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Risky Decisions and the Opportunity Cost of Time

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We investigate the trade-off between the costs of decisions and their quality in a simple model in which a decision maker trades off using time for arriving at a risky decision and for pursuing an alternative activity. When decision time increases the quality of the decision, rational agents consider the opportunity cost of time when deciding how much time to allocate to decision-making. In a lab experiment, we introduce exogenous variation in the opportunity costs of time allocated to making risky decisions by reducing the subjects' payoffs as decision time increases. Using structural estimations, we infer preferences and decision errors. We find that an increase in the opportunity cost of time reduces, ceteris paribus, decision time, and that reducing the time available for making decisions increases the probability of mistakes. Moreover, we show that using more time when making small-stake decisions does not necessarily indicate irrational behavior, and neither does a positive correlation between decision time and the probability of making mistakes. Such behavior is compatible with our model of rational decision-making.

JEL codes: D03, D81, D83

Keywords: decision under risk, time constraints, opportunity costs, rational behavior, lab experiment, structural estimation

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I. Introduction

The quality of many important economic decisions depends on individual characteristics of the decision maker and the resources invested in the process of decision-making. If investing more time improves decision-making, the optimal allocation of time and therefore the optimal quality of the decision depends on the opportunity costs of time. We introduce a parsimonious model in which a decision maker (DM) rationally trades-off the costs and the quality of a decision under risk. Our economic model is based on the seminal works of Becker (1965) and Mincer (1963) on how rational agents allocate time optimally, recognizing that time has a (shadow) price determined by the opportunity costs related to alternative uses of it. Therefore, we follow Rabin's approach (Rabin 2013b, 2013a) to provide a portable extension of existing models that is able to incorporate a psychologically more realistic notion of rationality.

The model predicts that a rise in opportunity costs leads to faster choices that are of lower quality. We test these predictions in a lab experiment in which we exogenously vary the opportunity costs of time spent on the choice between two monetary lotteries. Other behavioral studies use fixed decision deadlines to investigate behavior under risk (Kocher, Pahlke, and Trautmann 2013; Nursimulu and Bossaerts 2013), but we analyze how subjects trade off opportunity costs of time and improved decision quality. Therefore, we use time-dependent opportunity costs, such that each second spent thinking is costly (see also Kocher and Sutter, 2006).

Based on the revealed preferences of the decision maker, the quality of a decision is measured by the number of inconsistent choices in risky decisions. We first jointly estimate risk aversion and decision error using structural estimations (Fechner 1860; Hey and Orme 1994; Harrison, List, and Towe 2007; Harrison and Rutström 2008; Bruhin, Fehr-Duda, and Epper 2010; Caplin, Dean, and Martin 2011).

We find that risk aversion does not vary significantly when opportunity costs are higher. On the other hand, the likelihood of a decision error increases with higher opportunity costs, thus validating our model's prediction. When confronted with higher opportunity costs, the DM rationally chooses lower decision quality by investing less time in the decision, which is necessary to equalize the marginal utilities of time with respect to its different uses.

In our model, we assume that investing more time increases the quality of a decision and we predict that valuable time will not be spent on choices that do not matter, but instead on an alternative use. However, there are two findings from the literature that appear to be at odds with our model of rational decision-making. First, in some studies, subjects' response times were found to be longer in lottery decisions when the utility difference between two available lotteries was small (Dickhaut et al. 2013; Krajbich, Oud, and Fehr 2014). Second, longer decision times positively correlate with a higher incidence of decision errors (Dickhaut et al. 2013; Alós-Ferrer et al. 2016). We address these issues in our model and in the analysis by employing instrumental variable regressions, and the drift diffusion model (Ratcliff 1978; Krajbich, Oud, and Fehr 2014; Oud et al. 2016).

We find empirical evidence for the presence of the two puzzling results in our data. When using the estimated expected utility difference as the difficulty of a decision, we find a negative correlation between decision times and expected utility difference. However, when we insert decision difficulty as the expected utility difference into our model, we show that the negative correlation is also possible within our model. Concerning the second puzzle, when simply regressing decision time on making a correct choice, we find a negative correlation between decision time and correct choices. However, a causal interpretation is not possible if the difficulty of the decision is not controlled for because decision difficulty is likely to be positively correlated with decision time and negatively correlated with the probability of a correct choice. We circumvent these problems with our research design. Our randomized opportunity cost treatments provide us with the ideal instrument for the time invested in the decision. Instrumenting the decision time with opportunity costs reveals a strongly negative causal effect of decision time on errors, which is in line with the *”Thinking, Fast and Slow”* metaphor (Kahneman 2011).

As a last step, we focus on the drift diffusion model as it generally correctly predicts the puzzles (see (Fehr and Rangel 2011). We estimate the drift diffusion model parameters and simulate the marginal effects on decision quality when spending more time deciding. The analysis suggests that spending time increases decision quality. Further, higher opportunity costs are associated with lower boundaries. These lower boundaries can be interpreted as needing less evidence to make a choice which, in turn, leads to choosing the inferior lottery more often.

This paper makes several contributions to the literature. Several studies (Nursimulu and Bossaerts 2013; Dickhaut et al. 2013; Kocher, Pahlke, and Trautmann 2013) use fixed and exogenous time constraints in their experiments. In contrast, we investigate the endogenous investment of time in the decision-making process determined by the trade-off between the opportunity costs of time and the quality of the decision-making. Wilcox (1993) and Krajbich, Oud, and Fehr (2014) vary the monetary payoff of the decision task by changing either the stake of the decision itself or the magnitude of the payoff difference between the available options. We directly introduce exogenous variation in the opportunity costs of time, which is not confounded with and independent of the decision problem itself. In addition, there is an extensive literature on the correlation between decision time and decision quality in decision-making under risk (Wilcox 1993; Dickhaut et al. 2013), learning and belief updating (Achtziger et al. 2012), and strategic decisions (Kocher and Sutter 2006). Our research design allows us to identify the *causal effect* of decision time on decision quality. We provide a comparison between our extension of the expected utility model to the process-oriented drift diffusion model of Ratcliff (1978) and show that both models, correctly specified, provide similar predictions with respect to the nexus between decision time, difficulty of the decision, and quality of the decision. We are able to show that both the negative correlation between decision time and quality and the observation that more time is spent making a decision between options with rather similar utilities are compatible with a model of rational behavior that incorporates the opportunity costs of time.

In the next section, we review the relevant literature and look at the two puzzling results. In section III, we describe our model and how it relates to the puzzles. Section IV explains the experiment. Our structural estimation results are provided in Section V. We discuss puzzles related to our findings, the instrumental variable approach and how the drift diffusion model compares with and adds to our model in Section VI. Section VII discusses potential extensions of our approach and robustness checks. We conclude in Section VIII.

II. Literature Review

We analyze the investment of time in making quality economic decisions under risk. This relates our study to behavioral studies on how time pressure induced by fixed decision deadlines alters behavior under risk (Kocher, Pahlke, and Trautmann 2013; Nursimulu and Bossaerts 2013)[3], the economics of information as introduced by Stigler (1961) and rational inattention (Caplin and Dean 2015; Matějka and McKay 2015)[4]. Our study complements the work of Caplin, Dean, and Martin (2011) on the effect of information search on decision-making. Based on the idea of Simon (1955), Caplin, Dean, and Martin (2011) investigate decisions for which not all information is immediately available to the decision maker. Many important economic consumer decisions, such as choosing the right pension plan or savings contract, share this feature. Modern communication technologies can provide access to all information that is easily available. The evaluation of information can be seen as the binding constraint in the decision-making process, especially when risk is involved and risky decision-making is what we are interested in here.

Two results of previous studies seem to be in stark contrast to the predictions of our economic model. First, subjects have been found to invest more time in lottery decisions when the utility difference between two available lotteries is small. This implies that a better quality lottery decision increases expected utility only slightly (Moffatt 2005; Gabaix et al. 2006; Chabris et al. 2009; Dickhaut et al. 2013; Krajbich, Oud, and Fehr 2014) which is contrary to the economic intuition that valuable time should not be spent on choices that do not matter, but on an alternative. Alós-Ferrer et al. (2016) include an assumption in their model of preference reversals that divides choices into hard (small utility difference) and easy ones (large utility difference).

Second, longer decision times were found to correlate with a higher incidence of decision errors (Dickhaut et al. 2013; Alós-Ferrer et al. 2016). Alós-Ferrer et al. (2016) hypothesize and then confirm with their data that predicted reversal take longer than comparable non-reversals. These reversals can also be seen as inconsistent choices. In a related model, Achtziger and Alós-Ferrer (2013) show that the relation between a controlled process (Bayesian updating) and an automatic process (reinforcement

[3] In contrast to the experiments used in the literature on time pressure, in which a DM is forced by an exogenous time limit, our experimental setting investigates the effect of time pressure as an endogenous outcome of a decision maker's trade-off between costs and quality of a decision. In the former, a deadline either yields either no effect or a slightly increased risk aversion.

[4] We analyze decisions under risk in which all information is available. The decision maker decides on how much effort to exert to distinguish the two option (which is related to the second stage mentioned by Matějka and McKay (2015)). See also Caplin (2016) for a recent review on attention.

learning) predict response times of errors: if the two processes are aligned, then errors tend to be slower, while errors tend to be quicker if the processes yield contradicting predictions.

While expected utility (Neumann and Morgenstern 1944) has its roots in axiomatic theory, the drift diffusion model (DDM) claims to emulate the decision process the human brain. Decision values are encoded by neurons that transmit all-or-nothing information (Krajbich, Oud, and Fehr 2014): only when the signals add up to a sufficiently large boundary will a decision be made. Contrary to the process oriented DDM that portrays the neuropsychological process, the expected utility (EU) model is usually interpreted as an *as-if* model (Friedman and Savage 1952), that is, a black box that does not describe the underlying mechanisms governing the decision process. Ratcliff (1978) introduced the drift-diffusion model of dynamic evidence accumulation processing to predict both choice behavior and the distribution of decision time.[5] The DDM assumes that the decision maker observes two types of signals that indicate the value of the two available lotteries, and continuously updates the resulting relative decision value (RDV). This process continues until a choice specific threshold is reached. Using the notation of Krajbich, Oud, and Fehr (2014), the drift diffusion model predicts that decision time varies negatively with the expected utility difference. When the expected utility difference is small, the decision time is longer than when the expected utility difference is large, because it is more difficult to discriminate between the two lotteries (see Fehr and Rangel 2011).[6] As a result, the evidence accumulation process is slower. The DDM can also account for the second puzzling empirical regularity – a negative correlation between decision time and the probability of choosing the superior option. In the DDM, a longer decision time is mainly caused by both a low drift rate and large boundaries (neglecting a high non-decision time). Drift toward the preferred decision boundary makes a correct choice more likely. However, the lower the drift rate, the longer the accumulation process, and the more likely it becomes (conditional on the fact that the RDV has still not reached the boundary of the superior option) that the stochastic component of the DDM will cause the RDV to cross the boundary of the inferior option. Changes in the drift rate caused by a variation in the difficulty of a decision therefore produce a negative correlation between decision time and quality. The drift diffusion model has received a great deal of attention in the consumer search literature (for example, Reutskaja et al. 2011) and has been extended to dual stages or dual processes (Hübner, Steinhauser, and Lehle 2010; Caplin and Martin 2015; Alós-Ferrer 2016).

III. Economic Model

In this section, we present a model that describes a rational decision maker facing a risky decision. The decision maker trades off time in making a correct lottery choice against a well-defined opportunity cost of time. The risky choice is between two lotteries $\mathcal{L} = \{L, R\}$ where R (L) denotes the lottery with

[5] For a recent survey on the drift-diffusion model see Ratcliff and McKoon (2008). For description of the DDM, we rely on Fehr and Rangel (2011) and Krajbich, Oud, and Fehr (2014) who provide short surveys on the use of the DDM in the economic literature.
[6] Fehr and Rangel (2011) summarize stylized facts related to predictions of the DDM, including the prediction that difficulty, as measured by the utility difference, is positively related to decision time.

the higher (lower) expected utility.[7] The agent decides on the optimal allocation of total time T to spend on the lottery decision t_d and the alternative (other) use t_o. u_d denotes the expected utility related to the lottery choice, whereas u_o relates to the utility derived from the alternative use of time which is the opportunity cost of the lottery decision. The opportunity costs are deterministic and increasing in t_o ($\partial u_o/\partial t_o > 0$). Furthermore, opportunity costs may differ which is captured by α. A higher α is assumed to increase the marginal utility of an additional second not allocated to the lottery choice ($\partial^2 u_o/\partial t_o \partial\alpha > 0$). The expected utility of the lottery decision depends on the two available lotteries and the probability π of selecting the lottery with the higher expected utility (R). The probability π is increasing in the time invested in the decision ($\partial\pi/\partial t_d > 0$) and may also depend on the individual characteristics γ such as education, skills, and the difficulty of the lottery decision δ. The agent maximizes

$$\max_{t_o, t_d} u_d(\pi(t_d, \gamma, \delta), \mathcal{L}) + u_o(t_o, \alpha) \quad \text{s.t.} \qquad t_o + t_d = T \tag{1}$$

The first order conditions require equality of the marginal utilities related to both time use opportunities.

$$\underbrace{\frac{\partial u_d}{\partial\pi}\frac{\partial\pi}{\partial t_d}}_{MU_d} = \underbrace{\frac{\partial u_o}{\partial t_o}}_{MU_o} \tag{2}$$

A higher probability π increases $E[u_d]$ because it improves the chance of selecting the lottery with the higher expected utility.[8] The left-hand side of Equation (2) describes the positive marginal utility of time spent on the lottery decision. If we further assume $\partial^2\pi/\partial t_d^2 < 0$, we find that MU_d is decreasing in t_d.[9] The right-hand side of Equation (2) describes the marginal utility of time with respect to the alternative time use.

In our experiment, we use different treatments to vary the opportunity costs α related to the lottery decision. An increase of these costs is illustrated in Figure 1 by an upward shift of MU_o toward $MU_{o'}$.

[7] For the sake of a notational convenience, we assume $R \succ L \Leftrightarrow E[u(R)] > E[u(L)]$ throughout the paper.
[8] The increase of $E[u_d]$ is zero if the two available lotteries yield the same expected utility ($E[u(R)] = E[u(L)]$).
[9] This assumption is intuitive. The probability π has an upper bound of 1, leading to the intuitive assumption that π approaches 1 at a decreasing rate. In our two-lottery set up we can further assume $\pi(0, \gamma, \delta) = 0.5$, which corresponds to a random choice between the lotteries if no resources are invested in the lottery decision.

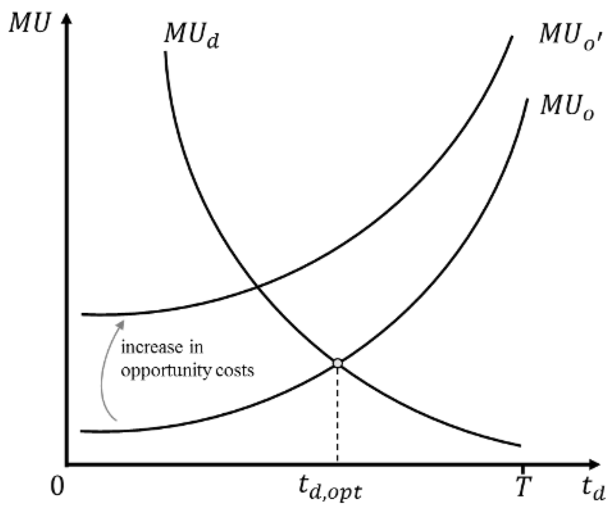

Figure 1. Optimal Time Invested in Decision Quality

Notes: The figure presents the equilibrium condition in Equation (2) based on the maximization problem (Equation(1)). In the equilibrium, the optimal decision time is chosen so that the marginal utilities from investing a unit of time in the lottery decision and in the alternative activity (MU_d and MU_o) are equalized. An increase in opportunity costs α shifts the MU_o upward to $MU_{o'}$ and leads to a lower optimal decision time.

From this simple model, we derive the following prediction: An increase in the opportunity costs reduces the optimal time invested in the lottery decision and therefore reduces the quality of the decision. In line with rational behavior, we expect to see more errors in the lottery decisions because investing more time to improve the lottery decision has to be traded off against the opportunity costs.

A. *Is Time Invested in Economic Decisions when the Decision Does Not Matter?*

Gabaix et al. (2006), Moffatt (2005), Chabris et al. (2009), Dickhaut et al. (2013), and Krajbich, Oud, and Fehr (2014) find that more effort—as measured by decision time—is expended when there is only a small difference in expected utility between the two possible choices. This is contrary to the economic intuition that valuable time should not be spent on choices that do not matter, but on an alternative. In our model, we substitute the time constraint into the maximization problem of Equation (1) such that the agent chooses an optimal time span t_d^* for selecting a lottery:

(3) $$\max_{t_d} U \equiv \pi(t_d, \gamma, \delta) \cdot E[u(R)] + \big(1 - \pi(t_d, \gamma, \delta)\big) \cdot E[u(L)] + u_o(1 - t_d, \alpha).$$

Based on the first order condition reported in Equation (4), a smaller utility difference $\Delta E[u] = E[u(R)] - E[u(L)]$ reduces the costs of a decision error, and requires a lower t_d, since $\partial\pi/\partial t_d$ is assumed to be positive.

(4) $$\frac{\partial U}{\partial t_d} = (E[u(R)] - E[u(L)]) \cdot \underbrace{\frac{\partial \pi}{\partial t_d}}_{>0} + \underbrace{\frac{\partial u_o}{\partial t_d}}_{<0} \stackrel{!}{=} 0$$

As mentioned above, however, several studies find exactly the opposite. We allow the difficulty δ of a decision to codetermine the probability $\pi(t_d, \gamma, \delta)$ of making a correct decision. In line with the reasoning of the DDM and that of (Alós-Ferrer et al. 2016), we assume that the difficulty δ is decreasing in $\Delta E[u]$ (a small value of $\Delta E[u]$ is associated with higher difficulty), and assume $\partial\pi/\partial(\Delta E[u]) > 0$. Reformulating the first-order condition from Equation (4) gives

(5) $$\frac{\partial U}{\partial t_d} = \underbrace{\Delta E[u]}_{\substack{importance\\ effect}} \cdot \underbrace{\frac{\partial \pi(t_d,\gamma,\Delta E[u])}{\partial t_d}}_{\substack{difficulty\\ effect}} + \underbrace{\frac{\partial u_o}{\partial t_d}}_{<0} \stackrel{!}{=} 0.$$

Equation (5) illustrates the trade-off between responding to a greater difficulty and a lesser importance of the decision. A lesser importance, denoted by a lower $\Delta E[u]$, enters the first factor of the product in Equation (5) and decreases ceteris paribus the optimal time invested in the decision (t_d^*) because π is assumed to be an increasing and concave ($\partial^2\pi/\partial t_d^2 < 0$) function in t_d. However, a lower $\Delta E[u]$ also increases the difficulty of identifying the superior lottery. Assuming that a lower $\Delta E[u]$ will not only decrease the probability of choosing the superior lottery at any given decision time ($\partial\pi/\partial\Delta E[u] > 0$), but also decreases the marginal utility from spending an additional unit of time on the lottery decision ($\partial^2\pi(t_d,\gamma,\Delta E[u])/\big(\partial t_d \partial(\Delta E[u])\big) < 0$), the *difficulty effect* will lead to more time invested in the lottery choice and thereby counteracts the *importance effect*. Signing $\partial t_d^*/\partial\Delta EU$ is therefore an empirical question. In contrast to the interpretation of Krajbich, Oud, and Fehr (2014), our results suggest that a negative correlation between t_d and $\Delta E[u]$ cannot be interpreted as evidence against the expected utility model. We rather interpret the ability of the expected utility model to reveal the two opposing effects that govern optimal decision time as a strength of the traditional model.

IV. Experimental Design

A. *Method*

112 subjects were recruited with ORSEE (Greiner 2015) among the students of the University of Konstanz. The experiment was programmed in z-Tree (Fischbacher 2007) and conducted at Lakelab, the economics laboratory at the University of Konstanz. The experiment lasted about 75 minutes and participants earned €14.29 on average (maximum €88.25, minimum €5.15). The experiments took place between May and June 2015. Table 5 in Appendix A provides summary statistics in regard to the socio-economic characteristics of all 112 subjects.

The experiment consisted of four parts (Figure 2). First, the participants completed all four questions of the Berlin Numeracy Test in multiple choice format (Cokely et al. 2012). Second, subjects completed Holt and Laury's (2002) incentivized Multiple Price List (MPL).[10]

After completing these two tasks, subjects played 180 lotteries with two states and a wide variety of probabilities.[11] We used a random lottery design that has been used in several experiments investigating decisions under risk (Harrison and Rutström 2008). Subjects had to decide between two options, where the probability of receiving the higher value in one option was equal to the probability of receiving the lower value in the other option. We mainly used the probability pairs 90-10, 75-25, 60-40, and 53-47. Two randomly drawn lotteries were paid out. At the end, subjects completed a smaller version of the Raven's Matrices.[12] Parts 1, 2, and 4 of the experiment were identical across treatments, while Part 3

[10] Only the Holt-Laury task and the lottery task were incentivized. The payoffs were determined at the end of the experiment (after the Raven's Test) to rule out potential endowment effects in later stages of the experiment.
[11] Appendix L presents the set of lottery pairs used in the experiment to gather the choice data.
[12] See Raven et al. (2005). We used every third item of the second set.

featured treatment-dependent opportunity costs. The treatment was the same for all subjects within a session.

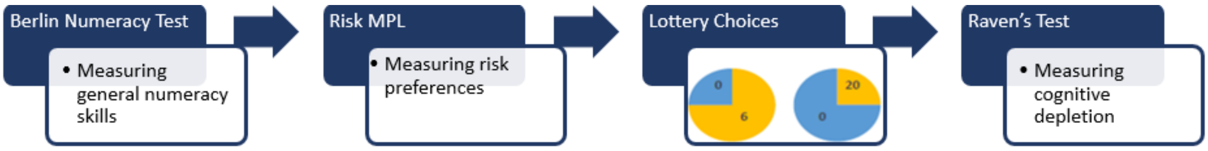

Figure 2. Experiment Setup

Notes: The figure presents the timeline during the experimental sessions. Parts 1, 2, and 4 were similar across treatment conditions. In Part 3, subjects in all treatments were confronted with the same set of 180 lottery choices, but with different opportunity costs related to the decision time.

In order to investigate the effect of different opportunity costs, we implemented time dependent costs in a between-subject design. We conducted four sessions and only the time-dependent costs in Part 3 varied between the sessions. The time costs ranged from 0 cents (no time costs) in the control group to 10 cents (low), 30 cents (medium), and 100 cents (high) in the three treatment groups. All subjects had a maximum of 15 seconds to make a lottery choice. Subjects, not in the time cost treatments, were told that they would receive the outcome from the lottery plus points from a "time account".

In each of the 180 rounds, there were €3 in the time account and the time account yielded no negative points. Every second (and millisecond) subjects lost[13] a treatment dependent amount from their time account (10 cents, 30 cents, 100 cents). There were 28 subjects in each of the three treatments with opportunity costs: another 28 subjects were assigned to the control treatment. For subjects in the *no costs* treatment, the time dependent costs of the lottery decision were equal to zero.

Several studies use strict or lenient deadlines and explore their effect on decision-making. We are mainly interested in the trade-off between spending more costly time and making a better decision such that every second spent thinking is costly to the alternative use. Therefore, we decided to use time-dependent costs instead of a deadline.

V. Estimation and Results

A. *Decision Time and Opportunity Costs*

The model described in Section III predicts a decrease in time invested in the lottery decision as opportunity costs increase. Figure 3 presents the average time spent on a lottery decision in each treatment. The decision time drops by more than 50% from 3.05 seconds in the treatment without opportunity costs to 1.3 seconds in the treatment with the highest opportunity costs. With the exception of the comparison between the *10 cents* and *30 cents* treatment, a t-test with standard errors clustered at the subject level reveals significant differences ($p < 0.01$) across the time spent on the lottery decision across all treatments.[14]

[13] To avoid a loss frame, the instructions stated "For every second faster than X seconds, you gain Y cents on your time account.
[14] These results also hold for alternative nonparametric tests described in the notes below Figure 3.

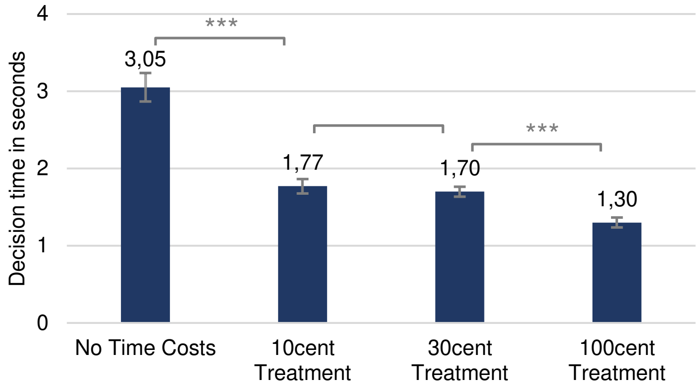

Figure 3. Time Invested in the Lottery Decision

Notes: This graph plots the average time subjects spent on a lottery decision in the corresponding treatment and standard errors clustered at the subject level based on 20,160 lottery decisions made by 112 subjects. Significance of pairwise comparison across treatments is calculated using a t-test clustered at the subject level. Similar significance levels are achieved when using a (blockwise) bootstrapped t-test clustered at the subject level with 1,000 replications and a clustered Mann-Whitney U test. All differences across the control group and each treatment condition are significant at the 1 percent level.
*** Significant at the 1% level.
** Significant at the 5% level.
* Significant at the 10% level.

B. *Risk Preferences and Decision Error*

We use a structural approach to test whether higher opportunity costs reduce the time invested in the quality of the lottery decision and therefore increase the number of choices in favor of the lottery with lower expected utility. We elicit the risk preferences that determine the expected utility associated with a lottery. To elicit risk preferences, we assume a CRRA utility function $u(x) = x^{1-\rho}/(1-\rho)$.[15] Given the risk preferences, we then determine errors in the lottery choices. Furthermore, we assume that errors in the lottery decision are more likely, when, ceteris paribus, the difference in the expected utility ($\Delta E[u]$) of the two available lotteries is small. A lottery decision in favor of the preferred lottery (R) depends on $\Delta E[u] = E[u(R)] - E[u(L)]$ and the realization of a random decision error $\varepsilon \sim N(0,1)$. This implementation of a decision error is known as the Fechner error specification (Fechner 1860; Hey and Orme 1994).[16] The standard normal distribution of ε ensures that large realizations of the error term are less likely than small ones. Whenever $\Delta E[u] + \tau \cdot \varepsilon < 0$, the DM chooses the inferior lottery L and deviates from the EU prediction.[17] The parameter τ measures the size of the error. A higher τ corresponds to more expected decision errors. Furthermore, the difference in expected utility $\big(EU(R) - EU(L)\big)$ is standardized, based on Wilcox (2011), to be bounded within the interval $[-1,1]$.

We jointly estimate our structural parameters ρ and τ to measure the risk preference and errors in the lottery decision using the data on the lottery *Choice* between the two available lotteries in lottery pairs $\mathcal{L}$ with the following equation:

(6) $$Choice^* = \Delta E[u(\rho; \mathcal{L})] + \tau \cdot \varepsilon, \; with \; \varepsilon \sim N(0,1),$$

[15] We relax the CRRA functional form assumption in Appendix G and obtain quantitatively similar results.
[16] The Fechner error specification is used as the main specification in several previous studies employing stochastic expected utility models; see, for instance, (Harrison, List, and Towe 2007; Bruhin, Fehr-Duda, and Epper 2010; Caplin, Dean, and Martin 2011). Starmer (2000) provides a comprehensive review of different error specifications.
[17] Appendix B presents a detailed derivation of our structural estimation procedure.

where $Choice = R$ if $Choice^* \geq 0$ and $Choice = L$ if the latent variable $Choice^*$ is negative. To test our theoretical predictions we allow ρ and τ to depend on the treatment condition. We also investigate potential heterogeneity with respect to individual characteristics of the subjects as well as estimates at the individual level.

Table 1 presents the structural estimates at the treatment level.[18] The first two models present results of structural estimations without an explicit error term. We find no treatment effect on the risk aversion parameter ρ. The estimates in Columns (3) to (5) correspond to a joint estimation of risk aversion and the decision error. We find no consistent evidence in favor of a change in risk preferences as a result of higher opportunity costs induced time pressure. Therefore, the stability of risk preferences is a valid (implicit) assumption of the economic model described in Section III.[19] However, we find a strong pattern in the magnitude of decision errors. The errors increase most in the *100 cents* treatment. In all three treatments, the increase in decision errors is statistically significant. Based on the estimated coefficients, we find evidence that the largest magnitude of decision errors occurs in the treatment with the highest opportunity costs. As the theoretical model predicts, lower investment (decision time) in the quality of the lottery decision leads to more decision errors. These errors are identified as deviations from the EU prediction. In Column (5), we allow for heterogeneity in risk preferences and decision quality with respect to gender (*male*), *age*, and numeracy skills (*BNT*). Male subjects make fewer decision errors and are less risk averse. We find some evidence that lower numeracy skills, measured by the Berlin Numeracy test (*BNT*) are correlated with lower decision quality.

[18] The interpretation of our t-tests in the results table is as follows: testing the treatment coefficients against zero, means we are attempting to reject the hypothesis that the preference or error parameter is different from the value of the control group (constant). Testing the coefficient of the constant in the risk preference (ρ) equation against zero means we are attempting to reject the null hypothesis of risk neutrality or expected value as choice criteria in the control group. Testing the coefficient of the constant in the decision error (τ) equation against zero constitutes an attempt to to reject the hypothesis of a deterministic utility theory with no decision errors, such that $EU(R) > EU(L) \Rightarrow \Pr(Choice = R) = 1$, $\Pr(Choice = L) = 0$ holds.

[19] Based on stable preferences, we can interpret our model as a normative EU model, explaining how the DM should decide. Deviations from the normative predictions thus can be interpreted as undesirable decision errors.

Table 1—Structural estimates

	Only Risk Measure		Risk & Error Measure					
	(1)	(2)	(3)		(4)		(5)	
Parameter:	ρ	ρ	ρ	τ	ρ	τ	ρ	τ
Treatments								
100cent Treatment	-0.247	-0.139	-0.073		-0.074	0.130***	-0.138	0.118***
	(3.146)	(1.956)	(0.125)		(0.136)	(0.026)	(0.149)	(0.028)
30cent Treatment	-0.589	-0.172	-0.164		-0.154	0.065***	-0.160	0.040**
	(7.109)	(5.858)	(0.137)		(0.125)	(0.018)	(0.118)	(0.019)
10cent Treatment	-0.624	-0.473	-0.181		-0.185	0.090***	-0.193*	0.051*
	(3.348)	(3.930)	(0.110)		(0.121)	(0.034)	(0.108)	(0.029)
Male		-0.657					-0.162*	-0.071***
		(1.065)					(0.093)	(0.026)
BNT Correct		-0.098					-0.040	-0.012*
		(0.194)					(0.038)	(0.007)
Age (18)		0.027					0.024	-0.004
		(0.079)					(0.015)	(0.004)
Constant	0.233	0.429	0.201***	0.221***	0.193***	0.153***	0.273**	0.234***
	(0.151)	(0.336)	(0.064)	(0.011)	(0.053)	(0.013)	(0.111)	(0.031)
p-value for joint significance in:								
Treatments	0.997	0.999	0.331	0.000	0.354	0.000	0.241	0.000
Log-Likelihood	-13049	-13010	-11998		-11931		-11796	
Subjects	112	112	112		112		112	
Observations	20160	20160	20160		20160		20160	

Notes: The dependent variables are the Arrow-Pratt measure of relative risk aversion (ρ) assuming CRRA utility and the Fechner error (τ). Results in Columns (1) and (2) correspond to estimations without any treatment dependent error specification. Results in Columns (3) – (5) correspond to joint estimates of ρ and τ. Block bootstrapped standard errors clustered at the individual level and based on 1,000 replications are reported in parentheses.[20]
*** Significant at the 1% level.
** Significant at the 5% level.
* Significant at the 10% level.

The results in Table 1 provide estimates on the treatment level. To check the robustness of our results, we estimate the structural model for each subject individually and check whether we can still identify the pattern of the estimates in Table 1. Figure 4 plots the individual estimates within each treatment and reveals a clear increase in the decision error as opportunity costs increase, whereas no clear trend is observable in the estimated risk preferences. Statistical inference on the treatment differences based on a nonparametric Mann-Whitney U test reveals quite similar p-values on the statistical differences across treatments ($p_{\Delta\rho:\,no\ vs.\ 10} = 0.140$, $p_{\Delta\rho:\,no\ vs.\ 30} = 0.334$, $p_{\Delta\rho:\,no\ vs.\ 100} = 0.973$). In contrast, we find a statistically significant increase in the decision error ($p_{\Delta\tau:\,no\ vs.\ 10} = 0.003$, $p_{\Delta\tau:\,no\ vs.\ 30} = 0.003$, $p_{\Delta\tau:\,no\ vs.\ 100} = 0.000$).

[20] Moffatt (2015) and Cameron and Miller (2015) provide the technical details on the bootstrap procedure.

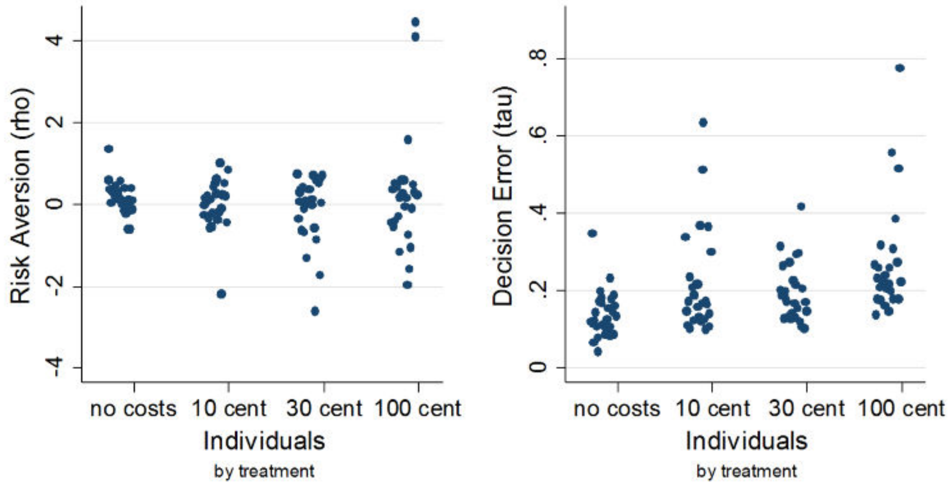

Figure 4. Individual Estimates

Notes: N=111. For one individual, the maximum likelihood estimator did not converge. The ρ estimates of four observations were smaller than -10 and are therefore omitted. The τ estimate of one observation exceeds 1.4 and is omitted from the figure. The statistical tests are performed on the entire sample, including the omitted outliers. Appendix C presents scatter plots including the outliers and details about the nonparametric test.

C. *Quantitative Size of Decision Errors*

We established the existence of a treatment effect on the decision error by reporting a statistically significant increase in the decision error. The question remains, however, whether this increase is economically significant or small enough that it can be ignored. The size of our decision error parameter τ is positive but nonlinearly related to the probability of choosing the inferior lottery. The following example illustrates the error mechanism for a representative lottery choice ($\Delta E[u] = 0.11$) assuming that the lottery R has a higher expected utility than lottery L. Based on the structural estimates in Column (4) of Table 1, Figure 5 illustrates the increase in the decision error as opportunity costs increase from zero (control group) to 100 cents. The blue curve illustrates the estimated relatively low decision error ($\tau = 0.153$) in the no time pressure control group. The yellow curve corresponds to high decision error ($\tau = 0.153 + 0.130 = 0.283$) estimate for the 100 cent treatment. Given a lottery choice with $\Delta E[u] = 0.11$, the estimated treatment effect of the decision error of $\tau = 0.130$ translates into an 11 percentage point increase in the probability of choosing the suboptimal lottery, that is, from 24% to 35%.[21]

Another way of illustrating the robustness of the decision error pattern is via out-of-sample predictions.[22] We randomly select 120 lotteries and estimate our structural parameters ρ and τ for every subject. Next, we calculate the predicted probability of making a correct choice in the remaining 60 lotteries. We run this procedure 1000 times with new randomly selected lotteries and then calculate the mean probability of making a correct choice in each treatment. In the control treatment, the probability of choosing the correct lottery in the remaining 60 lotteries is 71.27%, 66.58% in *10 cents* treatment, 67% in *30 cents* treatment, and 62.04% in the *100 cents* treatment. These probabilities reflect that

[21] A random choice would generate an error probability of 50%. Therefore, all improvements in the lottery decision are bounded within the range between 50% and 100%. An increase of 11 percentage points therefore represents a quantitatively large effect. The decision errors in both treatments increase as $\Delta E[u]$ becomes small. $\Delta E[u] = 0.11$ represents an average utility difference across lotteries.

[22] A comparison between the out-of-sample predictions of CRRA vs. Prospect Theory yields no significant difference. The results are available on request.

subjects' choices were most likely to be predicted correctly in the control treatment and that the choices of subjects in the *100 cents* treatment were the least likely to be predicted correctly.

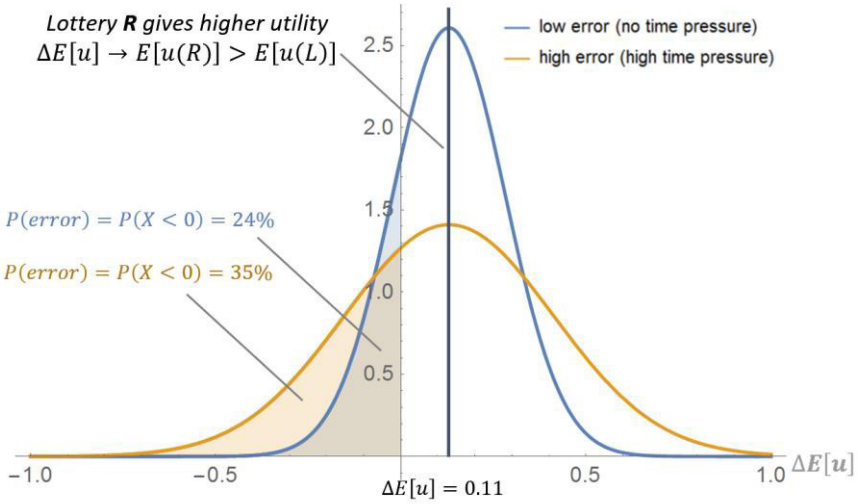

Figure 5. Effect of an Increase in the Decision Error

Notes: This figure illustrates the effect of the estimated error (τ) on the probability of choosing the lottery with lower expected utility. In the example, lottery R is the correct choice. The parameter values in the illustrated example are $\Delta E[u] = 0.11$, $\tau_{no} = 0.153$, and $\tau_{high} = 0.283$ ($0.153 + 0.130$). The estimated τs are taken from estimation results in Column (4) of Table 1. The low error corresponds to the control group, whereas the high error estimate is based on the results for the high pressure (100 *cents*) treatment group.

VI. Empirical Puzzles Related to the Investment of Time in Economic Decisions

In Section II, we mentioned two seemingly problematic findings in the literature. First, subjects spend more time on choices that do not matter very much, that is, e.g., when the expected utility difference between options is small. The second finding is that longer decision times are correlated with more errors. In this section, we show that estimated expected utility difference is negatively correlated with decision time. Then, we show that—despite the presence of a negative correlation—the causal effect of more time invested in the lottery decision on the quality of the decision is positive suggesting that time can be interpreted as a production factor in a *capital-labor production framework of decision quality* (Camerer and Hogarth 1999). As a final exercise, we estimate the treatment effect of an increase in opportunity costs within the DDM framework. The results suggest that the quantitative effects and the underlying mechanisms of higher opportunity costs are similar in the neuro-founded, and process-oriented DDM and the expected utility model. The exercise highlights that the as-if expected utility model does very well at representing the basic underlying choice mechanisms.

A. *Is Time Invested in Economic Decisions When the Outcome of Such Decisions Does not Matter?*

Based on the revealed preferences of the decision maker, the quality of a decision is measured by the number of inconsistent choices in risky decisions. Therefore, we use the estimated risk preferences to infer the expected utility of every option. Similar to Moffatt (2005), Dickhaut et al. (2013), and Krajbich, Oud, and Fehr (2014), we find a robust negative correlation between the time invested in the decision and the estimated expected utility difference (Figure 6).[23] We showed in Section III that this negative correlation is possible within our model.

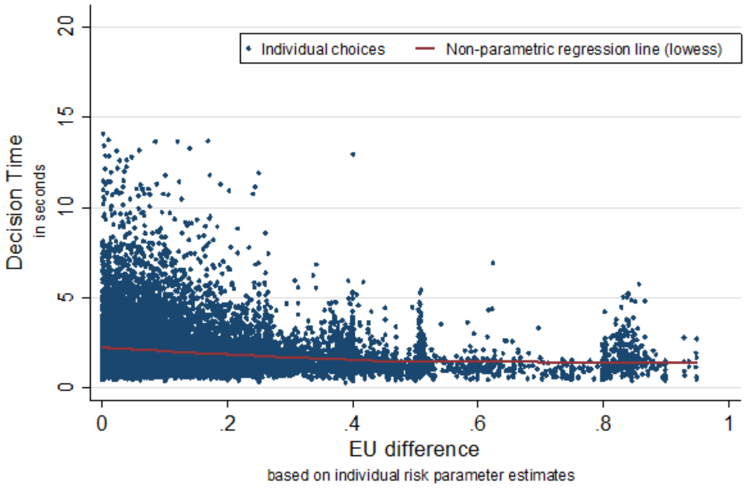

Figure 6. Estimated Expected Utility Difference and Decision Time

Notes: The scatter plot presents the decision times of 19980 individual lottery decisions made by from 111 subjects. A non-parametric regression line (lowess) is overlaid on top of the data.

B. *Is Time an Essential Resource in the Decision Production Function?*

To reproduce the negative correlation between decision time and quality, we estimate the coefficients of the following regression model:

(7) $$CorrectChoice \; = \beta_1 + \beta_2 \; DecisionTime + \boldsymbol{\beta}\mathbf{X} + \varepsilon,$$

where $\mathbf{X}$ denotes a vector of additional controls. Column (1) in Table 2 contains the estimate of β_2 based on the linear probability model. The coefficient is negative and highly significant suggesting that an additional second invested in the lottery decision reduces the probability of choosing the superior lottery by 1.4 percentage points. However, a causal interpretation is not possible as long as the difficulty of the decision is not controlled for, because decision difficulty is likely to be positively correlated with *DecisionTime* and negatively correlated with the probability of a *CorrectChoice*. Based on the standard omitted variable formulae, β_2 is downward biased. A straightforward approach to correct for the omitted variable bias is to control for the difficulty of the decision. In Column (3) of Table 2, we include the expected utility distance as a proxy variable for the difficulty.[24] The effect of the expected utility difference (normalized to be between 0 and 1) is positive and significant. The correlation between decision time and the correct choice probability is essentially zero after including the expected utility difference as a proxy for decision difficulty. The expected utility difference is, of course, not an ideal measure of difficulty: this proxy uses a specific functional form and the inherent subjective nature of

[23] A bivariate linear regression of decision time on $\Delta E[u]$ reveals a highly significant negative slope coefficient of -1.35 ($t = 8.19, p-value < 0.001, n = 19{,}906$). Standard errors were clustered at the subject level.

[24] The underlying risk preferences used to calculate the expected utility difference are based on individual estimations for each subject as presented in Figure 4. For a similar approach see Moffatt (2005).

the difficulty of a decision is not captured.[25] Therefore, it is perhaps unwise to claim that after controlling for the expected utility difference, β_2 can be interpreted as causal effect.

We circumvent these problems with our research design. Our randomized opportunity cost treatments provide us with the ideal instrument for the time invested in the decision. The increase in the opportunity costs across our treatment conditions has a negative effect on the decision time, but is—conditional on the decision time—completely unrelated to the lottery choice. We therefore use standard instrumental variable techniques to identify the causal effect of decision time on decision quality, as measured by the probability of choosing the superior lottery. The results are presented in Columns (4) to (6) of Table 2. The measured negative relation between opportunity costs and decision time in the first stage as the effect of the treatment dummies on decision time results in an F-statistic on the instruments of above 30.[26] Based on the IV estimates, the resulting causal effect of a time investment on decision quality is positive, statistically significant, and ranges from an improvement of 2.3 to 3.7 percentage points in the probability of a correct choice for an additional second invested in the lottery decision.

Table 2— Decision Quality and Time invested in the Decision

Dep. Variable:	Correct Lottery Choice (binary)					
	LPM (OLS)			2SLS		
	(1)	(2)	(3)	(4)	(5)	(6)
Decision Time	-0.014***	-0.012**	-0.001	0.023***	0.023***	0.037***
	(0.005)	(0.005)	(0.005)	(0.008)	(0.008)	(0.008)
EV difference (abs)		0.049***			0.051***	
		(0.003)			(0.003)	
EU difference (abs)			0.593***			0.646***
			(0.039)			(0.037)
Constant	0.773***	0.715***	0.657***	0.699***	0.644***	0.574***
	(0.013)	(0.013)	(0.013)	(0.019)	(0.020)	(0.020)
Instrument for Decision Time	–	–	–	Treatment Dummies		
First Stage F-Stat	–	–	–	30.71	30.71	31.37
Subjects	111	111	111	111	111	111
Observations	19460	19460	19460	19460	19460	19460

Notes: OLS estimates (Columns (1) – (3)) and IV 2SLS (Columns (4) – (6)) are reported. The dependent variable is a binary variable equal to 1 if the lottery with higher expected utility is chosen by the subject and 0 otherwise. The underlying risk preferences are based on individual estimates of the CRRA coefficient (presented in Figure 4). Heteroskedasticity-robust standard errors are reported in parentheses.
*** Significant at the 1% level.
** Significant at the 5% level.
* Significant at the 10% level.

C. *The Drift Diffusion Model*

The drift diffusion model is capable of incorporating both of the puzzles discussed in Section II. The DDM assumes that the decision maker observes two types of signals that indicate the value of the two available lotteries, and continuously updates the resulting relative decision value (RDV). This process continues until a choice specific threshold is reached. Figure 7 is a graphical representation of the DDM. The bold line shows how the RDV develops across time. The dashed line represents the drift rate (μ).

[25] See, for instance, Chabris et al. (2009) and Moffatt (2005) for alternative functional forms of the decision difficulty proxy variable. In general, the construction of any difficulty measure seems to include some arbitrary and non-testable modeling choices.
[26] The quantitative dimension of the first-stage results can be observed in Figure 3 and it is explained in Section V.A.

The horizontal long-dashed lines represent the threshold values (B) that trigger the choice of the respective lottery. *NDT* denotes the non-decision part of time, usually interpreted as the time needed to encode the information stimulus and to move to response execution (Ratcliff and McKoon 2008).[27]

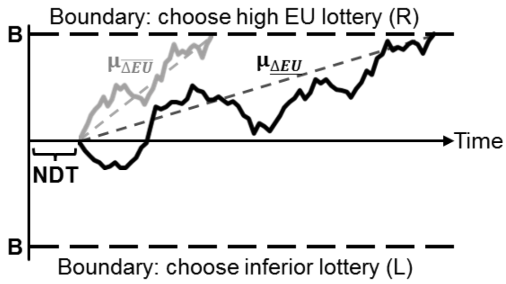

Figure 7. The Drift Diffusion Model

Notes: The example presented in the figure illustrates two evidence accumulation processes in which the decision maker decides in favor of the superior lottery R (upper boundary). The two processes differ w.r.t. the drift or on how quickly the evidence accumulation process drifts toward the correct lottery decision.

The evolution of the RDV is a Brownian motion with a constant drift rate (μ). The Brownian motion represents the stochastic part of the decision, whereas the drift rate toward the preferred option is governed by the decision maker's ability to discriminate between the lotteries and the quality of the signals (possibly related to lottery difficulty). If the thresholds are relatively small and/or the drift rate is low, the stochastic element of the process can dominate choice behavior and give rise to errors. In Figure 7, this would mean that the RDV path hits the lower boundary.

Following Krajbich, Oud, and Fehr (2014), the difficulty of a decision and therefore the drift rate is decreasing in the utility difference between the two available lotteries. The RDV evolves according to:

(8) $$RDV_t = RDV_{t-1} + v \times \Delta E[u] + \varepsilon.$$

The drift rate is determined by the product $v \times \Delta E[u]$. The stochastic element of the choice process is represented by $\varepsilon \sim N(0, \sigma^2)$.

Subsequently, we will show that the drift diffusion model essentially predicts a positive causal effect of decision time on decision quality, despite the fact that many studies using the DDM find a negative correlation. As described above, a more difficult decision results in a lower drift rate. In turn, lower drift rate leads to longer decision times, as well as more frequently erroneous decisions. In addition, closer boundaries are also affected by the *speed-accuracy trade-off* (Ratcliff and McKoon 2008).[28] Closer boundaries decrease the decision time and, consequently, the opportunity costs of the decision at the expense of more decision errors. Figure 8 illustrates the effect of closer boundaries. In the right panel (b), closer boundaries decrease the expected time and can lead to an unfavorable choice. However, it also becomes more likely that the stochastic component of the accumulation process will shift the RDV toward crossing the lower boundary and trigger an inferior lottery choice (Figure 8 (b)).

[27] In our experiment, the non-decision time (*NDT*) could be interpreted as the time subjects needed to use the computer mouse to indicate their lottery choice as well as the time needed to visually recognize the information provided on the computer screen.
[28] The *speed-accuracy trade-off* is the term used in the psychological literature to describe the trade-off between faster and more accurate decisions.

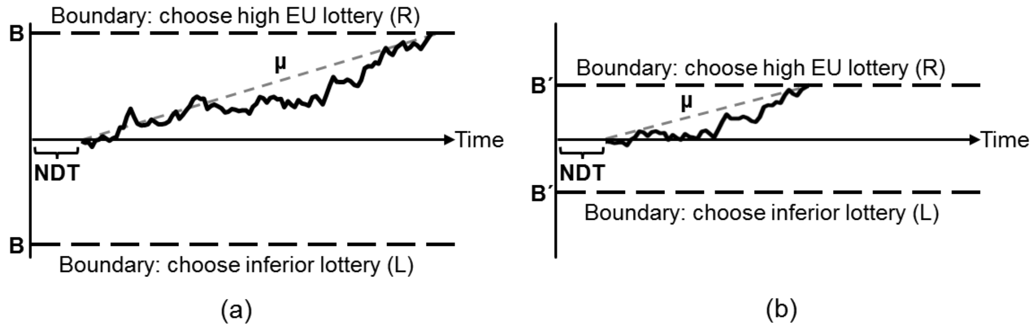

Figure 8. Effect of a Decrease in the Boundaries of the Drift Diffusion Model

Notes: Panels (a) and (b) illustrate the change in the trade-off between costs of the decision, measured by the time invested in the decision, and the quality of the decision, denoted as probability to choose the high EU lottery. Closer boundaries in panel (b) result in a shortening of the time until a decision is triggered, but increase the likelihood of arriving at the lower boundary and choosing the inferior lottery. In line with the comparative static results of the expected utility model, the change of the boundaries in the DDM can be interpreted as a result of an agent's optimal solution of the trade-off between the opportunity costs of time and the quality of the decision.

Empirical models that lack exogenous variation in the opportunity costs of time may identify a negative correlation between decision time and quality because of variation in difficulty across decisions. These models are therefore unable to establish causality. In the DDM, the omitted variable bias arises if (i) the boundaries are not allowed to be chosen endogenously or (ii) if exogenous variation in the decision time that is independent of the difficulty of the decision problem is not modeled. To estimate the causal effect of time with the DDM, we first estimate the DDM parameters at the treatment level, using the *fast-DM* software (Voss and Voss 2007; Voss, Voss, and Lerche 2015). Table 3 reports the results.

Table 3—Estimates of the Drift Diffusion Model

	Decision Criteria: Expected Utility			
	no cost	10 cent	30 cent	100 cent
Decision Boundaries (B)	2.73	1.70	1.60	1.34
p-value (H_0: no cost = treatment)	–	[0.000]	[0.000]	[0.000]
Drift Rate (μ)	0.35	0.42	0.48	0.40
p-value (H_0: no cost = treatment)	–	[0.058]	[0.011]	[0.227]
Non-Decisional Time (*NDT*)	1.25	1.07	1.09	0.87
p-value (H_0: no cost = treatment)	–	[0.044]	[0.056]	[0.000]

Notes: Parameter estimates of the drift diffusion model based on the estimation results in Model 5 of Table 1 (N=112). P-values based on pairwise t-test on the difference between subjects in the control group (no cost) and subjects in the corresponding treatment are reported in brackets. We set $\sigma = 1$ in the stochastic component of the DDM ($\varepsilon \sim N(0, \sigma^2)$) to identify the parameters of the DDM (see e.g. Ratcliff, (1978), Krajbich, Oud, and Fehr,(2014)). Since the position of the two lotteries was randomized and both lotteries were presented simultaneously, we fix the starting point of the RDV at the middle between the two lotteries (no initial bias toward a specific lottery). In addition to the fitted parameters B, μ, and *NDT*, we also estimate the parameters related to the variability of the drift rate μ and the starting point of the RDV (results available on request). Rather similar results are obtained when using risk preferences from individual estimations (see Appendix H, Table 12).

In line with the economic intuition derived from the expected utility model, we find a statistically significant decline in the boundaries as the opportunity costs of time increase. We also find some (mixed) evidence for an increase in the drift rate. A higher drift could indicate that subjects put more effort into the task by increasing their signal-to-noise ratio, which leads to a higher quality, whereas lower boundaries increase the likelihood of choosing the inferior lottery. To quantify the overall effect on decision quality of an opportunity cost induced change in decision time, we estimate the partial effect of a change in the drift rate, the boundaries, and both simultaneously on decision quality, while keeping all other parameters of the DDM constant at their sample means.

Table 4—Predictions of the Drift Diffusion Model

	Pred. Prob. of Correct Choice ($\hat{\pi}$)				Pred. Decision Time ($\widehat{t_d}$)			
	no cost	10 cent	30 cent	100 cent	no cost	10 cent	30 cent	100 cent
Prediction of the DDM due to change in								
Boundaries (ΔB)	75.1%	66.6%	65.5%	63.2%	2.73	1.76	1.68	1.50
Drift ($\Delta\mu$)	65.3%	68.2%	70.4%	67.3%	1.88	1.87	1.86	1.87
Both (ΔB & $\Delta\mu$)	71.8%	66.9%	68.0%	62.7%	2.78	1.76	1.67	1.50

Notes: Predictions of the DDM for the probability of a correct choice ($\hat{\pi}$) and the decision time ($\widehat{t_d}$) are presented. The predictions are based on 500,001 simulations with all remaining parameters set at their sample mean values. The correct choice is determined from the utility difference based on the estimation results in Model 5 in Table 1. Rather similar results are obtained when using risk preferences from individual estimations (see Appendix H, Table 13).

The simulation results (Table 4) based on the DDM suggest that a change in boundaries predicts a decline of the correct choice probability from 75.1 % in the *no cost* control group to 63.2 % in the *100 cents* treatment. This effect is partially offset by the simultaneous change in the drift rate. Overall, based on the simulations of the DDM, an increase in opportunity costs from zero to 100 cents per second decreases the time invested in the lottery decision from 2.78 to 1.5 seconds, which causes a decline in the probability of correct choice by more than 9 percentage points. Just like the empirical and theoretical prediction of expected utility theory, DDM points toward a positive causal effect of time investment on the quality of the decision.

In the final analysis, the expected utility model performs just as well as the neuro-founded and decision process oriented DDM. The results from the DDM add additional explanatory power to our argument that important mechanisms related to the trade-off between the opportunity costs of time and the quality of decisions can be explained by a rational utility model as simple as the one we suggest in this study. More specifically, we found that higher opportunity costs induce lower boundaries. Lower boundaries lead to quicker and more erroneous decisions and therefore support our model.

VII. Further Research and Limitations of the Study

We successfully test several comparative static properties of the economic model introduced in Section III and demonstrate that decision errors cannot be simply interpreted as irrational behavior. However, our theoretical framework does not provide an exact point estimate of the optimal allocation of time. This would require further structural assumptions on the decision-making process captured by π in our model. The specific functional form of π determines the rate of improvement in the lottery decision and is therefore instrumental in determining the exact optimal time to invest in the lottery choice.

There are several versions of the drift diffusion model that employ dual stages or dual processes (Hübner et al., 2010; Alos-Ferrer, 2016; Caplin and Martin, 2016). These models offer the possibility of either (1) two stages in which the second applies only when the first stage does not hit a boundary or (2) that the decision maker chooses between whether to make a considered, but effort-costly, choice or a very fast and non-considered decision. In such models, it could be the case that π is dependent on which system is used, and whether there are conflicts between the predictions stemming from the two systems (see also (Achtziger and Alós-Ferrer 2013).

Another open question concerns the influence of the decision maker's *prior beliefs* on the range of outcomes. We present an extension of our model in Appendix I to capture the effect of such prior beliefs. In our model, the entire uncertainty related to the lottery decision is captured in the probability π, whereas the utility difference $\Delta E[u]$, which can be interpreted as a measure of the stake of the lottery decision, is predetermined and known to the decision maker. We relax this assumption in Appendix I and assume that $\Delta E[u]$ is not deterministic but an a priori unknown random variable, whose properties can be learned by interpreting signals at a very early stage of the decision-making process. As we demonstrated in Section III.A, even without an early stage, our basic model is able to produce predictions similar to those of the process-oriented DDM.[29]

A straightforward implication of such an initial learning stage is that the DM will invest more resources in the decision-making process if the early gathered information changes his or her beliefs about what is at stake in the decision. Indeed, we find that higher payoffs, lead to fewer decision errors.[30] The extension of the model provides additional insights into the decision-making process at the cost of increased model complexity and reduced ability to easily apply the model in other areas of economics in which the process of decision-making is of minor interest. We believe that our basic model can describe the most important economic mechanisms of decision-making.

A. *Further Results and Alternative Specifications*

In Appendix F, we discuss the influence of different measures of cognitive ability and education on erroneous choice. The economic model of rationality described in Section III explicitly allows for a correlation between individual characteristics γ and decision quality, defined as the probability π to choose the superior lottery, where π is (negatively) related to the Fechner error τ in the econometric specification of decision errors. We find some evidence for a positive relation between measures of cognitive skills and decision quality. Contrary to Dohmen et al. (2010), but in line with Sutter et al. (2013) and Andersson et al. (2016), we find no evidence for a link between cognitive abilities and risk preferences.

In Appendix D, we check the robustness of our structural estimation and compare the risk preferences obtained from our structural estimations to the estimates based on the Holt-Laury task (Holt and Laury 2002). The estimates from the Holt-Laury tasks are correlated with the structural estimates when the decision error is included. The Holt-Laury estimates might also serve as a control for individual heterogeneity in risk preferences within and across treatments.

[29] Psychological models of decision making such as the drift diffusion model (see, e.g., Ratcliff and McKoon (2008) incorporate an initial stage of the decision making process by estimating a non-decision time in which the DM scans the available information before embarking on the decision process.
[30] Results are provided in Table 14 in Appendix I.

The model described in Section III assumes additive separable utility with respect to utility derived from the lottery decision and the alternative opportunity. The rationale of additive utility comes from the potential underlying trade-off between investing resources in a decision and deriving utility from spending these resources on other utility-generating activities.[31] Our estimates, however, are robust against relaxing these assumptions. In Table 8 in Appendix E, we provide evidence that the error patterns and the stability of the risk preferences described in our main results remain unchanged if we assume that the DM integrates the entire payoff from both the time account and the lottery choice into the lottery decision. The results also remain unchanged if we assume different initial endowments, suggesting that our results are not sensitive to different assumptions about narrow bracketing or mental accounting.

Appendix K provides results of our estimates for subsamples of our lottery menu. The results are quantitatively similar in each subsample, suggesting that potential learning effects do not interact with our main results. In Appendix J, we fix different values of ρ across subjects in order to investigate whether the pattern of the decision errors continues to prevail. Again, we find the same pattern: errors are lowest in the *no cost* treatment. We obtain similar results when we relax the assumption of constant relative risk aversion and use the more flexible expo-power utility function first proposed by Saha (1993). The corresponding results are presented in Appendix G.

VIII. Conclusion

We introduce a simple model in which a rational decision maker trades off the quality and the opportunity costs of a decision in a rational manner.

In contrast to related models (Chabris et al. 2009; Dickhaut et al. 2013), our model is parsimonious and simple enough to be integrated in applied economic work. It is in line with basic economic reasoning that investing more resources in the *production of sound economic decisions* improves decision quality. The model provides a number of testable predictions.

To test the prediction that decision errors can be rationalized by high opportunity costs, we test the main implications of our model using a structural econometric approach. We find that decision errors vary positively with the opportunity costs of decision-making. This finding is in line with the prediction that decision errors are more likely when higher opportunity costs induce less time investment in decision quality. Despite a negative correlation between decision time and quality, we find a strong positive causal impact of an increase in time invested in the lottery decision on the quality of the decision, which supports the applicability of our economic model. We find no evidence that risk preferences vary with decision time. This allows a normative interpretation of the model based on the stable preference assumption (Stigler and Becker 1977).

The notion of irrational behavior has often led to paternalistic policies or, more recently, nudges in an attempt to improve individual decisions. This has been criticized as they assume that some authority

[31] One could, for instance, think of a situation in which a decision maker has to decide between alternative insurance contracts and the extra time spent time in studying and understanding the consequences of each insurance contract has to be traded-off against spending this time on leisure or work.

knows what is best for the individual. Our approach suggests that despite the presence of decision errors, agents are indeed able to behave rationally and that public policy-makers, even without full information about preferences, can engage in a great many freedom-preserving measures that have the potential to improve decision quality, that is, by reducing decision complexity and information costs, or increasing the decision-making ability of agents.

In the final analysis, our results suggest that many so-called behavioral anomalies manifested as errors in complex decisions are simply the consequence of a rational trade-off between high opportunity costs of time and less than optimal levels of and individual decision-making skills. Decision errors, in this view, are a result of utility maximization under given time constraints.

IX. Appendix

A. *Further Descriptive Statistics*

Table 5—Descriptive Statistics

Treatment:	100 cent				30 cent				10 cent				control			
	N	mean	SD	median	N	mean	SD	median	N	mean	SD	median	N	mean	SD	median
BNT (corr. A.)	28	1.54	1.37	1	28	1.61	1.1	1.5	28	1.39	1.03	1	28	1.32	1.09	1
Time for H-L	28	68.4	29	63.6	28	69.4	39.7	56	28	72.2	43.4	63.3	28	75	33.1	68.4
Raven (corr. A)	28	8.71	2.37	9	28	8.96	2.06	9.5	28	8.82	2.09	9.5	28	8.29	2.32	8.5
Stress	28	3	1.12	3	28	3.04	1.29	3	28	2.93	1.18	2.5	28	3.07	1.05	3
Partic. CogLab	28	0.32	0.48	0	28	0.04	0.19	0	28	0.14	0.36	0	28	0.07	0.26	0
Male	28	0.5	—	—	28	0.39	—	—	28	0.54	—	—	28	0.39	—	—
Age	28	21.5	2.44	21	28	21.1	2.01	21	28	21.1	2.25	21	28	21.7	2.09	21
German	28	0.93	—	—	28	0.89	—	—	28	0.96	—	—	28	0.93	—	—
Working	28	0.07	0.26	0	28	0.25	0.44	0	28	0.07	0.26	0	28	0.32	0.48	0
Monthly Inc.	28	343	160	300	28	306	188	270	28	304	124	300	27	379	184	350
A-level grade	28	2.05	0.6	2.1	28	2.02	0.61	2	28	2.14	0.54	2	28	2.09	0.52	2
German grade	28	1.92	0.77	2	28	1.81	0.71	2	28	2.43	0.91	2	28	2.01	0.72	2
Math grade	28	2.39	1.2	2	28	2.04	0.94	2	28	2.19	0.91	2	28	2.42	0.95	2.5
Know exp. val	28	3.93	2.14	3	28	4.39	1.87	4	28	3.96	2.08	4	28	4	2.21	5
Politics	28	2.04	0.96	2	28	2.25	0.84	2	28	1.96	0.84	2	28	2.04	0.74	2
Right/left wing	28	3.32	0.77	3	28	3.25	1.24	3	28	3.57	1.23	4	28	3.5	0.96	3
Rely on answ.	28	1.46	0.74	1	28	1.39	0.57	1	28	1.32	0.61	1	28	1.21	0.5	1
Experim. time	28	2213	298	2279	28	2201	240	2212	28	2034	270	2012	28	1906	227	1923
Viol. 1st o. StD	28	0.11	—	—	28	0.36	—	—	28	0.11	—	—	28	0.36	—	—

B. *Estimation Strategy for Structural Estimates*

We estimate the Arrow-Pratt measure of constant relative risk aversion (ρ) assuming the utility function,

$$u(x) = \frac{x^{1-\rho}}{1-\rho}, \tag{9}$$

where x presents the state-dependent lottery payoff. The individual chooses the lottery with the higher expected utility. The utility difference between the right (R) and the left (L) lottery is given by,

$$\Delta E[u] = E[u(R)] - E[u(L)]. \tag{10}$$

The econometric specification assumes a cumulative distribution function of the normal distribution $\Phi(\Delta E[u])$ connecting $\Delta E[u]$ to the actual lottery choice.

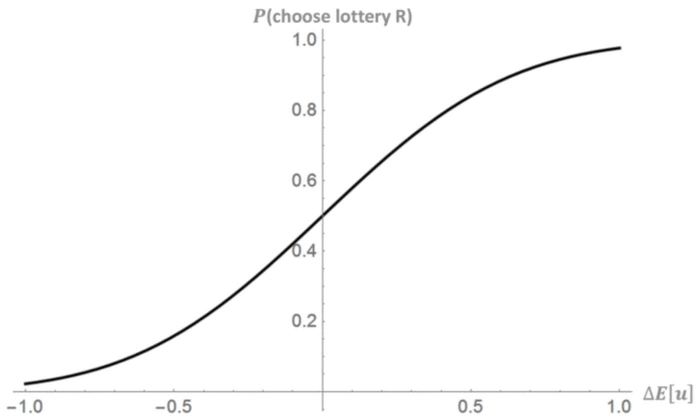

Figure 9. Cumulative Distribution Function of the Normal Distribution

Notes: The cumulative distribution function of the normal distribution $\Phi(\Delta E[u])$ is used to map the probability of choosing the right lottery to the difference in the expected utilities of two available lotteries $(E[u(R)] - E[u(L)])$.

To account for treatment-dependent decision errors, we use the Fechner error specification

$$(11) \qquad \Delta E[u] + \tau \cdot \varepsilon,\ with\ \varepsilon \sim N(0,1).$$

τ denotes the structural error parameter and $N(0,1)$ the standard normal CDF. We estimate ρ and τ with the following structural equation

$$(12) \qquad Choice^* = \underbrace{\left(p_{R,1} \cdot \frac{x_{R,1}^{1-\rho}}{1-\rho} + p_{R,2} \cdot \frac{x_{R,2}^{1-\rho}}{1-\rho}\right) - \left(p_{L,1} \cdot \frac{x_{L,1}^{1-\rho}}{1-\rho} + p_{L,2} \cdot \frac{x_{L,2}^{1-\rho}}{1-\rho}\right)}_{EU(R)-EU(L)} + \tau \cdot \varepsilon + \epsilon,$$

$$with\ Choice = \begin{cases} 1\ (R),\ if\ Choice^* \geq 0, \\ 0\ (L)\ \ otherwise. \end{cases}$$

Furthermore the difference in expected utility $(EU(R) - EU(L))$ is standardized, based onWilcox (2011), to be bounded within the interval $[-1,1]$, through dividing by the maximum expected utility difference (w) that can be generated by the states of two available lotteries. The error term is denoted by ϵ.

We allow ρ and τ to depend on the treatment condition represented here by the change in the opportunity costs α and a vector of other variables $\boldsymbol{z}$, which might absorb socio-economic characteristics and variables related to properties such as the difficulty of the lottery decision.

$$(13) \quad Choice^* = \left(p_{R,1} \cdot \frac{x_{R,1}^{1-\rho(\alpha,\boldsymbol{z})}}{1-\rho(\alpha,\boldsymbol{z})} + p_{R,2} \cdot \frac{x_{R,2}^{1-\rho(\alpha,\boldsymbol{z})}}{1-\rho(\alpha,\boldsymbol{z})}\right) - \left(p_{L,1} \cdot \frac{x_{L,1}^{1-\rho(\alpha,\boldsymbol{z})}}{1-\rho(\alpha,\boldsymbol{z})} + p_{L,2} \cdot \frac{x_{L,2}^{1-\rho(\alpha,\boldsymbol{z})}}{1-\rho(\alpha,\boldsymbol{z})}\right) + \tau(\alpha,\ \boldsymbol{z}) \cdot \varepsilon + \epsilon$$

Estimates for $\rho(\alpha,\ \boldsymbol{z})$ and $\tau(\alpha,\ \boldsymbol{z})$ in Equation (13) are obtained by using maximum-likelihood estimation. Let $\Delta_W E[u] = \Delta E[u]/w$ designate the standardized utility difference (Wilcox 2011) and $P(R)$ the probability of choosing the right lottery. We can derive the log-likelihood function as follows,

$$(14) \qquad P(R) = P(\Delta_W E[u] + \tau \cdot \varepsilon > 0)$$

$$= P\left(\varepsilon > -\frac{\Delta_W E[u]}{\tau}\right)$$

Since we assume $\varepsilon \sim N(0,1)$, we estimate $P(R)$ with

$$P(R) = 1 - \Phi\left[-\frac{\Delta_W E[u]}{\tau}\right]$$
$$= \Phi\left[\frac{\Delta_W E[u]}{\tau}\right]$$

where $\Phi[\cdot]$ denotes the CDF of the standard normal distribution. The log-likelihood is therefore given by

(15) $\ln L(\rho, \tau; choice, \alpha, \boldsymbol{z}) = \sum_{i=1}^{n}\left(Choice \cdot \ln\left(\Phi\left[\frac{\Delta_W E[u]}{\tau}\right]\right) + (1 - Choice) \cdot \ln\left(1 - \Phi\left[\frac{\Delta_W E[u]}{\tau}\right]\right)\right).$

Generating a variable yy_i with $yy_i = 1$ if the right lottery is chosen and $yy_i = -1$ if the left lottery is chosen, we can rewrite (15) in more compact form. Using the detailed formulation of (13) gives

(16) $\ln L(\rho, \tau; Choice, \alpha, \boldsymbol{z}) = \sum_{i=1}^{n} \ln\left(\Phi\left[yy_i \frac{\left(p_{R,1} \cdot \frac{x_{R,1}^{1-\rho(\alpha,z)}}{1-\rho(\alpha,z)} + p_{R,2} \cdot \frac{x_{R,2}^{1-\rho(\alpha,z)}}{1-\rho(\alpha,z)}\right) - \left(p_{L,1} \cdot \frac{x_{L,1}^{1-\rho(\alpha,z)}}{1-\rho(\alpha,z)} + p_{L,2} \cdot \frac{x_{L,2}^{1-\rho(\alpha,z)}}{1-\rho(\alpha,z)}\right)}{w \cdot \tau(\alpha, \boldsymbol{z})}\right]\right),$

from which we estimate our structural risk preference (ρ) and decision error (τ) parameters, which depend on the lottery choice, opportunity costs (α), and a vector of socio-economic characteristics ($\boldsymbol{z}$).[32]

C. *Non-parametric Tests for Treatment Differences Based on Individual Structural Estimates*

In this section, we detail the statistical procedure used to examine the effect of higher time costs on the quality of the decision and the revealed risk preferences. All estimates are based on estimates conducted for each subject separately. Our sample size for the following tests is therefore equal to the number of subjects across all treatments ($N = 111$).[33]

In contrast to Figure 4, Figure 10 plots the structural risk and error estimates for all subjects. The left panel plots the distribution of the estimated CRRA coefficient ρ for all individuals across the treatment condition. The right panel plots the estimates of the Fechner error estimate. Instead of somewhat arbitrary dropping the extreme observations visible in the left figure for risk preferences and in the right figure for decision errors, we account for these observations by using, in addition to a t-test on the difference in the means of ρ and τ across treatments, a Mann-Whitney U rank sum test that treats the individual ρ and τ estimates as ordinal data, thus effectively controlling for the influence of extremely large observations.[34]

[32] Equation (16) also presents the functional form of the likelihood function used in the STATA program.
[33] For one subject from the 100cent treatment the maximum likelihood estimator did not converge. In 92% of the decisions, this subject chose the lottery with the highest payoff possible, thus manifesting in extremely risk-seeking behavior. The resulting CRRA coefficient of risk aversion is $\rho < -150$, and cannot be exactly determined. The Fechner error estimate is relatively low around $\tau \approx 0.2$, because errors are unlikely if an individual follows a simple strategy that mimics extremely risk-seeking behavior. The joint estimates presented in table 1 do not change substantially when we omit this subject's lottery decisions (the risk aversion difference across the control group and 100 cent treatment becomes slightly smaller, error estimates are not altered, no change in statistical significance).
[34] Using expected utility, we implicitly assume cardinal measurement of utility. The t-test on the difference in means requires ρ and τ to be measured on the interval scale. In contrast, the ordinality assumption required by the Mann-Whitney U test does not require a higher measurement scale than usually assumed in the expected utility framework.

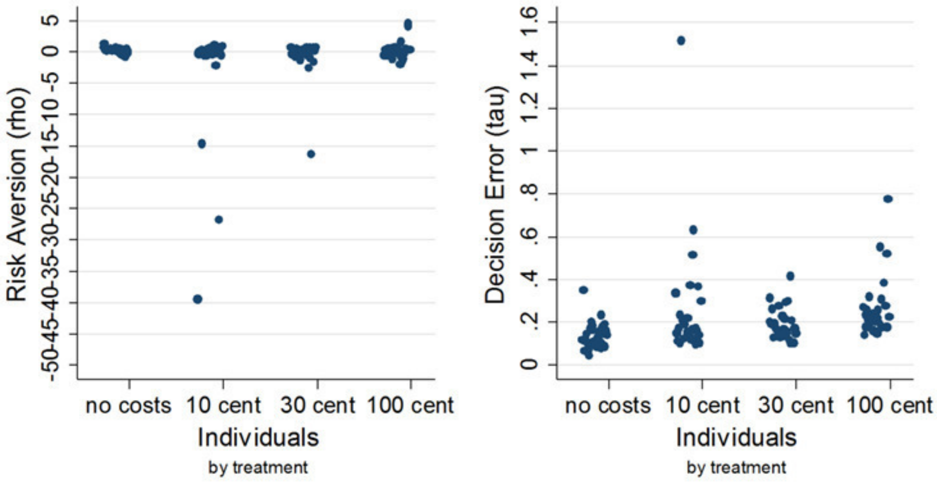

Figure 10. Individual Estimates (Full Estimation Sample)

Note: N=111.

In Table 6, we provide the results of a t-test as well as the Mann-Whitney U test comparing the treatment conditions. A t-test on the difference in risk preferences reveals no convincing statistical evidence for a change in risk preferences across treatments. As shown in the left panel of Figure 10, the large difference in ρ between the *10cent* and the *no costs* treatment is driven by three implausibly small ρ estimates in the *10cent* treatment. The corresponding Mann-Whitney U test provides a p-value of 0.140 on the null hypothesis of equality in ρ. Based on the Mann-Whitney U test, the probability $P(\rho_T < \rho_C)$ that a subject from the *10cent* condition is more risk seeking (lower ρ) is 61 percent[35] where the 95 percent confidence interval (0.45, 0.77) contains the random ordering probability of 50 percent.

Both the parametric and non-parametric test results support the findings from Table 1 that higher opportunity costs decrease decision quality. The number of decisions deviating from expected utility τ is significantly higher in all treatments. Interpreting the result of the Mann-Whitney U test on the difference across the *100cent* treatment, we find that the probability of a subject having a worse decision quality (larger τ) than a subject in the *no costs* treatment is 90 percent (with a 95 percent confidence interval of (0.81, 0.98)).

[35] In Table 6, we report $P(\rho_T > \rho_C)$, hence the probability $P(\rho_T < \rho_C)$ is equal to $1 - P(\rho_T > \rho_C)$.

Table 6—Non-parametric Tests for Treatment Differences (Individual Estimates)

	t-Test		M-W U Test			t-Test		M-W U Test	
Risk Preference	$\Delta\rho$	p-value	$P(\rho_T>\rho_C)$	p-value	*Decision Error*	$\Delta\tau$	p-value	$P(\rho_T>\rho_C)$	p-value
100cent - no	0.08	0.760	0.50	0.973	100cent - no	0.13	0.000	0.90	0.000
30cent - no costs	-0.86	0.160	0.42	0.334	30cent - no costs	0.05	0.005	0.73	0.003
10cent - no costs	-3.06	0.084	0.39	0.140	10cent - no costs	0.12	0.024	0.73	0.003

Notes: N=111. p-values based on a robust t-test and a Mann-Whitney U test are reported. $\Delta\rho$ denotes mean difference across the CRRA coefficient estimates across treatments, whereas $\Delta\tau$ denotes the corresponding difference for the Fechner error. $P(\rho_T>\rho_C)$ is the likelihood that a subject of the corresponding treatment group (100 cent, 30cent, or 10 cent) has a higher ρ (τ) than a subject from the control group (no costs) (for interpretation of the test statistic, see Conroy 2012).

D. *Including Holt-Laury Risk Measure*

As presented in Figure 2, the Holt-Laury procedure[36] was conducted before subjects engaged in making the 180 lottery choices. The task was identical for all treatments and subjects faced no time pressure when making their decisions.

We find no significant relation between the Holt-Laury risk measure and the structural risk measure without the Fechner error in estimates (1) and (2) in Table 7. In Models (3) - (5), including the decision errors, we find a significant correlation slightly above 0.3 between the Holt-Laury and structural risk preference estimates. A correlation of below 1 is reasonable because the Holt-Laury CRRA measure is effectively bounded within the range of $(-0.95, 1.37)$,[37] whereas the structural CRRA measure is not. Furthermore, Andersson et al. (2016) show that in Holt-Laury tasks, decision errors bias the elicited CRRA risk preferences toward risk neutrality, which also explains the relatively low correlation.[38]

[36] A screenshot of the Holt-Laury task is provided in the online appendix.
[37] Based on the set of the 10 lotteries used in the Holt-Laury task, a subject always choosing option B (option A) has a CRRA coefficient of < -0.95 ($\rho > 1.37$).
[38] A correlation of the Holt-Laury risk measure with decision errors is a strong argument for not including this measure in the main specification of the structural estimations since introducing a decision error proxy into our structure risk preference estimation, while jointly estimating the structural decision error, creates the strong impression of a misspecified model.

Table 7—Structural Estimates – Including Holt-Laury Measure

	Only Risk Measurement		Risk & Error Measurement					
	(1)	(2)	(3)		(4)		(5)	
Parameter:	ρ	ρ	ρ	τ	ρ	τ	ρ	τ
Treatments								
100cent Treatment	-0.314	-0.420	-0.070	0.130***	-0.102	0.112***	-0.120	0.118***
	(1.864)	(0.682)	(0.128)	(0.030)	(0.132)	(0.030)	(0.139)	(0.032)
30cent Treatment	-0.140	-0.222	-0.079	0.037*	-0.081	0.028	-0.080	0.027
	(4.659)	(2.682)	(0.117)	(0.020)	(0.109)	(0.018)	(0.101)	(0.020)
10cent Treatment	-0.332	-0.491	-0.133	0.069**	-0.153	0.036	-0.151	0.039
	(3.556)	(2.282)	(0.109)	(0.030)	(0.104)	(0.026)	(0.096)	(0.028)
Holt/Laury ρ	0.994	1.345	0.326***		0.343***		0.322***	
	(0.741)	(0.971)	(0.112)		(0.111)		(0.120)	
Male		-0.718			-0.192**	-0.073***	-0.177**	-0.070***
		(1.091)			(0.085)	(0.022)	(0.082)	(0.023)
BNT Correct		-0.121					-0.034	-0.007
		(0.204)					(0.034)	(0.007)
Age (18)		0.007					0.019	-0.004
		(0.074)					(0.014)	(0.004)
Constant	-0.404	-0.073	0.010	0.160***	0.113	0.209***	0.105	0.228***
	(0.477)	(0.493)	(0.078)	(0.014)	(0.087)	(0.024)	(0.101)	(0.030)
p-value for joint significance in:								
Treatments	0.998	0.416	0.636	0.000	0.487	0.003	0.430	0.004
Log-Likelihood	-12988	-12936	-11806		-11706		-11672	
Subjects	112	112	112		112		112	
Observations	20160	20160	20160		20160		20160	

Notes: The dependent variables are the Arrow-Pratt measure of relative risk aversion (ρ) assuming CRRA utility and the Fechner error (τ). Results in Columns (1) and (2) correspond to estimations without any treatment dependent error specification. Results in Columns (3) - (5) correspond to joint estimates of ρ and τ. Block bootstrapped standard errors clustered at the individual level and based on 1,000 replications are reported in parentheses.
*** Significant at the 1% level.
** Significant at the 5% level.
* Significant at the 10% level.

Note that the structure of the sequence of lottery choices in the Holt-Laury task makes observing deviation from expected utility quite unlikely,[39] since subjects would have to switch more than once between the columns. However, 13 out of 112 subjects did just this in the experiment. The Holt-Laury measure used in Table 7, is based on the number of safe choices made by each subject and ignores choice inconsistencies.

Unlike the lotteries used in the Holt-Laury task, the 180 lotteries used in the main part of the study (see Appendix L for the lottery set) were constructed to cover a broad range of outcomes and probabilities. The order in which they were presented and their position on the computer screen (left or right) was randomized to avoid framing effects related to the order of the choices, which have been found in Holt-Laury tasks (Lévy-Garboua et al. 2011).

[39] As a result, the Holt-Laury task is not well suited to systematically investigating the quality of risky decisions. Furthermore, decision errors might be undetected if the individual mistakenly switches early toward the risk choice and then stays with the risky choice until the end of the table so as to behave consistently. For a review of the critique on the use of the Holt-Laury task for risk preference elicitation see Friedman et al. (2014). Harrison and Rutström (2008) provide an extensive comparison of risk elicitation procedures and a description of related econometric estimation techniques.

E. *Assumptions About Mental Accounting and Reference Points (Wealth, Income)*

Throughout the paper, a von Neumann-Morgenstein (vNM) utility function is assumed. In the main specification, we rely on the CRRA utility $(x) = \frac{x^{1-\rho}}{1-\rho}$. We do not explicitly define the utility about final wealth, but instead calculate the utility over the lottery payoff. We add one cent to the lottery payoff to circumvent computational problems that could arise in calculating the utility over a zero payoff.[40] The Rabin Paradox (Rabin 2000) arises if one defines utility over final wealth levels and risk-averse behavior is observed in low-stake lottery decisions. As noted in Rubinstein (2006), the vNM axioms do not require expected utility to be defined over final wealth levels. Cox and Sadiraj (2006) and Palacios-Huerta and Serrano (2006) show that rejecting small gambles —as we find in our experimental data —is consistent with expected utility theory if one defines utility over income (changes in wealth) rather than wealth levels.

As the estimates in Table 8 suggest, the treatment effect of higher opportunity costs on decision quality as well as the stability of risk preferences hold for different assumptions about the argument of the utility function. In Model (1) we replicate our main specification from Table 1. We find mild risk aversion in all treatments. Incorporating €3, which is a typical show-up fee in lab experiments, in addition to the lottery payoff gives similar results. In line with the theoretical predictions, the estimated degree of risk aversion increases if we assume higher initial wealth values to be integrated into the lottery decision. As we assume the integration of the subject's monthly income[41] (Model (4)), we obtain implausibly high CRRA coefficients, suggesting that assuming utility over *changes* in wealth (payoffs from the lotteries) is an appropriate assumption in our experimental setting. In general, our results are robust to different assumptions about money in addition to the lottery payoff integrated into the utility function. Even if we assume an instantaneous integration of the money earned from the alternative use of time (Model (5) in Table 8) our results remain qualitatively unchanged.

[40] Wakker (2008) provides a discussion on the behavior of power utility function when the argument is zero.

[41] Monthly income is defined as income net of fixed costs for rent and health insurance. The average monthly income is slightly above €300.

Table 8—Results for Different Wealth Assumptions

	Risk & Error Measurement									
	(1)		(2)		(3)		(4)		(5)	
Endowment Assumption.:	0.01 €		3 €		100 €		Monthly Income		Time Money	
Parameter:	ρ	τ	ρ	τ	ρ	τ	ρ	τ	ρ	τ
Treatments										
100cent Treatment	-0.074	0.130***	-0.144	0.128***	-0.864	0.124***	8.818	0.116***	0.047	0.130***
	(0.144)	(0.025)	(0.309)	(0.027)	(3.303)	(0.029)	(9.332)	(0.030)	(0.213)	(0.028)
30cent Treatment	-0.154	0.065***	-0.374	0.063***	-4.049	0.058***	-0.419	0.046**	-0.087	0.064***
	(0.126)	(0.018)	(0.279)	(0.019)	(2.958)	(0.022)	(6.176)	(0.023)	(0.226)	(0.019)
10cent Treatment	-0.185	0.090***	-0.391	0.086***	-3.625	0.080**	0.502	0.067**	-0.103	0.087***
	(0.113)	(0.033)	(0.264)	(0.033)	(2.937)	(0.033)	(6.359)	(0.034)	(0.229)	(0.033)
Constant	0.193***	0.153***	0.479***	0.154***	5.031***	0.161***	5.506	0.170***	0.187***	0.154***
	(0.053)	(0.013)	(0.116)	(0.013)	(1.413)	(0.015)	(4.112)	(0.017)	(0.052)	(0.013)
p-value for joint significance in:										
Treatments	0.315	0.000	0.350	0.000	0.433	0.000	0.804	0.001	0.942	0.000
Log-Likelihood	-11931		-11904		-11923		-11829		-11928	
Subjects	112		112		112		111		112	
Observations	20160		20160		20160		19980		20160	

Notes: The dependent variables are the Arrow-Pratt measure of relative risk aversion (ρ) assuming CRRA utility and the Fechner error (τ). Results in Columns (1) – (5) correspond to joint estimates of ρ and τ. Block bootstrapped standard errors clustered at the individual level and based on 1,000 replications are reported in parentheses.
*** Significant at the 1% level.
** Significant at the 5% level.
* Significant at the 10% level.

F. *Cognitive Skills and Decision Errors*

To investigate the predictive power of cognitive skills on decision errors defined as τ in Equation (6), we allow several measures related to cognitive ability to be linearly correlated with decision errors. In Column (5) in our main specification (Table 1), we report a negative correlation between the Berlin Numeracy Test score and decision errors. Table 9 provides further results. In addition to the Berlin Numeracy Test, we conducted a Raven Test, designed to measure fluid intelligence, after the experiment. A higher measure of fluid intelligence is correlated with fewer decision errors. We find no evidence for correlation of self-reported stress and math grades with decision errors. Subjects who reported being knowledgeable about the concept of expected value were significantly less likely to make decision errors. Finally, we conduct a plausibility check and create a dummy indicating whether a subject was able to *not* violate first order stochastic dominance. As expected, subjects with the ability to detect the dominant lottery are also less likely to make errors in the entire lottery sample.

Table 9—Structural Estimates – Potential Decision Error Correlates

	(1)		(2)		(3)		(4)		(5)	
Parameter:	ρ	τ	ρ	τ	ρ	τ	ρ	τ	ρ	τ
Treatments										
100cent Treatment	-0.070	0.125***	-0.075	0.129***	-0.075	0.132***	-0.083	0.131***	-0.082	0.089***
	(0.136)	(0.024)	(0.144)	(0.027)	(0.140)	(0.026)	(0.143)	(0.022)	(0.132)	(0.020)
30cent Treatment	-0.155	0.063***	-0.156	0.064***	-0.137	0.068***	-0.159	0.068***	-0.150	0.062***
	(0.122)	(0.018)	(0.127)	(0.019)	(0.138)	(0.019)	(0.127)	(0.017)	(0.123)	(0.018)
10cent Treatment	-0.183	0.094***	-0.185	0.089***	-0.182	0.089***	-0.176	0.097***	-0.191*	0.037*
	(0.118)	(0.031)	(0.123)	(0.033)	(0.115)	(0.032)	(0.111)	(0.031)	(0.101)	(0.022)
Raven Test Ans.		-0.008*								
		(0.004)								
Stress				0.003						
				(0.009)						
Math Grade						0.009				
						(0.013)				
Know Exp. Value								-0.011**		
								(0.005)		
No Viol. 1. Ord. SD										-0.141***
										(0.045)
constant	0.192***	0.220***	0.193***	0.148***	0.190***	0.126***	0.191***	0.197***	0.207***	0.288***
	(0.053)	(0.042)	(0.051)	(0.026)	(0.053)	(0.041)	(0.050)	(0.028)	(0.052)	(0.047)
p-value for joint significance in:										
Treatments	0.318	0.000	0.325	0.000	0.383	0.000	0.301	0.000	0.219	0.000
Log-Likelihood	-11922		-11929		-11917		-11917		-11880	
Subjects	112		112		112		112		112	
Observations	20160		20160		20160		20160		20160	

Notes: The dependent variables are the Arrow-Pratt measure of relative risk aversion (ρ) assuming CRRA utility and the Fechner error (τ). Results in Columns (1) – (5) correspond to joint estimates of ρ and τ. Block bootstrapped standard errors clustered at the individual level and based on 1000 replications are reported in parentheses.
*** Significant at the 1% level.
** Significant at the 5% level.
* Significant at the 10% level.

Equation (6) specifies the nonlinear relationship between the measure of risk aversion included in the utility difference $\Delta E[u(\rho; \mathcal{L})]$ and the decision error τ. Allowing for a linear correlation between proxies of cognitive skills and decision errors might affect the risk aversion measure ρ indirectly by effecting the decision error τ. In addition to the indirect link between risk aversion and cognitive skills, one could also allow cognitive skills to be directly correlated with the risk aversion measure.

Since our structural estimation approach, already allows for a (nonlinear) association between the risk measure and decision errors, we have neither a theoretical prediction nor a sufficient understanding of the indirect and direct effects of cognitive skills on risk aversion. For completeness, we provide the results in Table 10, but acknowledge that the specification on which the results are based, has no economic foundation. Similar to the absence of a correlation between numeracy skills and risk aversion in our main specification (Table 1, Column (5)), we find no evidence of a correlation between any of the cognitive skills proxy and risk aversion. This result is in contrast to Benjamin, Brown, and Shapiro (2013) and Dohmen et al. (2010). However, both those studies rely on a reduced-form estimate of risk preferences, ignoring an explicit consideration of decision errors. Furthermore, their results are based on a Holt-Laury choice list (Holt and Laury 2002). Andersson et al. (2016) replicate the results of Dohmen et al. (2010) and find that the correlation between risk aversion and cognitive skills is an artifact of the choice list procedure. In line with Andersson et al. (2016) and the results in our paper, (Sutter et al. 2013)) find no evidence for any correlation between risk aversion and cognitive skills as measured by math and German school grades.

Table 10—Structural Estimates – Potential Decision Error Correlates II

	Risk & Error Measurement									
	(1)		(2)		(3)		(4)		(5)	
Parameter:	ρ	τ	ρ	τ	ρ	τ	ρ	τ	ρ	τ
Treatments										
100cent Treatment	-0.071	0.125***	-0.073	0.129***	-0.069	0.133***	-0.081	0.129***	-0.063	0.091***
	(0.141)	(0.024)	(0.148)	(0.027)	(0.144)	(0.028)	(0.143)	(0.022)	(0.135)	(0.022)
30cent Treatment	-0.155	0.063***	-0.148	0.062***	-0.114	0.054**	-0.158	0.068***	-0.147	0.060***
	(0.125)	(0.017)	(0.122)	(0.019)	(0.126)	(0.024)	(0.130)	(0.016)	(0.123)	(0.018)
10cent Treatment	-0.184	0.094***	-0.177	0.088***	-0.181	0.088***	-0.177	0.099***	-0.177*	0.040*
	(0.116)	(0.032)	(0.120)	(0.031)	(0.119)	(0.030)	(0.117)	(0.030)	(0.100)	(0.022)
Raven Test Ans.	-0.002	-0.008*								
	(0.017)	(0.004)								
Stress			0.017	0.001						
			(0.039)	(0.009)						
Math Grade					-0.046	0.012				
					(0.049)	(0.013)				
Know Exp. Value							-0.009	-0.011**		
							(0.020)	(0.006)		
No Viol. 1. Ord. SD									0.205	-0.144***
									(0.174)	(0.046)
Constant	0.207	0.220***	0.151	0.151***	0.315**	0.120***	0.231**	0.197***	0.011	0.290***
	(0.170)	(0.044)	(0.114)	(0.025)	(0.141)	(0.041)	(0.105)	(0.029)	(0.175)	(0.048)
p-value for joint significance in:										
Treatments	0.337	0.000	0.393	0.000	0.445	0.000	0.347	0.000	0.282	0.000
Log-Likelihood	-11922		-11929		-11917		-11915		-11865	
Subjects	112		112		112		112		112	
Observations	20160		20160		20160		20160		20160	

Notes: The dependent variables are the Arrow-Pratt measure of relative risk aversion (ρ) assuming CRRA utility and the Fechner error (τ). Results in Columns (1) – (5) correspond to joint estimates of ρ and τ. Block bootstrapped standard errors clustered at the individual level and based on 1,000 replications are reported in parentheses.
*** Significant at the 1% level.
** Significant at the 5% level.
* Significant at the 10% level.

G. *Alternative Utility Function —Expo-Power Utility*

The CRRA utility function is *the* utility function in economic models of decision-making under risk in economics (Wakker 2008). Holt and Laury (2002) relied on CRRA utility when constructing the Holt-Laury risk elicitation procedure in experimental economics. CRRA utility nests the analytically tractable log utility, which is predominant in theoretical models in micro- and macroeconomics. Following the ideas outlined in Rabin (2013a, 2013b), our aim is to develop a simple model that incorporates the trade-off between decision quality and costs so as to incrementally improve economic theory. Our economic model is technically trivial, which (we hope) makes it a portable extension of existing models (Rabin

2013b) and provides an easy way to incorporate a psychologically more realistic notion of rationality in a wide range of economic applications.

To empirically validate the predictions of our model, we find it natural to choose a utility function that is widely used in empirical and theoretical work in economics. To check how robust our results are with respect to the specification of the utility function,[42] we estimate the *expo-power utility* function, suggested by Holt and Laury (2002) and first proposed by Saha (1993) of the following form: $u(x) = (1 - \exp(-ax^{1-\rho}))/a)$ with $a \neq 0$, $1 - \rho \neq 0$, and $a \cdot (1 - \rho) > 0$. Since $-u''(x) \cdot x/u'(x) = \rho + a(1 - \rho)x^{1-\rho}$, the function includes constant absolute and constant relative risk aversion as special cases. When a goes to zero, ρ can be interpreted as the CRRA coefficient, whereas with ρ approaching zero and $a > 0$, the function exhibits CARA of a. For cases in-between, with a and $(1 - \rho)$ being positive, the function has the properties of increasing relative, and decreasing absolute, risk aversion.

Similar to our main specification, we rely on the Fechner error specification to reflect decision errors and include the utility normalization according to Wilcox (2011). Table 11 presents the results. Column (1) presents estimates without allowing for heterogeneity of decision errors (no Fechner error). The parameter a seems to be stable across treatments and is not statistically different from zero; therefore ρ can be (approximately) interpreted as CRRA coefficient. The results of Model (1) in Table 11 suggest implausibly high estimates of $\rho = -2.667$ for the control group, suggesting that this group is extremely fond of takings risks. The estimates in Columns (2) and (3) include the Fechner error and support the previously established pattern of increasing decision errors as a reaction to higher opportunity costs. We also obtain quantitatively much smaller and more plausible estimates of the risk preferences. The parameter estimates of ρ and a in Columns (2) and (3) jointly determine the risk preferences. Since both ρ and a are imprecisely measured, an interpretation of the change in risk preferences would be speculative. The resulting high p-values of the joint treatment effect seem to provide no hard evidence against the assumption of stable risk preferences with respect to changes in the opportunity costs of decision-making. However, note that, for example, in Column (2), ρ and a are positive for the control group suggesting increasing relative risk aversion.

In summary, the results presented in Table 11 indicate that both the increase in decision errors and the absence of systematic change in risk preferences caused by higher opportunity costs are not artifacts of the imposed CRRA utility function in our main specification. In Section J of this appendix, we further show that the same decision error pattern can be found when the parameter free expected value choice criteria (imposing risk neutrality) is used.

[42] In Section J, we reproduce our results with respect to the pattern in decision quality, under the assumption that the decision maker is risk neutral und uses the parameter-free concept of maximizing the expected value.

Table 11—Structural Estimates – Expo-Power Utility

	Risk & Error Measurement							
	(1)		(2)			(3)		
Parameter:	ρ	a	ρ	a	τ	ρ	a	τ
Treatments								
100cent Treatment	2.198*	0.034	-0.156	0.011	0.133***	-0.300	0.005	0.122***
	(1.244)	(0.062)	(0.154)	(0.020)	(0.026)	(0.329)	(57.495)	(0.029)
30cent Treatment	2.224*	-0.007	-0.099	-0.025	0.064***	-0.107	-0.031	0.041**
	(1.246)	(0.046)	(0.130)	(0.021)	(0.018)	(0.268)	(15.370)	(0.020)
10cent Treatment	1.927	0.001	-0.232**	-0.005	0.090***	-0.219	-0.012	0.053*
	(1.218)	(0.034)	(0.114)	(0.017)	(0.034)	(0.156)	(0.974)	(0.031)
Male						-0.095	-0.034	-0.073***
						(0.168)	(0.037)	(0.028)
BNT Correct						-0.034	-0.006	-0.012
						(0.059)	(0.011)	(0.008)
Age (18)						0.032	-0.000	-0.004
						(0.020)	(0.007)	(0.005)
Constant	-2.667**	0.016	0.125**	0.029***	0.155***	0.124	0.066*	0.237***
	(1.104)	(0.029)	(0.063)	(0.010)	(0.013)	(0.115)	(0.038)	(0.033)
p-value for joint significance in:								
Treatments	0.316	0.939	0.206	0.552	0.000	0.482	1.000	0.001
Log-Likelihood	-12989		-11911			-11751		
Subjects	112		112			112		
Observations	20160		20160			20160		

Notes: The dependent variables are the Arrow-Pratt measure of relative risk aversion (ρ) assuming expo-power utility ($u(x) = (1 - \exp(-ax^{1-\rho}))/a$) and the Fechner error (τ). Results in Columns (1) – (3) correspond to joint estimates of ρ, a and τ. Block bootstrapped standard errors clustered at the individual level and based on 1,000 replications are reported in parentheses.
*** Significant at the 1% level.
** Significant at the 5% level.
* Significant at the 10% level.

H. *Results of the Drift-Diffusion Model for Individual Risk and Error Estimates*

In this section, we provide additional results on the comparison across treatments of the DDM estimates. In the main text, we used the risk preferences elicited in Model 5 of Table 1. Heterogeneity across individuals is allowed to be across treatments as well as across the social-economic controls included in Model 5 of Table 1. The following two tables reproduce the results presented in Table 3 and Table 4 in the main text, allowing for full individual heterogeneity. The risk preferences, used to determine the correct choice, are obtained from individual estimates (Figure 4).

Table 12—Estimates of the Drift Diffusion Model

	Decision Criteria: Expected Utility			
	no cost	10 cent	30 cent	100 cent
Decision Boundaries (B)	2.74	1.74	1.66	1.36
p-value (H_0: no cost = treatment)	–	[0.000]	[0.000]	[0.000]
Drift Rate (μ)	0.42	0.59	0.72	0.68
p-value (H_0: no cost = treatment)	–	[0.004]	[0.000]	[0.001]
Non-Decisional Time (*NDT*)	1.26	1.07	1.08	0.86
p-value (H_0: no cost = treatment)	–	[0.029]	[0.031]	[0.000]

Notes: Parameter estimates of the drift diffusion model based on individual estimates for each subject in all treatments (N=111). P-values based on pairwise t-test on the difference between subjects in the control group (no cost) and subjects in the corresponding treatment are reported in brackets. We set $\sigma = 1$ in the stochastic component of the DDM ($\varepsilon \sim N(0, \sigma^2)$) to identify the parameters of the DDM (see e.g. Ratcliff, (1978); Krajbich, Oud, and Fehr et al., (2014)). Since the position of the two lotteries was randomized in the experiment and both lotteries were presented simultaneously, we fix he starting point of the RDV as the middle between the two lotteries (no initial bias toward a specific lottery). In addition to the fitted parameters B, μ, and *NDT*, we also estimate the parameters related to the variability of the drift rate μ and the starting point of the RDV (results available on request).

Table 13—Predictions of the Drift Diffusion Model

	Pred. Prob. of Correct Choice ($\hat{\pi}$)				Pred. Decision Time ($\widehat{t_d}$)			
	no cost	10 cent	30 cent	100 cent	no cost	10 cent	30 cent	100 cent
Prediction of the DDM due to change in								
Boundaries (ΔB)	83.5%	73.7%	72.8%	69.2%	2.60	1.75	1.70	1.50
Drift ($\Delta\mu$)	68.7%	74.9%	79.0%	78.3%	1.90	1.86	1.83	1.84
Both (ΔB & $\Delta\mu$)	75.7%	73.3%	76.3%	71.5%	2.74	1.75	1.68	1.50

Notes: Predictions of the DDM for the probability of a correct choice (($\hat{\pi}$) and the decision time ($\widehat{t_d}$) are presented. The predictions are based on 500001 simulations with all remaining parameters set at their sample mean values. The correct choice is determined from the utility difference based on the individual estimates of the CRRA coefficient (Figure 4).

I. *Lottery Stake Size*

One natural factor altering the incentives to allocate time between decision-making and the alternative income opportunity is the amount of money at stake in the lottery decision. Several information cues might help the decision maker to get a rough estimate of the importance of the lottery decision. In Table 14 we include different covariates, such as a dummy variable that equals 1 if one lottery has the potential to create a payoff larger than €20, as well as the sum, mean, and maximum of all lottery outcomes in the structural estimation of risk and decision errors to account for potential information cues. Although we find no evidence for a systematic change in risk preferences, we find significant lower error rates in all specification in Table 14 w.r.t. to higher potential size of the outcomes.

Table 14—Structural Estimates and Lottery Stake Size

	Risk & Error Measurement							
	(1)		(2)		(3)		(4)	
Parameter:	ρ	τ	ρ	τ	ρ	τ	ρ	τ
Treatments								
100cent Treatment	-0.067	0.130***	-0.063	0.127***	-0.063	0.127***	-0.063	0.128***
	(0.147)	(0.026)	(0.135)	(0.026)	(0.142)	(0.026)	(0.148)	(0.028)
30cent Treatment	-0.149	0.063***	-0.148	0.061***	-0.148	0.061***	-0.145	0.059***
	(0.126)	(0.019)	(0.122)	(0.019)	(0.121)	(0.019)	(0.128)	(0.022)
10cent Treatment	-0.176	0.087***	-0.172	0.084**	-0.172	0.084***	-0.171	0.082**
	(0.111)	(0.032)	(0.119)	(0.034)	(0.118)	(0.031)	(0.118)	(0.033)
High Stake (>20€)	-0.043	-0.049***						
	(0.041)	(0.019)						
Sum of Outcomes			0.000	-0.001***				
			(0.001)	(0.000)				
Mean of Outcomes					0.000	-0.003***		
					(0.003)	(0.001)		
Max of Outcomes							-0.001	-0.001***
							(0.001)	(0.000)
Constant	0.189***	0.155***	0.184***	0.168***	0.184***	0.168***	0.197***	0.169***
	(0.053)	(0.013)	(0.060)	(0.015)	(0.061)	(0.015)	(0.061)	(0.014)
p-value for joint significance in:								
Treatments	0.322	0.000	0.396	0.000	0.375	0.000	0.421	0.000
Log-Likelihood	-11929		-11925		-11925		-11920	
Subjects	112		112		112		112	
Observations	20160		20160		20160		20160	

Notes: The dependent variables are the Arrow-Pratt measure of relative risk aversion (ρ) assuming CRRA utility and the Fechner error (τ). Results in Columns (1) – (4) correspond to joint estimates of ρ and τ. Block bootstrapped standard errors clustered at the individual level and based on 1,000 replications are reported in parentheses.
*** Significant at the 1% level.
** Significant at the 5% level.
* Significant at the 10% level.

Note that based on our econometric specification, the probability of making a decision error (Equation (14)) is a function of τ and $\Delta E[u]$. If the decision error is dependent on lottery characteristics such as the information cues about the importance of the lottery decision as introduced in Table 14, then these characteristics must have an influence on the decision error conditional on $\Delta E[u]$. One way to incorporate a rational response to information cues in the economic model introduced in Section III is presented below. Assuming again that $R \succ L$, including the time constraint in the maximization problem from Equation (1), and defining the structure of the utility related to the lottery decision as $U \equiv \pi(t_d, \gamma, \delta) \cdot E[u(R)] + \left(1 - \pi(t_d, \gamma, \delta)\right) \cdot E[u(L)]$ gives the following maximization problem:

$$(17) \qquad \max_{t_d} \ \pi(t_d, \gamma, \delta) \cdot E[u(R)] + \left(1 - \pi(t_d, \gamma, \delta)\right) \cdot E[u(L)] + u_o(1 - t_d, \alpha),$$

the optimal allocation of time invested in the lottery decision t_d is given by

$$(18) \qquad (E[u(R)] - E[u(L)]) \frac{\partial \pi}{\partial t_d} = -\frac{\partial u_o}{\partial t_d}.$$

In addition to the assumption that more time invested in the lottery decision increases the quality of the decision ($\partial\pi/\partial t_d > 0$), we assume that the increase in the decision quality becomes smaller as more time is invested ($\partial^2\pi/\partial t_d^2 < 0$). This seems natural since the probability π cannot exceed 1; hence an appropriate structure of the function for π should suffice $\lim_{t_d \to \infty} \pi = 1$. The LHS of Equation (18) denotes the (positive) marginal utility of time invested in the lottery decision, while the RHS describes the marginal decline in utility derived from the alternative opportunity $\partial u_o / \partial t_d < 0$.

The expected utility difference $\Delta E[u] = E[u(R)] - E[u(L)]$ in the optimality condition (18) can be interpreted as importance of the decision, as it determines the size of the utility gain from a correct lottery choice. To account for information cues regarding the importance of the lottery decision assume further that the decision maker's prior belief (before the information about the lotteries is presented) about the expected utility difference is given as a random variable with zero mean and standard deviation σ such that $\widetilde{\Delta E[u]} \sim N(0, \sigma^2)$. In the optimality condition (18), we assume $R \succ L \Leftrightarrow \Delta E[u] > 0$. Since we assumed $\widetilde{\Delta E[u]} \sim N(0, \sigma^2)$, $\Delta E[u]$ is truncated and normally distributed within the interval $\Delta E[u] \in (0, \infty)$. The conditional expectation of $\Delta E[u]$ is given by $E[\Delta E[u] | \Delta E[u] > 0] = \sigma \sqrt{2/\pi i} \approx 0.8\sigma$, where $\pi i \approx 3.14159$, refers to the mathematical constant.[43] Replacing $E[u(R)] - E[u(L)]$ with $E[\Delta E[u] | \, \Delta E[u] > 0] = \sigma \sqrt{2/\pi i}$ in Equation (18) gives

$$\text{(19)} \qquad \sigma \sqrt{2/\pi i} \, \frac{\partial \pi}{\partial t_d} = -\frac{\partial u_o}{\partial t_d}.$$

Further assume that high lottery payoffs are interpreted as a signal for the possibility of a large $\Delta E[u]$, represented by a higher variance σ^2 in $\Delta E[u]$. A high lottery payoff could then —without changing the a priori mean of the distribution of $\widetilde{\Delta E[u]}$, which is still zero ($\widetilde{\Delta E[u]} \sim N(0, \sigma^2)$) —lead to more time being invested in the decision because a higher σ would require a lower $\partial \pi / \partial t_d$, which requires a larger t_d due to the concavity of π in t_d.

The extension of the model presented in this section can be interpreted as a two-stage process. In the first stage, the decision maker evaluates the importance of the lottery decision by making a heuristic judgment based on the lottery payoffs. Based on this judgment, the decision maker decides how much time he wants to invest in the lottery decision based on the optimality condition (19)). In the second stage, the decision maker decides among the lotteries.

J. *Structural Estimates with Parameter Constraints*

Table 15 sets out results of structural estimations using different parameter constraints. In specification (1), we restrict ρ to be equal to zero. In this case the expected utility model for decision-making under risk collapses to a parameter free expected value model, which is the preferred choice model under risk for many psychologists and some economists (Friedman et al. 2014). Using expected value as decision criteria, we find that the decision error pattern[44] is quite similar to our main specifications. In specification (2), we fix ρ to $\rho = 0.193$ for all treatment groups, which corresponds to

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[43] The general form of the conditional expectation of $\Delta E[u]$ with $\Delta E[u] > a$ and mean $E[\Delta E[u] | \, \Delta E[u] > 0] = \sigma \cdot \lambda(\alpha)$, where $\lambda(\alpha)$ denotes the Inverse Mills Ratio $\lambda(\alpha) = \phi(\alpha) / (1 - \Phi(\alpha))$ and $\alpha = (a - \mu)/\sigma$. With $\mu = 0$ and $a = 0$, the conditional expectation of $\Delta E[u]$ can be simplified to $E[\Delta E[u] | \, \Delta E[u] > 0] = \sigma \sqrt{2/\pi i}$.

[44] The interpretation of τ as decision error depends on the specification of the decision criteria. In specification (1) in Table 15, a decision error is therefore defined as "choosing the lottery with lower expected value." If expected utility is the preferred normative model and one assumes mild risk aversion (as appears to be the case for the majority of the subjects in our experiment), then a choice against the lottery with the highest expected value might still be a normatively correct decision.

estimate for the control group in our main specification (Table 1, Column (4)). In specification (3), we somewhat arbitrarily restrict ρ to be $\rho = 0.5$. In both specifications, we see similar decision error patterns. Compared to specification (2), estimates for τ, the parameter representing decision errors, are higher in specification (3). This is what one would expect when fixing ρ to a value farther away from the true value of the risk aversion parameter (which is based on the results in Table 1, Column (4) in the range $\rho = [0.008{,}0.193]$). In specification (4), we allow for no heterogeneity in the decision error. By fixing $\tau = 1$, we obtain a result similar to the one obtained from a model without an explicit Fechner error (compare Table 1, Column (1)).

Table 15—Structural Estimates with parameter Constraints

	Risk & Error Measurement							
	(1)		(2)		(3)		(4)	
Constraints:	Exp. Val.: $\rho_{treat} = 0$		$\rho_{treat} = 0.193$		$\rho_{treat} = 0.5$		$\tau_{treat} = 1$	
Parameter:	ρ	τ	ρ	τ	ρ	τ	ρ	τ
Treatments								
100cent Treatment		0.119***		0.132***		0.166**	-0.247	
		(0.033)		(0.026)		(0.071)	(2.777)	
30cent Treatment		0.044*		0.071***		0.151**	-0.589	
		(0.025)		(0.019)		(0.073)	(7.102)	
10cent Treatment		0.066*		0.097***		0.185***	-0.624	
		(0.037)		(0.033)		(0.071)	(2.973)	
Constant	0	0.178***	0.193	0.153***	0.5	0.265***	0.233	1
		(0.017)		(0.013)		(0.029)	(0.151)	
p-value for joint significance in:								
Treatments	–	0.002	–	0.000	–	0.006	0.996	–
Log-Likelihood	-12026		-12002		-12772		-13049	
Subjects	112		112		112		112	
Observations	20160		20160		20160		20160	

Notes: The dependent variables are the Arrow-Pratt measure of relative risk aversion (ρ) assuming CRRA utility and the Fechner error (τ). Results in Columns (1) – (4) correspond to joint estimates of ρ and τ. Block bootstrapped standard errors clustered at the individual level and based on 1,000 replications are reported in parentheses.
*** Significant at the 1% level.
** Significant at the 5% level.
* Significant at the 10% level.

K. *Learning During the Experiment and Results from Subsamples*

In each of the treatment conditions, subjects had to make the same 180 lottery decisions. The order of the lottery was randomized but similar for all 112 subjects. To investigate potential learning effects, we split the lottery sample into four subsamples of 45 lotteries. We also investigate the entire sample, but include a linear and a reciprocal time trend by including the variables *round #* and *1 / round #*. Four subsamples and two time trend conditions give us $3 \times (4 + 2) = 18$ coefficients for each structural parameter. With respect to the risk aversion parameter ρ, we find one coefficient to be significant at the 5% level and one coefficient significant at the 10% level, which can be interpreted as driven by chance. The coefficient estimates of the decision error τ are significant at least at the 10% level in 17 out of 18 cases. The analysis of the subsamples does not reveal an unambiguous learning pattern in the treatment effects of the structural estimates. In general, the results in all specifications in Table 16 are fairly similar to the main specification reported in Table 1 and provide further robustness to the results of our main specification.

Table 16—Subsamples and Trends

	Risk & Error Measurement											
	Subsamples á 45 Lotteries								Linear Trend (round)		1/round	
	(1)		(2)		(3)		(4)		(5)		(6)	
Parameter:	ρ	τ	ρ	τ	ρ	τ	ρ	τ	ρ	τ	ρ	τ
Treatments												
100cent Treatm.	0.145	0.129***	-0.155	0.094***	-0.115	0.140***	-0.178	0.126***	-0.057	0.122***	-0.071	0.117***
	(0.116)	(0.029)	(0.147)	(0.027)	(0.153)	(0.050)	(0.189)	(0.039)	(0.126)	(0.026)	(0.133)	(0.024)
30cent Treatment	-0.065	0.072***	-0.156	0.073***	-0.198	0.059**	-0.181	0.044*	-0.142	0.061***	-0.151	0.059***
	(0.128)	(0.021)	(0.155)	(0.023)	(0.125)	(0.027)	(0.142)	(0.024)	(0.118)	(0.018)	(0.123)	(0.018)
10cent Treatment	-0.070	0.162***	-0.236*	0.068**	-0.257**	0.029	-0.112	0.093**	-0.172	0.088***	-0.174	0.075***
	(0.143)	(0.052)	(0.130)	(0.029)	(0.102)	(0.025)	(0.126)	(0.042)	(0.111)	(0.032)	(0.108)	(0.029)
Round #									-0.001***	-0.000		
									(0.000)	(0.000)		
1 / Round #											1.809***	0.494***
											(0.385)	(0.094)
constant	0.247***	0.134***	0.186***	0.146***	0.228***	0.181***	0.102	0.143***	0.319***	0.155***	0.144***	0.144***
	(0.054)	(0.015)	(0.061)	(0.016)	(0.052)	(0.015)	(0.066)	(0.017)	(0.054)	(0.016)	(0.054)	(0.012)
p-value for joint significance in:												
Treatments	0.469	0.000	0.243	0.001	0.051	0.011	0.502	0.003	0.363	0.000	0.328	0.000
Log-Likelihood	-2947		-2966		-3107		-2840		-11900		-11872	
Subjects	112		112		112		112		112		112	
Observations	5040		5040		5040		5040		20160		20160	

Notes: The dependent variables are the Arrow-Pratt measure of relative risk aversion (ρ) assuming CRRA utility and the Fechner error (τ). Standard errors clustered at the individual level and based on 1000 replications are reported in parentheses.
*** Significant at the 1% level.
** Significant at the 5% level.
* Significant at the 10% level.

Despite no evidence of learning effects with respect to the treatment parameters, we find that subjects become slightly less risk averse in later lottery decisions (Column (5) and (6), Table 16). The reciprocal trend specification reveals a strong negative effect of learning, approximated by lottery choice experience in the experiment, on decision errors. While the learning effect on decision errors is significant at the 1% level in the reciprocal specification (Column (6)), it is not to be found in the linear specification (Column (5)). On explanation might be that learning occurs mainly during the first lottery decisions of the experiment, with no further improvement as further lottery decisions are made.

L. *Table of Lotteries Played in the Experiment*

The following table presents the exact lottery pairs played by each individual in all treatment conditions. The lotteries were constructed to cover a broad variation of probabilities and outcomes. After construction of the lottery pairs, the position of each lottery (left or right) was determined using a random mechanism. The first 90 lotteries share the property that the lowest payoff of each lottery was always zero. This assumption was relaxed for the last 90 lotteries. The order of the lotteries in the two blocks of 90 lotteries was determined using a random number generator, which produced the order denoted in Table 17.

The first six lottery pairs *control 1* to *control 6* were used in the instructions of the experiment and were not incentivized. Subjects had to correctly answer control questions concerning the lottery payoffs and the time payoffs. The experiment started with pair 1 and ended with pair 180. Each individual had to make 180 lottery choices. In each opportunity cost treatment, subjects faced the same lottery pairs in the same order. At the end of the experiment, we used an individual random lottery incentive procedure (Starmer and Sugden 1991) to determine two of the 180 lottery pair decisions to use in paying off subject.[45] The two selected lotteries in both lottery pairs were then played using a random number generator to determine the subject's payoff. This procedure was used to avoid problems caused by reference-point or wealth effects (Starmer and Sugden 1991). The absence of feedback and the large number of uncorrelated lotteries from which two are chosen for payoff purposes are properties of our experimental design that reduce the likelihood of problems described in Cox et al. (2014) related to the random lottery incentive scheme based on the integration of all lottery choices as one compound lottery.

[45] The random lottery mechanism is used in several prominent experiments investigating decisions under risk: for a survey, see Harrison and Rutström (2008).

Table 17— Lottery Set

Lottery Number	Left Lottery				Right Lottery				Lottery Number	Left Lottery				Right Lottery			
	p_1	p_2	x_1	x_2	p_1	p_2	x_1	x_2		p_1	p_2	x_1	x_2	p_1	p_2	x_1	x_2
control 1	90	10	4.5	0	10	90	3.5	0	88	90	10	0.2	0	10	90	15	0
control 2	67	33	6	0	33	67	10	0	89	90	10	0.5	0	10	90	4.5	0
control 3	80	20	5	0	20	80	5	0	90	40	60	3	0	60	40	1.3	0
control 4	25	75	4	0	75	25	2	0	91	75	25	1	0.7	25	75	8	0
control 5	50	50	3	0.1	50	50	4	0.1	92	75	25	6.5	1	25	75	15	1
control 6	60	40	10	0.4	40	60	15	0.2	93	53	47	17	0.1	47	53	20	0.1
1	53	47	4.7	0	47	53	5.3	0	94	40	60	9.5	0.1	60	40	0.1	0.1
2	75	25	3.2	0	25	75	15	0	95	50	50	10	0	100	0	5	0
3	90	10	5.1	0	10	90	4.9	0	96	25	75	26	0	100	0	6.5	0
4	25	75	20	0	75	25	2.3	0	97	80	20	7.5	0	100	0	6	0
5	90	10	3.5	0	90	10	3.5	0	98	95	5	9	0	100	0	7	0
6	75	25	1	0	25	75	5	0	99	50	50	16	0	100	0	6.5	0
7	47	53	7.5	0	53	47	6.8	0	100	5	95	100	0	100	0	5.5	0
8	60	40	8.5	0	40	60	15	0	101	40	60	3	0	60	40	1.3	1.1
9	25	75	6	0	75	25	1.5	0	102	75	25	4.5	0.5	75	25	4.5	0.5
10	40	60	4.2	0	60	40	5.1	0	103	50	50	5	0	50	50	6	0
11	53	47	5.1	0	47	53	6	0	104	75	25	2.3	0.1	25	75	5	0
12	75	25	1.5	0	25	75	7.5	0	105	60	40	2.9	1	40	60	5	2
13	60	40	6.5	0	40	60	9	0	106	90	10	0.2	0.1	10	90	20	0.1
14	75	25	3.8	0	25	75	9	0	107	40	60	5.5	0.1	60	40	4.5	1.2
15	40	60	15	0	60	40	0.2	0	108	47	53	14	0.2	53	47	12	1.3
16	10	90	81	0	90	10	1	0	109	60	40	4.5	3.3	40	60	9.9	0.1
17	40	60	9.5	0	60	40	0.1	0	110	90	10	2.7	1	10	90	15	1.2
18	25	75	7.5	0	75	25	0.8	0	111	75	25	0.1	0.1	25	75	9.5	0.1
19	25	75	20	0	75	25	8.5	0	112	47	53	8	0.1	53	47	1	0.1
20	53	47	5.9	0	47	53	7.5	0	113	40	60	7.5	0.1	60	40	5.4	0.1
21	40	60	6	0	60	40	3.3	0	114	47	53	7.5	0.1	53	47	5.9	0.1
22	40	60	15	0	60	40	6.7	0	115	10	90	6	0.1	90	10	0.4	0.1
23	25	75	2	0	75	25	4	0	116	90	10	0.1	0	10	90	9	0
24	10	90	20	0	90	10	0.2	0	117	75	25	2.3	1	25	75	20	0.1
25	53	47	5.5	0	47	53	6	0	118	100	0	7	0	95	5	9	0
26	40	60	15	0	60	40	10	0	119	75	25	1	0.1	25	75	3	0.1
27	25	75	15	0	75	25	1.6	0	120	100	0	6.5	0	50	50	16	0
28	25	75	9	0	75	25	1.2	0	121	60	40	8.5	2.5	40	60	15	0.1
29	10	90	15	0	90	10	0.2	0	122	25	75	20	1.5	75	25	8.5	0.1
30	60	40	3.4	0	40	60	7.5	0	123	47	53	15	0.1	53	47	14	0.1
31	10	90	9	0	90	10	0.1	0	124	60	40	2	0.1	40	60	6	0.1
32	10	90	15	0	90	10	2.7	0	125	75	25	5	0.3	25	75	15	0.1
33	40	60	5.1	0	60	40	5	0	126	25	75	7.5	0.1	75	25	1.5	1.1
34	10	90	20	0	90	10	3.7	0	127	40	60	15	0.1	60	40	11	0.1
35	40	60	7.5	0	60	40	5.4	0	128	100	0	6	0	80	20	7.5	0
36	90	10	1	0	10	90	9	0	129	60	40	6.5	0.1	40	60	9	0.1
37	53	47	8.7	0	47	53	13	0	130	40	60	4.2	0.5	60	40	5.1	0.1
38	47	53	6	0	53	47	4.7	0	131	100	0	5.5	0	5	95	100	0
39	60	40	4.5	0	40	60	9.9	0	132	10	90	6	0.1	90	10	0.1	0.1
40	90	10	3	0	10	90	27	0	133	40	60	15	0.1	60	40	6.7	0.1
41	25	75	6	0	75	25	0.6	0	134	53	47	7.1	0.1	47	53	9	0.1
42	60	40	4.5	0	40	60	5.5	0	135	53	47	4	1.5	47	53	3.5	2
43	47	53	15	0	53	47	14	0	136	25	75	9	0.1	75	25	1.2	0.1
44	60	40	4.4	0	40	60	6	0	137	25	75	1.5	0.1	75	25	0.5	0.1
45	75	25	0.7	0	25	75	9	0	138	10	90	9	0.1	90	10	1	0.1
46	75	25	0.1	0	25	75	9.5	0	139	47	53	5.3	0.8	53	47	4.7	0.5
47	75	25	4.1	0	25	75	20	0	140	25	75	26	0	100	0	6.5	0
48	25	75	3	0	75	25	1	0	141	10	90	6	0.1	90	10	1.1	0.1
49	40	60	7.5	0	60	40	5	0	142	90	10	5.1	1.2	10	90	4.9	0.1
50	90	10	0.1	0	10	90	18	0	143	90	10	0.2	0.1	10	90	15	0.1
51	25	75	5.5	0	75	25	4.5	0	144	10	90	4.5	0	90	10	0.5	0.3
52	75	25	5.1	0	25	75	4.9	0	145	60	40	4.2	1.6	40	60	7.5	0.5
53	10	90	9	0	90	10	1.6	0	146	53	47	5.3	0.1	47	53	6	0.1
54	47	53	8	0	53	47	1	0	147	90	10	1	0.1	10	90	81	0.1
55	10	90	9	0	90	10	0.5	0	148	40	60	5	0.1	60	40	2.2	0.1
56	90	10	0.7	0	10	90	15	0	149	40	60	20	0.1	60	40	11	0.1
57	25	75	1.5	0	75	25	0.5	0	150	10	90	9	1.3	90	10	3	0.1
58	40	60	18	0	60	40	7	0	151	25	75	7	0	75	25	3.3	2.2
59	60	40	4	0	40	60	6	0	152	40	60	5.1	0.1	60	40	5	0.1
60	47	53	3.5	0	53	47	4	0	153	53	47	9.9	2	47	53	10	1
61	60	40	2.9	0	40	60	5	0	154	75	25	5.1	0.1	25	75	4.9	0.1
62	10	90	6	0	90	10	0.4	0	155	47	53	7.5	0.1	53	47	6.3	0.1
63	25	75	15	0	75	25	0.2	0	156	40	60	6	0.1	60	40	4.4	0.1
64	53	47	5.1	0	47	53	4.9	0	157	40	60	7.5	0	60	40	3.4	0.1
65	47	53	6	0	53	47	5.3	0	158	50	50	10	0	100	0	5	0
66	47	53	15	0	53	47	12	0	159	10	90	18	0.1	90	10	0.1	0.1
67	25	75	15	0	75	25	5	0	160	75	25	1.6	0.1	25	75	15	0.1
68	47	53	2.8	0	53	47	2.5	0	161	10	90	2	0.1	90	10	4	0.1
69	75	25	3.3	0	25	75	9.9	0	162	25	75	20	0.1	75	25	4.1	2.1
70	53	47	7.1	0	47	53	9	0	163	40	60	15	0.1	60	40	0.2	0.1
71	60	40	4.2	0	40	60	7.5	0	164	75	25	3.8	0.1	25	75	9	0.3
72	60	40	2.2	0	40	60	5	0	165	10	90	20	0.1	90	10	3.7	0.1
73	47	53	10	0	53	47	9.9	0	166	53	47	5.1	0.1	47	53	4.9	0.1
74	40	60	6	0	60	40	2	0	167	75	25	1	0.5	25	75	3	0.1
75	25	75	15	0	75	25	6.5	0	168	47	53	6	0.1	53	47	4.7	0.1
76	60	40	11	0	40	60	15	0	169	53	47	5	2	47	53	5.1	1
77	53	47	7.5	0	53	47	7.5	0	170	40	60	18	0.1	60	40	7	0.1
78	47	53	10	0	53	47	1.2	0	171	25	75	6	0.1	75	25	2.6	0.1
79	10	90	7.5	0	90	10	0.1	0	172	10	90	15	0.1	90	10	0.7	0.4
80	90	10	1.1	0	10	90	6	0	173	40	60	15	0.5	60	40	10	0.1
81	53	47	6.3	0	47	53	7.5	0	174	25	75	9.5	1.5	25	75	9.5	1.5
82	75	25	2.6	0	25	75	6	0	175	53	47	8.7	0.1	47	53	13	0.1
83	53	47	5	0	47	53	5.1	0	176	90	10	0.2	0.1	10	90	15	0.1
84	10	90	6	0	90	10	0.1	0	177	75	25	0.8	0	25	75	7.5	0
85	53	47	17	0	47	53	20	0	178	75	25	0.2	0.1	25	75	15	0.1
86	60	40	11	0	40	60	20	0	179	90	10	5	2	10	90	21	0.1
87	60	40	3	0	40	60	5.1	0	180	53	47	2.5	0.1	47	53	2.8	0.1

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Online Appendix

Figure 2 presents the timeline of our experiment. The following online appendix provides screenshots of each of the four stages of the experiment (in German).

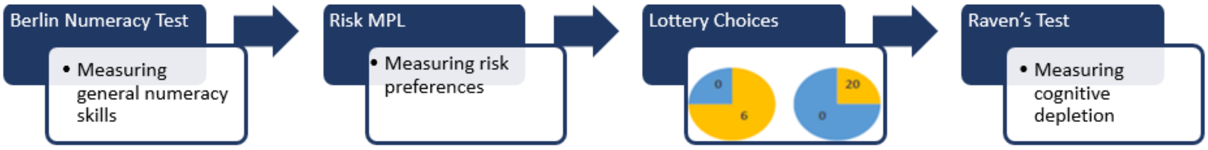


Figure 2. Setup of the Experiment (Reproduced from the Paper)

Notes: The figure presents the timeline during the experimental sessions. After the experiment, a questionnaire on socio-economic characteristics was given. Some subjects had to wait for nearly 30 minutes at the end, but they were allowed to play a version of Tetris and Minesweeper when done.

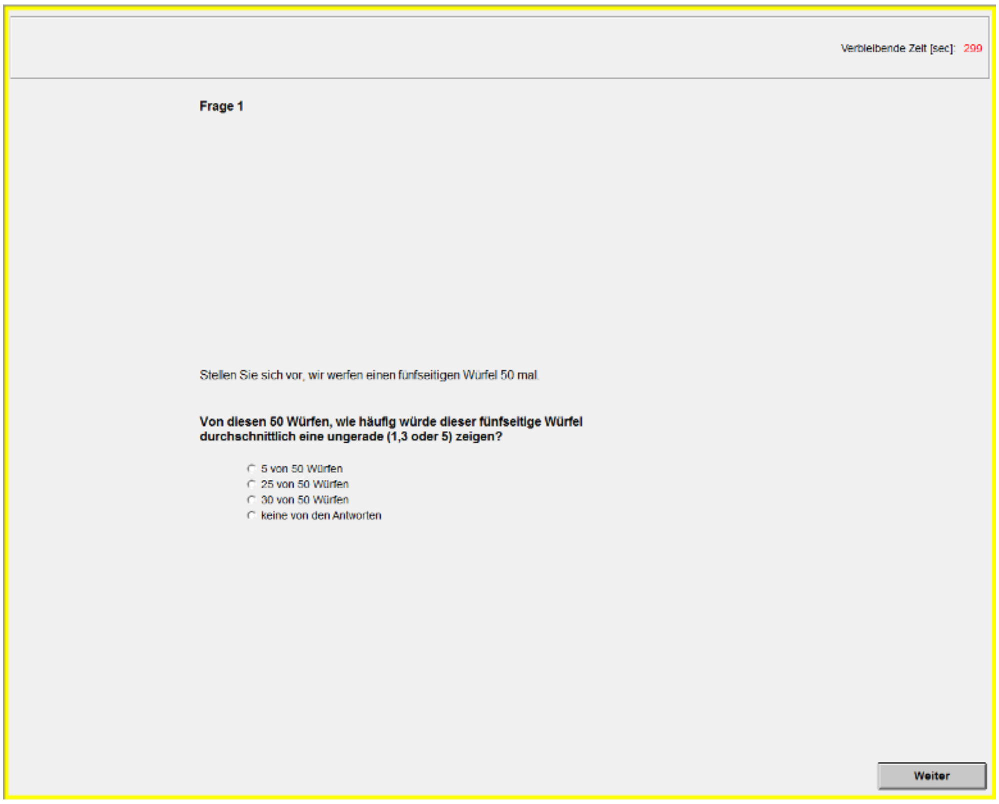
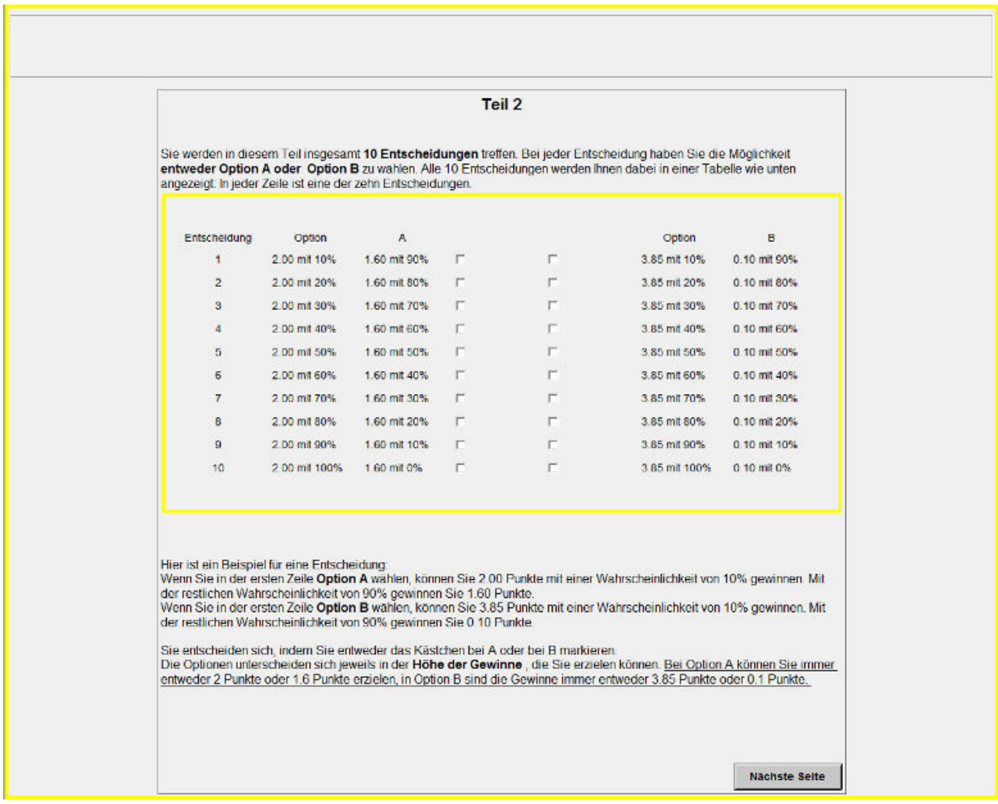


Figure 11. Example Question from the Berlin Numeracy Test



Teil 2

Sie werden in diesem Teil insgesamt **10 Entscheidungen** treffen. Bei jeder Entscheidung haben Sie die Möglichkeit **entweder Option A oder Option B** zu wahlen. Alle 10 Entscheidungen werden Ihnen dabei in einer Tabelle wie unten angezeigt. In jeder Zeile ist eine der zehn Entscheidungen.

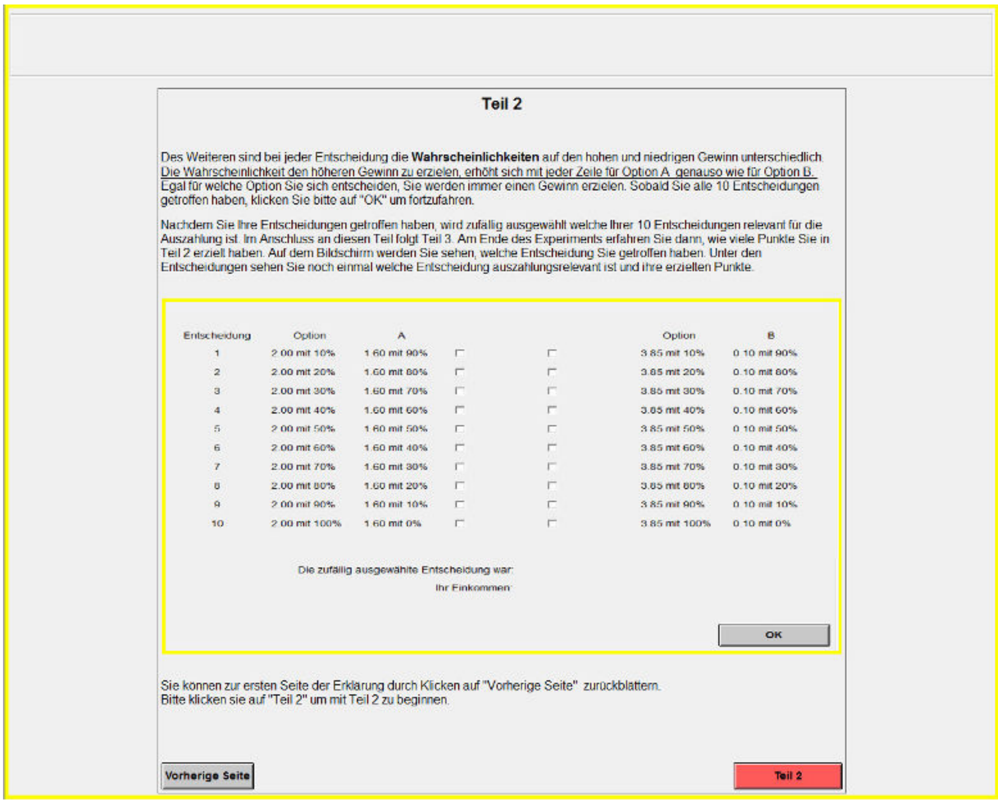
Entscheidung	Option	A			Option	B
1	2.00 mit 10%	1.60 mit 90%	☐	☐	3.85 mit 10%	0.10 mit 90%
2	2.00 mit 20%	1.60 mit 80%	☐	☐	3.85 mit 20%	0.10 mit 80%
3	2.00 mit 30%	1.60 mit 70%	☐	☐	3.85 mit 30%	0.10 mit 70%
4	2.00 mit 40%	1.60 mit 60%	☐	☐	3.85 mit 40%	0.10 mit 60%
5	2.00 mit 50%	1.60 mit 50%	☐	☐	3.85 mit 50%	0.10 mit 50%
6	2.00 mit 60%	1.60 mit 40%	☐	☐	3.85 mit 60%	0.10 mit 40%
7	2.00 mit 70%	1.60 mit 30%	☐	☐	3.85 mit 70%	0.10 mit 30%
8	2.00 mit 80%	1.60 mit 20%	☐	☐	3.85 mit 80%	0.10 mit 20%
9	2.00 mit 90%	1.60 mit 10%	☐	☐	3.85 mit 90%	0.10 mit 10%
10	2.00 mit 100%	1.60 mit 0%	☐	☐	3.85 mit 100%	0.10 mit 0%

Hier ist ein Beispiel für eine Entscheidung:
Wenn Sie in der ersten Zeile **Option A** wählen, können Sie 2.00 Punkte mit einer Wahrscheinlichkeit von 10% gewinnen. Mit der restlichen Wahrscheinlichkeit von 90% gewinnen Sie 1.60 Punkte.
Wenn Sie in der ersten Zeile **Option B** wählen, können Sie 3.85 Punkte mit einer Wahrscheinlichkeit von 10% gewinnen. Mit der restlichen Wahrscheinlichkeit von 90% gewinnen Sie 0.10 Punkte.

Sie entscheiden sich, indem Sie entweder das Kästchen bei A oder bei B markieren.
Die Optionen unterscheiden sich jeweils in der **Höhe der Gewinne** , die Sie erzielen können. Bei Option A können Sie immer entweder 2 Punkte oder 1.6 Punkte erzielen, in Option B sind die Gewinne immer entweder 3.85 Punkte oder 0.1 Punkte.

Nächste Seite

Figure 12. Instructions and Lottery Choices in the Holt-Laury Task I



Teil 2

Des Weiteren sind bei jeder Entscheidung die **Wahrscheinlichkeiten** auf den hohen und niedrigen Gewinn unterschiedlich. Die Wahrscheinlichkeit den höheren Gewinn zu erzielen, erhöht sich mit jeder Zeile für Option A genauso wie für Option B. Egal für welche Option Sie sich entscheiden, Sie werden immer einen Gewinn erzielen. Sobald Sie alle 10 Entscheidungen getroffen haben, klicken Sie bitte auf "OK" um fortzufahren.

Nachdem Sie Ihre Entscheidungen getroffen haben, wird zufällig ausgewählt welche Ihrer 10 Entscheidungen relevant für die Auszahlung ist. Im Anschluss an diesen Teil folgt Teil 3. Am Ende des Experiments erfahren Sie dann, wie viele Punkte Sie in Teil 2 erziel haben. Auf dem Bildschirm werden Sie sehen, welche Entscheidung Sie getroffen haben. Unter den Entscheidungen sehen Sie noch einmal welche Entscheidung auszahlungsrelevant ist und ihre erziellen Punkte.

Entscheidung	Option	A			Option	B
1	2.00 mit 10%	1.60 mit 90%	☐	☐	3.85 mit 10%	0.10 mit 90%
2	2.00 mit 20%	1.60 mit 80%	☐	☐	3.85 mit 20%	0.10 mit 80%
3	2.00 mit 30%	1.60 mit 70%	☐	☐	3.85 mit 30%	0.10 mit 70%
4	2.00 mit 40%	1.60 mit 60%	☐	☐	3.85 mit 40%	0.10 mit 60%
5	2.00 mit 50%	1.60 mit 50%	☐	☐	3.85 mit 50%	0.10 mit 50%
6	2.00 mit 60%	1.60 mit 40%	☐	☐	3.85 mit 60%	0.10 mit 40%
7	2.00 mit 70%	1.60 mit 30%	☐	☐	3.85 mit 70%	0.10 mit 30%
8	2.00 mit 80%	1.60 mit 20%	☐	☐	3.85 mit 80%	0.10 mit 20%
9	2.00 mit 90%	1.60 mit 10%	☐	☐	3.85 mit 90%	0.10 mit 10%
10	2.00 mit 100%	1.60 mit 0%	☐	☐	3.85 mit 100%	0.10 mit 0%

Die zufällig ausgewählte Entscheidung war:
Ihr Einkommen:

OK

Sie können zur ersten Seite der Erklärung durch Klicken auf "Vorherige Seite" zurückblättern.
Bitte klicken sie auf "Teil 2" um mit Teil 2 zu beginnen.

Vorherige Seite

Teil 2

Figure 13. Instructions and Lottery Choices in the Holt-Laury Task II

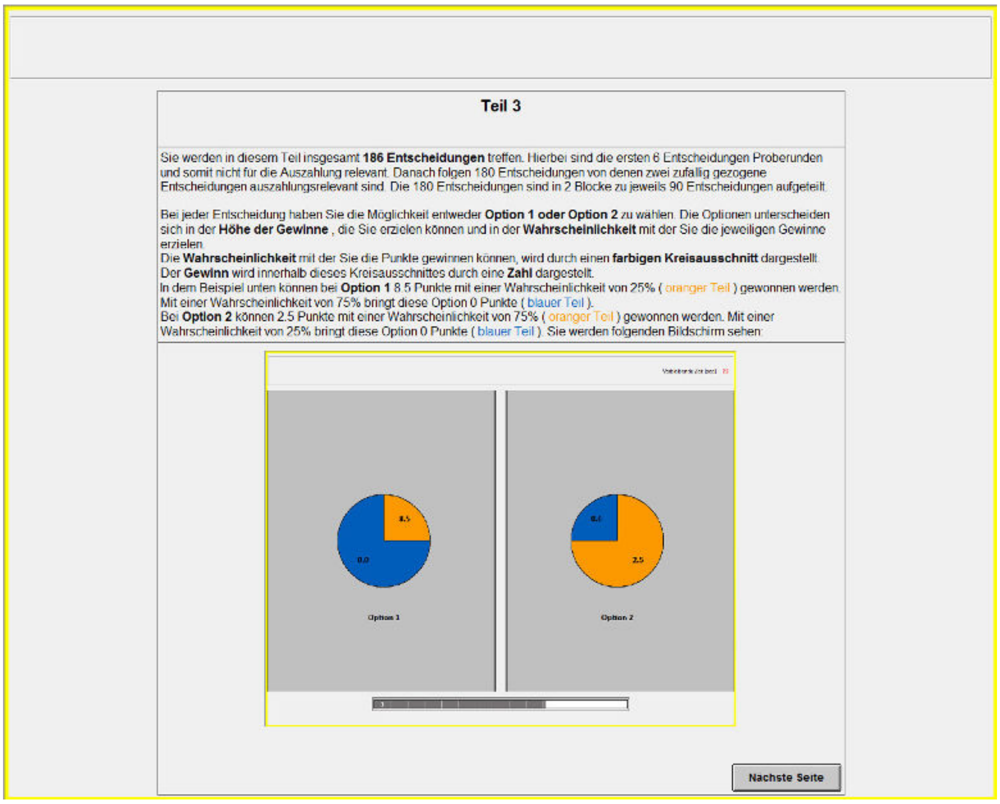


Figure 14. Instructions for Making a Lottery Decision

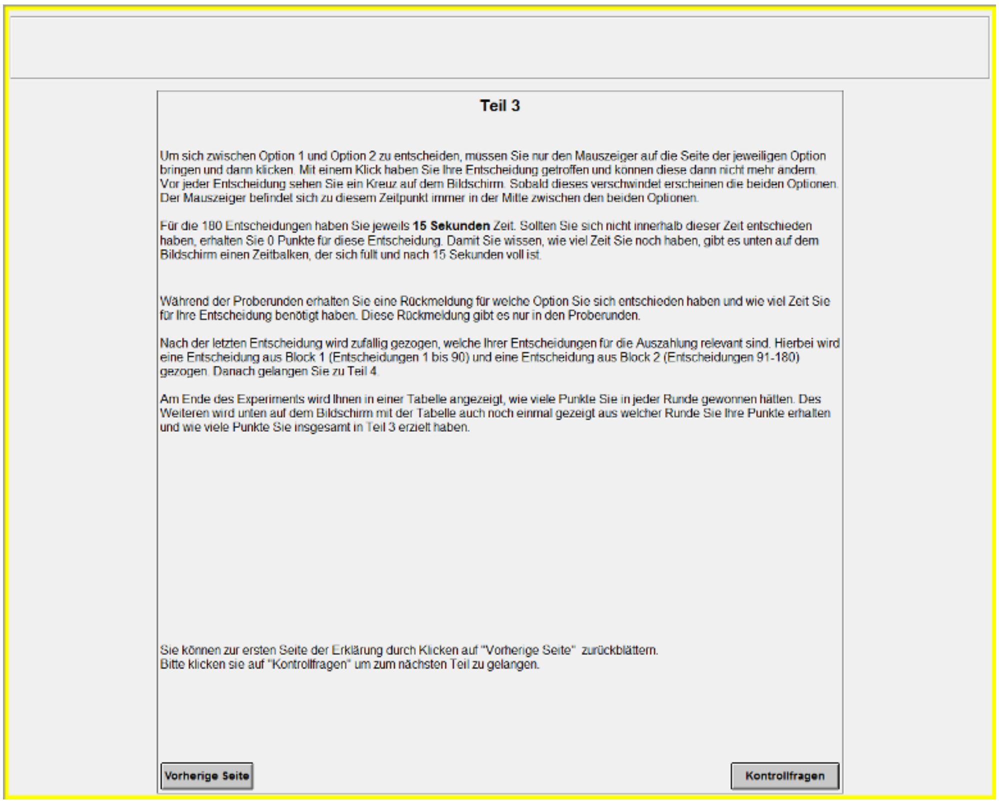


Figure 15. Instructions for Making a Lottery Decision (No Time Costs)

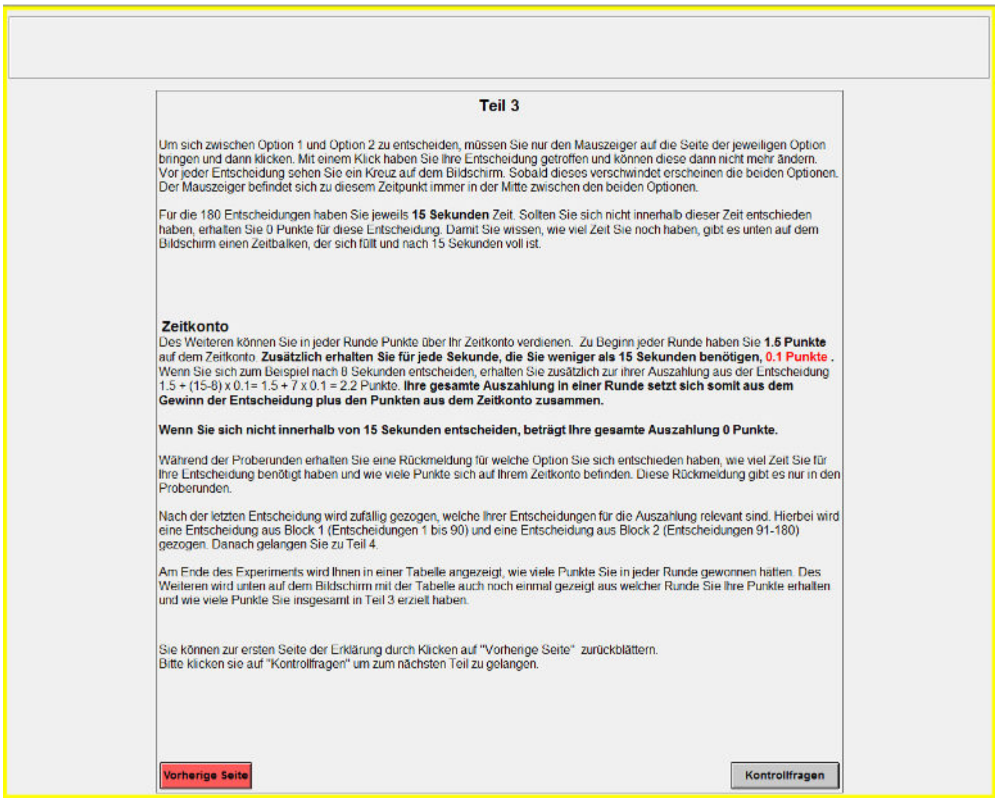


Figure 16. Instructions for Making a Lottery Decision (10 Cent Treatment)

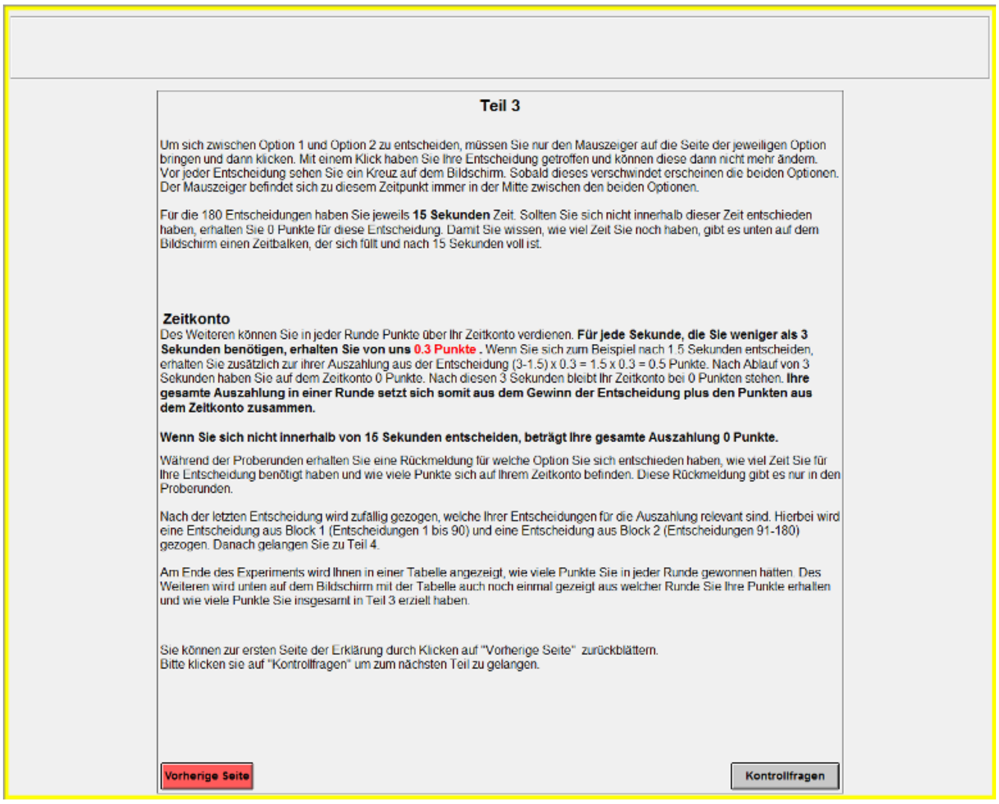


Figure 17. Instructions for Making a Lottery Decision (30 Cent Treatment)

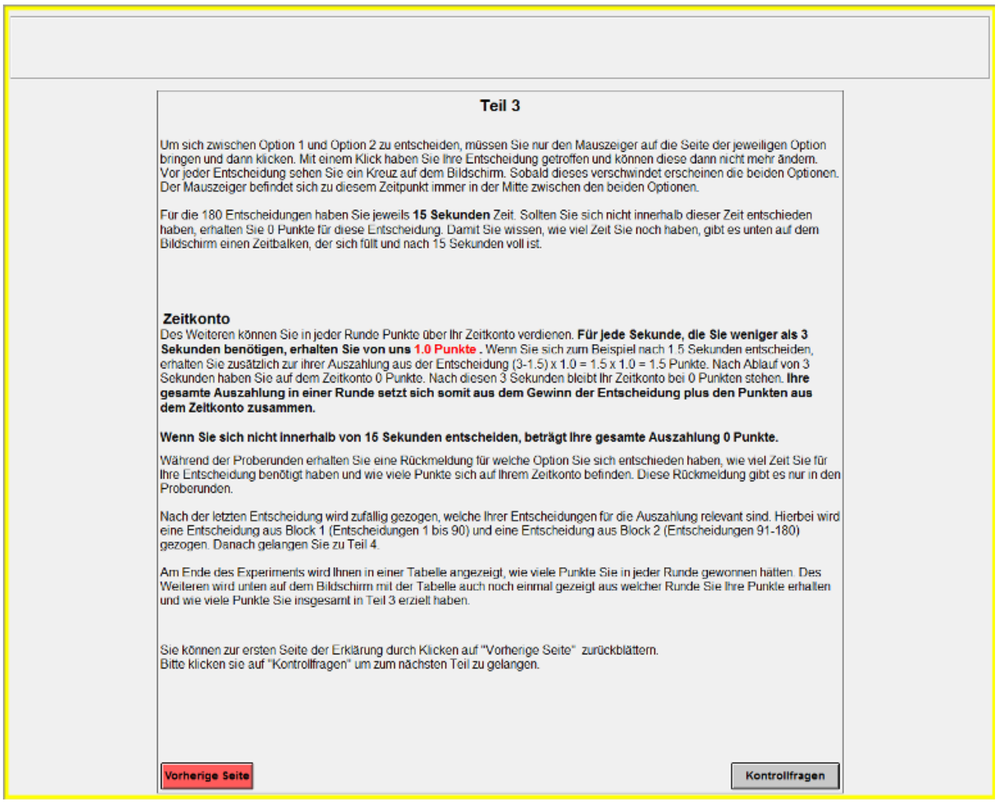


Figure 18. Instructions for Making a Lottery Decision (100 Cent Treatment)

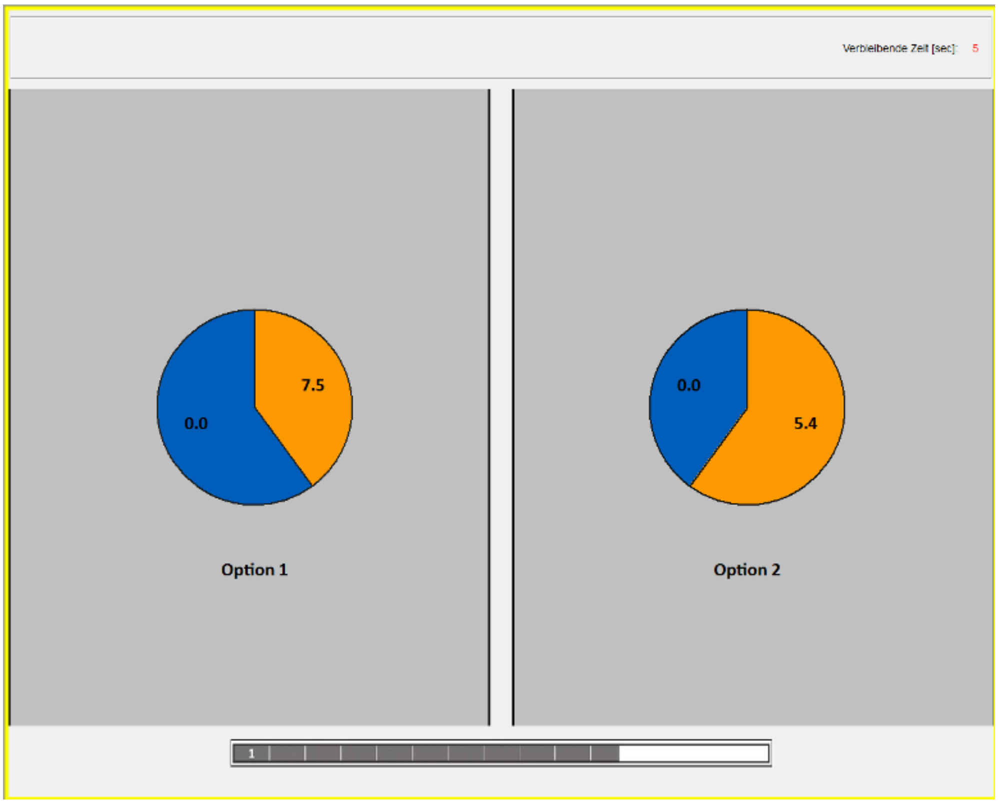


Figure 19. Screen of Lottery Decision from the Lottery Sample (Same for All Treatments)

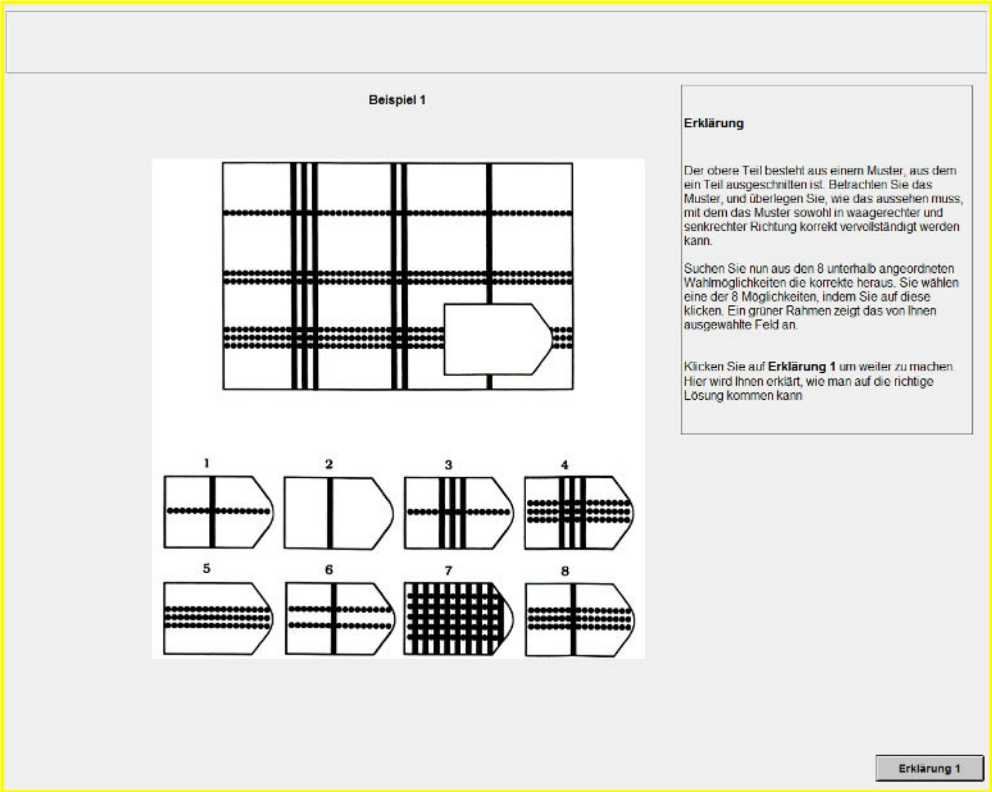


Figure 20. Raven Test Instructions

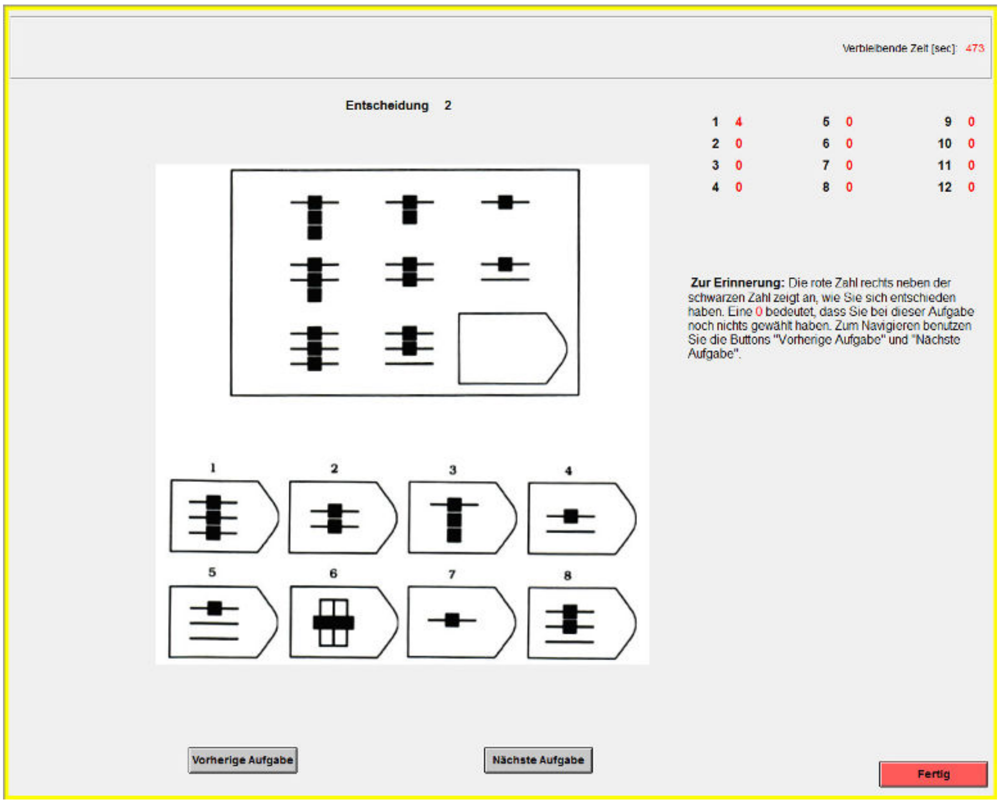


Figure 21. Raven Test – Easy Task (Task 2 out of 12)

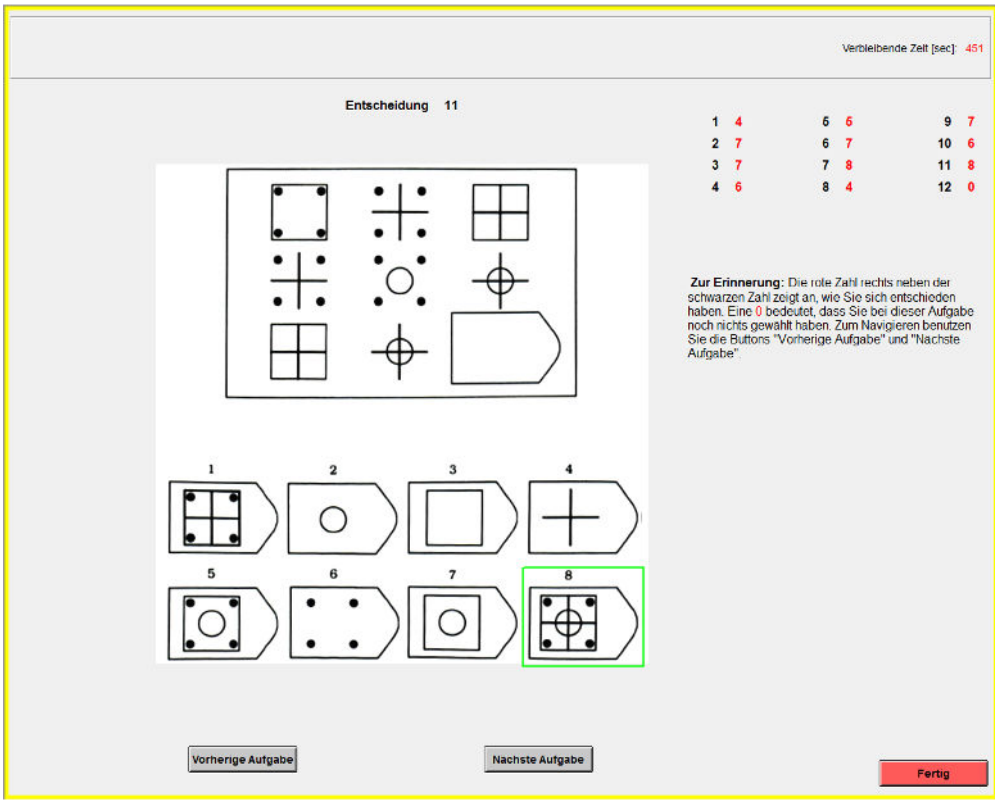


Figure 22. Raven Test – Hard Task (Task 11 out of 12)

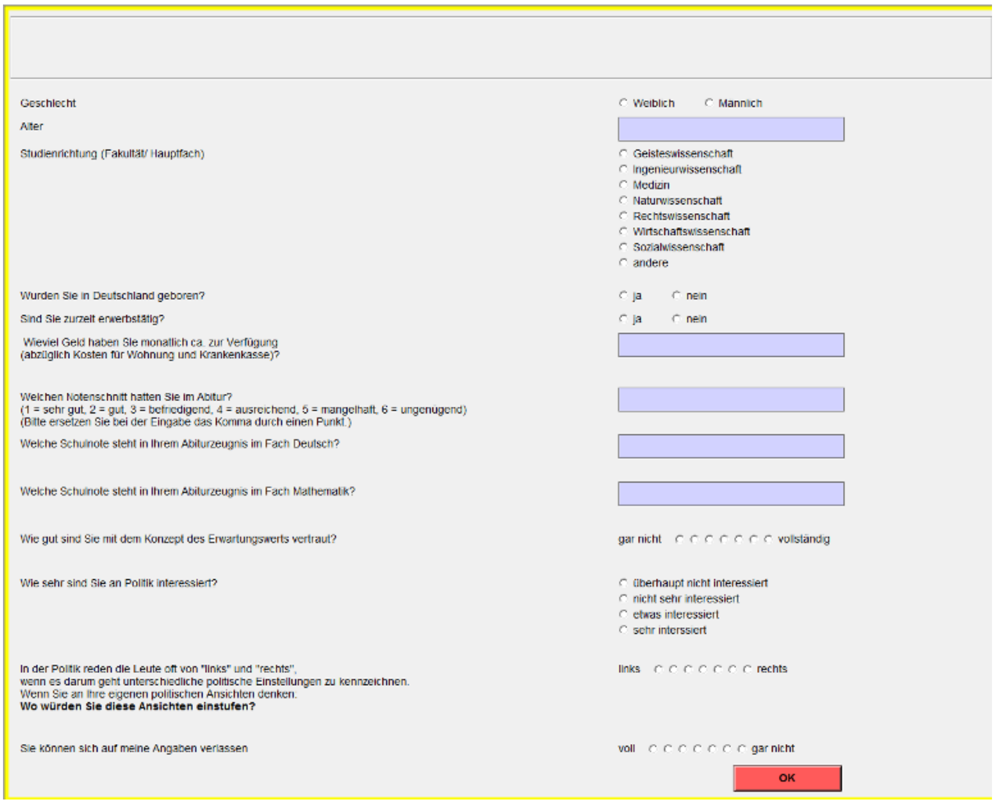


Figure 23. Questionnaire on Socio-economic Characteristics

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