 choice tables in this first part. Once you click the NEXT button, your choices on the current page will be recorded and you will not be able to revise them. You will not have the opportunity to navigate back during this task. So please think carefully before you leave a page.

Payoff
Your payoffs in this task will be paid today, right after the experiment, by transfer to your PayPal account. Once you have completed all choice tables, the computer will randomly draw one of the decisions you have made in this task for payoff. If in that decision you have chosen the guaranteed payoff (Option B), you will receive that payoff. However, if you have chosen the lottery (Option A), we will first resolve the lottery and determine its outcome. That is, you will be paid either the low or the high payoff. The lotteries will be resolved at the end of the study, which means that you will learn about your earnings in this task at the end of this study as well.

Example
Let's assume the computer has randomly drawn row 3 from figure 1 for payment and you have chosen the lottery (Option A) in that decision. Further, suppose the lottery was resolved and by chance the high outcome was determined for payment. Then you would receive €12 for this task at the end of our study.

Please click the Next button if you understood the instructions and you feel ready to continue. On the next page, you will have to answer two questions before you can start with the actual task.

Next

Figure B3: Quiz for Part 1

Task 1 - Quiz

Please consider the choice table below. Then answer the two questions at the bottom of the page.

Option A	Your Choice A	Your Choice B	Option B
€8 with a probability of 40% or €2 with a probability of 60%.	○	◉	€7 guaranteed
	○	◉	€6.50 guaranteed
	○	◉	€6 guaranteed
	○	◉	€5.50 guaranteed
	○	◉	€5 guaranteed
	◉	○	€4.50 guaranteed
	◉	○	€4 guaranteed
	◉	○	€3.50 guaranteed

Question 1
Suppose the computer has chosen the decision in row 2 for payment and you chose the guaranteed option (Option B) in that row.

€8 with a probability of 40% or €2 with a probability of 60%.	○	◉	€6.50 guaranteed

How much money would you earn? (Please use "." to separate Euro and Cent values):

[ ] €

Question 2
Suppose the computer has chosen the decision in row 8 for payment and you chose the lottery option (Option A) in that row.

€8 with a probability of 40% or €2 with a probability of 60%.	◉	○	€3.50 guaranteed

How much money would yo earn in the worst case scenario? (Please use "." to separate Euro and Cent values):

[ ] €

Next Instructions

Figure B4: Choice List for Part 1 (Example)

Choice Table 1

Option A	Your Choice A	Your Choice B	Option B
€12.00 with a probability of **50%** or **€0.00** with a probability of **50%**	○	○	**€8.00** guaranteed
	○	○	**€7.50** guaranteed
	○	○	**€7.00** guaranteed
	○	○	**€6.50** guaranteed
	○	○	**€6.00** guaranteed
	○	○	**€5.50** guaranteed
	○	○	**€5.00** guaranteed
	○	○	**€4.50** guaranteed
	○	○	**€4.00** guaranteed
	○	○	**€3.50** guaranteed
	○	○	**€3.00** guaranteed
	○	○	**€2.50** guaranteed
	○	○	**€2.00** guaranteed
	○	○	**€1.50** guaranteed
	○	○	**€1.00** guaranteed
	○	○	**€0.50** guaranteed

Next Instructions

Figure B5: Instructions Part 2 – Elicitation of Time Preferences

Instructions

The next part of this experiment will consist of two tasks. We will start by explaining the first task. Once you have completed the first task, we explain task 2.

Part 2 - Task 1

In the first task you will have to choose between different lottery alternatives, which will be paid out at two different points in time. The alternative, which we refer to as the "Tomorrow Lottery" will be paid out tomorrow. Since this alternative will be paid out "sooner", the two pote amounts you can earn in that lottery are usually low. The second alternative, which we refer to as the 4 Weeks Lottery" will be paid out in 4 weeks on Sunday, 17 April 2022). Since this alternative will be paid out "later", the two potential amounts you can earn in that lottery are usually higher. example below illustrates this. Comparing the outcomes of the two lotteries, you can see how both the outcome in the best case scenario and outcome in the worst case scenario are higher in the 4 Weeks Lottery.

Your task is to choose between the Tomorrow Lottery and the 4 Weeks Lottery. Each lottery will pay you either the high or the low amc depending on the outcome of a coin toss. So for each amount, there exists a 50/50 chance that it will materialize.

Which alternative do you prefer?

The "Tomorrow Lottery"	or	The "4 Weeks Lottery"
which pays €9.00 tomorrow if coin shows heads or €4.00 tomorrow if coin shows tails .	○ ○	which pays €12.00 in 4 weeks if coin shows heads or €6.50 in 4 weeks if coin shows tails.

This task will consist of 3 rounds each containing 6 choices. That means, you will make a total of 18 choices similar to the example above. For a choices the payment dates remain the same. However, the monetary amounts of the lotteries differ. Within one round, the amounts of the "Tomoı Lottery" remain constant. They only change once you start a new round. The amounts of the "4 Weeks Lottery", on the other hand, differ from ch to choice. It is very important that you pay attention to those changes when you make your decision.

At the end of this study, we will randomly select one your choices in this part of the study (either from task 1 or from task 2) and pay them out at respective date of payment (via PayPal). This means your choices in this first task have the same probability of being selected as your choices in ta: If the computer selects one of the choices from this task, it will solve the lottery by simulating a coin toss. According to the outcome of the coin you will then either receive the higher amount if the coin shows heads or the lower amount if the coin shows tails. Since all of your choices have same probability to be chosen for payment, it is always in your best interest to choose the option you prefer the most.

Please note again that the questions are not designed to test you. There are no correct or incorrect answers. Simply choose the payment option you prefer the most.

Please think carefully about your decision before you leave a page. Once you click the NEXT button on the bottom of a decision page, your cho will be recorded and you will not be able to revise them. You will not have the opportunity to navigate back during this task.

Continue with control questions

Figure B6: Quiz for Part 2

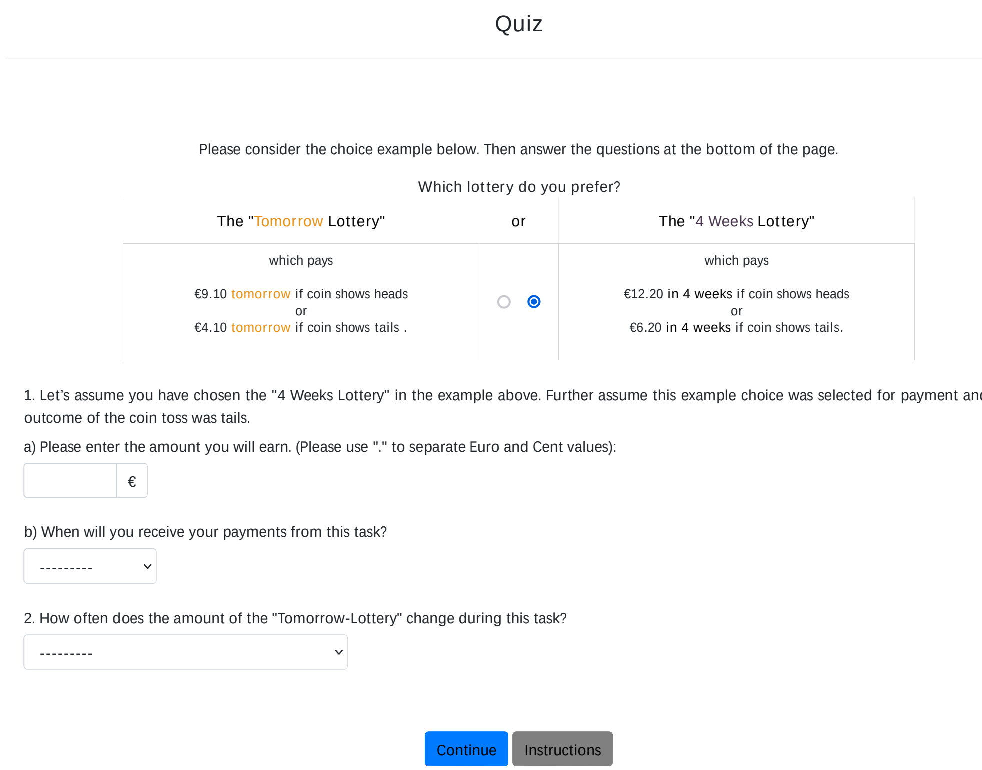


Figure B7: Choice for Part 2

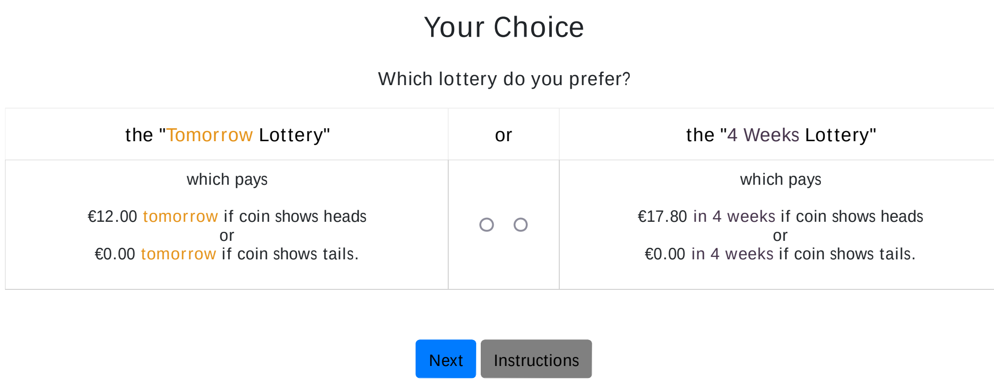


Figure B8: Choice for Part 3

Your Choice

Which alternative do you prefer?

the "Tomorrow Alternative"	or	the "4 Weeks Alternative
which pays €6.00 tomorrow if coin shows heads	○ ○	which pays €8.20 in 4 weeks if coin shows heads

Next Instructions

Figure B9: Ambiguity Task Instructions

Part 3 - Instructions

Task

In the third task of our study, you will be presented with one table, which consists of multiple decision rows. For each row, you will have to choose between drawing a ball from “Urn A” or from “Urn B”. Both urns contain 100 balls in total. However, while it is known that Urn A has 50 green balls and 50 blue balls, Urn B has an unknown number of green and blue balls. In addition to the choice from which urn to draw a ball, you will select your Success Color, which can be either green or blue. Then, no matter which urn you choose, you are successful whenever the drawn ball matches your Success Color. Figure 1 provides an example for the choice table of this task:

Please choose your Success Color		
Green	○ ○	Blue

Urn A (50 green balls, 50 blue balls)	Your Choice A	Your Choice B	Urn B (? green balls, ? blue balls)
€20 if ball is Success Color or €0 otherwise.	○	○	€37 if ball is Success Color or €0 otherwise.
	○	○	€34 if ball is Success Color or €0 otherwise.
	○	○	€30 if ball is Success Color or €0 otherwise.
	○	○	€26 if ball is Success Color or €0 otherwise.

Figure 1 – Example of choice table.

As you can see, the payments in the left column (Urn A) are constant throughout the whole table while the payments in the right column (Urn B) vary from row to row. For Urn B, they start out being relatively attractive, but then decrease in attractiveness as you move down the table. Therefore, people usually choose Urn B in the first row, but then switch to Urn A at some row further down in the table.

Once you have switched from Urn B to Urn A, the computer will automatically mark all remaining choices as Urn A. This implies that you can only switch once. So, think carefully!

Please note that our questions are not designed to test you. There are no correct or incorrect answers. For every row, simply choose the option you prefer.

Payoff

In this part, one out of 20 players will be chosen for payment. If you are chosen, the payoffs from this part will be paid today, right after the study. Once you completed all choices, the computer will determine one row for payoff and will draw one ball from the urn you chose. If the ball color matches your chosen success color you win the respective amount. If the ball color does not match your success color, you will not win anything.

Example

Let’s assume you were chosen for payment and you picked Green as your success color. Further, the computer has randomly chosen row 1 and your choice in this row was Urn B. Finally, suppose a green ball was drawn from that urn. Then, you receive €37 at the end of the experiment.

Please click the “Next” button, so that we can start the task.

Next

Figure B10: Ambiguity Task

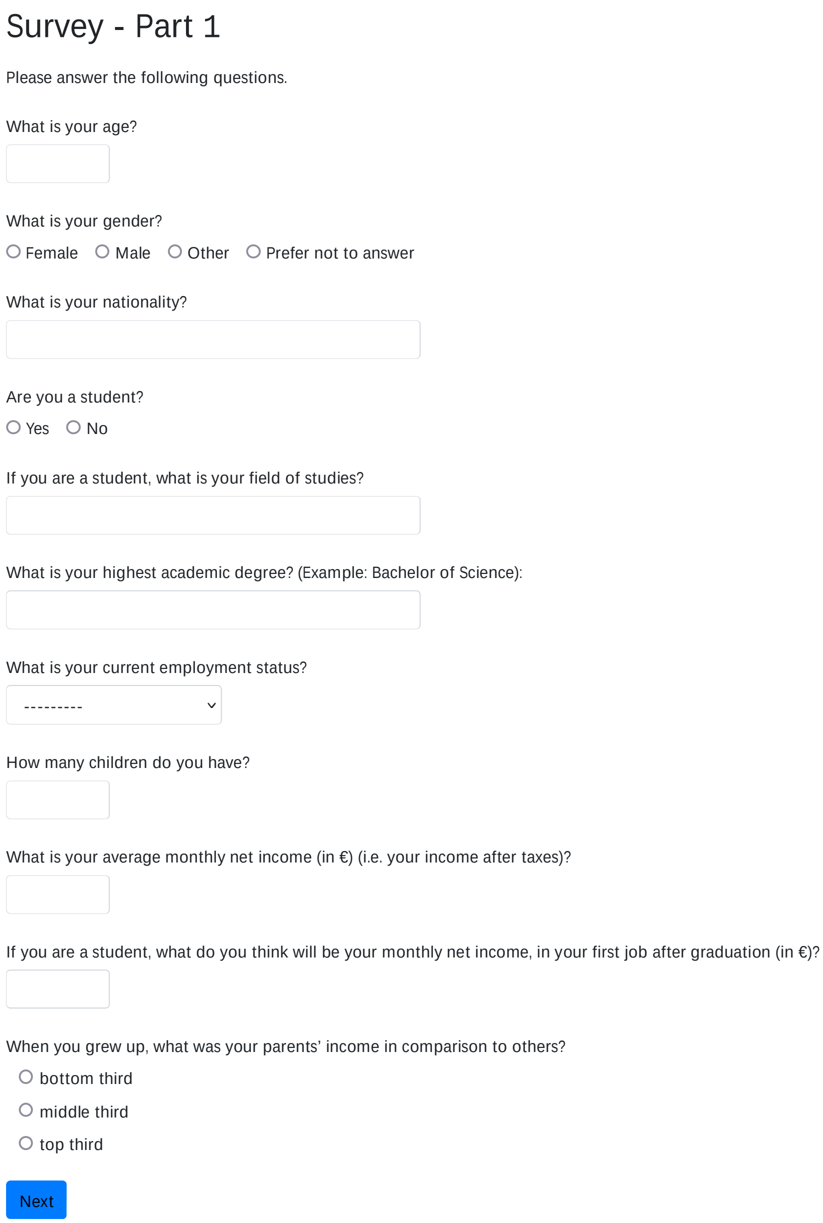
Choice Table 1

Please choose your Success Color		
Green	○ ○	Blue

Urn A (50 green balls, 50 blue balls)	Your Choice: A	Your Choice: B	Urn B (? green balls, ? blue balls)
€30.00 if ball is **Success Color** or **€0.00** otherwise	○	○	**€45.00** if ball is **Success Color** or **€0.00** otherwise
	○	○	**€43.00** if ball is **Success Color** or **€0.00** otherwise
	○	○	**€41.00** if ball is **Success Color** or **€0.00** otherwise
	○	○	**€39.00** if ball is **Success Color** or **€0.00** otherwise
	○	○	**€37.00** if ball is **Success Color** or **€0.00** otherwise
	○	○	**€35.00** if ball is **Success Color** or **€0.00** otherwise
	○	○	**€33.00** if ball is **Success Color** or **€0.00** otherwise
	○	○	**€31.00** if ball is **Success Color** or **€0.00** otherwise
	○	○	**€29.00** if ball is **Success Color** or **€0.00** otherwise
	○	○	**€27.00** if ball is **Success Color** or **€0.00** otherwise
	○	○	**€25.00** if ball is **Success Color** or **€0.00** otherwise
	○	○	**€23.00** if ball is **Success Color** or **€0.00** otherwise
	○	○	**€21.00** if ball is **Success Color** or **€0.00** otherwise
	○	○	**€19.00** if ball is **Success Color** or **€0.00** otherwise
	○	○	**€17.00** if ball is **Success Color** or **€0.00** otherwise
	○	○	**€15.00** if ball is **Success Color** or **€0.00** otherwise

Next Instructions

Figure B11: Final Survey – Part 1



Survey - Part 1

Please answer the following questions.

What is your age?

What is your gender?

○ Female ○ Male ○ Other ○ Prefer not to answer

What is your nationality?

Are you a student?

○ Yes ○ No

If you are a student, what is your field of studies?

What is your highest academic degree? (Example: Bachelor of Science):

What is your current employment status?

How many children do you have?

What is your average monthly net income (in €) (i.e. your income after taxes)?

If you are a student, what do you think will be your monthly net income, in your first job after graduation (in €)?

When you grew up, what was your parents' income in comparison to others?

○ bottom third

○ middle third

○ top third

Next

Figure B12: Final Survey – Part 2

Survey - Part 2

Please answer the following questions.

How willing are you to give up something that is beneficial for you today in order to benefit more from that in the future?

- 0 - not at all
- 1
- 2
- 3
- 4
- 5
- 6
- 7
- 8
- 9
- 10 - very much

In general, how willing are you to take risks?

- 0 - not at all
- 1
- 2
- 3
- 4
- 5
- 6
- 7
- 8
- 9
- 10 - very much

How much do you agree with the following statement: "I assume that people have only the best intentions.":

- 0 - do not agree at all
- 1
- 2
- 3
- 4
- 5
- 6
- 7
- 8
- 9
- 10 - totally agree

How much do you trust the organizer of this study that you receive your promised payments?

- 0 - not at all
- 1

2

3

4

5

6

7

8

9

10 - very much

In your opinion, how is your health condition?

0 - very bad

1

2

3

4

5

6

7

8

9

10 - very good

How many days per week do you consume alcoholic beverages?

Do you smoke?

Yes No

How many days per week do you exercise?

Have you experienced the loss of a close family member or friend?

Yes No

How would you rate the level of safety in your neighborhood on a scale from 1 to 10?

0 - very unsafe

1

2

3

4

5

6

7

8

9

10 - very safe

How many months in advance do you usually book your summer holidays?

Do you usually buy a cancellation insurance when you buy train/flight tickets?

○ Yes ○ No

Do you usually buy an add-on insurance when you buy e.g. a new computer or a new camera?

○ Yes ○ No

How certain are you about how your life will be in 1 year?

0 - very uncertain
1
2
3
4
5
6
7
8
9
10 - very certain

How certain are you about how your life will be in 5 years?

0 - very uncertain
1
2
3
4
5
6
7
8
9
10 - very certain

How certain are you about how your life will be in 10 years?

0 - very uncertain
1
2
3
4
5
6
7
8
9
10 - very certain

Next

Figure B13: Final Survey – Part 3

Survey - Part 3

Please answer the following questions.

A concert ticket and a drink cost $44 in total. The ticket costs $40 more than the drink. How many $ does the drink cost?

If it takes 7 persons 7 hours to repair 7 computers, how many hours would it take 100 persons to repair 100 computers?

A scientist observes the growth of bacteria. Every hour, the bacteria doubles in size. If it takes 24 hours for the bacteria to cover the entire area under the microscope, how many hours would it take the bacteria to cover half area?

Out of 1,000 people in a small town 500 are members of a choir. Out of these 500 members in a choir 100 are men. Out of the 500 inhabitants that are not in a choir, 300 are men. What is the probability that a randomly drawn man is a member of the choir (in %)? Please indicate the probability as a number between 0 an 100. :

Next