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Behavioral Time Choices in Speed-Accuracy Trade-offs*

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In many economic contexts, people need to solve trade-offs between doing an activity (e.g., solving a task) *faster* and doing it *better*. While time choices in speed-accuracy trade-offs have been extensively studied in cognitive science for motor-response and perception tasks, little evidence is available for more deliberate economic decision-making, where people's choices often fail to maximize payoffs. Conversely, the impact of behavioral biases – key explanans of said failure – on time choices has yet to be explored. We present a theoretical model linking time choices in speed-accuracy trade-offs to an agent's abilities, subjective beliefs and uncertainty attitudes. We test the predictions of the model in an experiment for two distinct (but otherwise identical) environments: prospective time choices before solving a task and simultaneous time choices while solving a task. Correlational analyses indicate that overconfidence (in one's ability) and uncertainty aversion affect time choices in the prospective but not in the simultaneous environment. Probabilistic structural estimations, aimed at capturing the optimization process on the individual level, support this conclusion. This suggests that long-known behavioral biases influence decisions beyond classical domains like risk and intertemporal choice, but may "play out" differently in planned versus actual actions.

Keywords: speed-accuracy trade-off, time allocation, beliefs, probability weighting
JEL-Codes: C91, D01, D83, D90, D91

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1 Introduction

Humans frequently face trade-offs between doing a task *faster* or *better*. For example, imagine an employee in a company working on a task. The faster this employee finishes their task, the better for them (e.g., to engage in other responsibilities), at the same time, the more time the employee spends on the task, the higher the quality of the work, which similarly increases possible rewards. Thus, the worker must decide how much time they spend on their task to optimally balance the potential reward from finishing the task fast(er) or with high(er) accuracy.

Such trade-offs between speed and accuracy are of course not restricted to work settings and prevalent much more generally. Accordingly, extensive literature in psychology and neuroscience investigates human behavior in speed-accuracy trade-offs in perception and motor-control tasks (see the review in Heitz, 2014). This literature suggests that humans typically *optimally* trade off speed and accuracy in the presence of perceptual and motor uncertainty and choose time to maximize expected payoffs. Such optimal behavior is documented in tasks that require humans to identify the direction of motion of dots (Bogacz et al., 2006), to hit a target (Dean et al., 2007), to plan a precise movement (Trommershäuser et al., 2006), or to compare visual magnitudes (Bogacz et al., 2010; Desender et al., 2019).

However, whether these findings generalize to more complex environments is questionable. Many economics tasks require cognitively more demanding skills, while perception and motor-control tasks rely on "lower-level" cognitive processes. Thus, while humans often solve motor-control and perception tasks automatically and instinctively, their decisions in typical economic tasks are often more deliberate. For such deliberative decision-making, extensive literature in economics has established that humans seldomly make payoff-maximizing choices if they face risk and uncertainty (Kahneman & Tversky, 1979; Tversky & Kahneman, 1974, 1992) and often hold biased beliefs, e.g., about their ability (Moore & Healy, 2008). Moreover, economic environments often feature a "second type" of time choice where humans have to *plan* time prospectively, i.e., before working on a task. This is stark contrast to speed-accuracy trade-offs in motor-control tasks, which are solved *simultaneously* while doing the task. Related, for such prospective time choices, a literature in economics documents the impact of biases, such as an overoptimistic forecast of completion time, a phenomenon known as the "planning fallacy" (see e.g., Buehler & Griffin, 2015; Buehler et al., 1994).

In sum, it thus remains unclear how people resolve speed-accuracy trade-offs in more complex, deliberate, or prospective decision environments. How does a person choose time in a cognitively demanding task? Why do two similarly productive persons spend or plan time differently for the same task? What role do behavioral biases play in time decisions in such trade-offs? These questions are only poorly understood so far and this paper aspires to take a first step to understanding them better.

In this paper, we investigate time choices in speed-accuracy trade-offs in a cognitively demanding task. Specifically, we ask whether time choices in speed-accuracy trade-offs are affected by individuals' subjective beliefs about their ability and their uncertainty attitudes. Furthermore, we investigate if these effects differ between a deliberate environment, where time choices are made prospectively, and a simultaneous decision environment, where time is chosen while working on a task.

To study these questions, we propose a simple theoretical framework where an agent solves a speed-accuracy trade-off. Building on two-step models (Fox & Tversky, 1998; Wu & Gonzalez, 1999), we incorporate subjective beliefs about performance and uncertainty attitudes into an agent's decision-making process. Based on this framework, we derive hypotheses on how time choices are affected by the cost of time, as well as participants' performance, subjective beliefs, and uncertainty attitudes. We additionally derive a hypothesis on the difference between the determinants of time choices in prospective and simultaneous decision environments based on literature from psychology and neuroscience.

To test our predictions, we design a two-part laboratory experiment around a novel "cognitive visual search task". In the first part of the experiment, we measure time-dependent performance, beliefs about performance, and uncertainty attitudes toward working on the task in incentive-compatible ways. In the second part, we introduce a speed-accuracy trade-off in the visual search task by implementing a reward scheme where rewards depend on the correctness of the solution *and* time choices. We elicit participants' time choices in four situations, which vary along two dimensions (i.e., we implement a within-participant 2×2 design). The first dimension is the decision environment. We implement a "prospective" environment, in which participants have to pre-specify a time before working on the task, and a "simultaneous" environment, where participants make their time choices while working on the task. The second dimension is the cost of time, where we change the reward scheme and implement a high and low cost of time. We, therefore, investigate the influence of subjective beliefs and uncertainty attitudes along each of our two dimensions of the choice environment.

The main finding of this paper is that subjective beliefs and uncertainty attitudes (in addition to the cost-of-time and individual performance) predict how people solve speed-accuracy trade-offs and choose time in the prospective decision environment, which is in line with the theoretical framework. Conversely, but in line with the literature-based hypothesis, we do not find an association between either subjective beliefs or uncertainty attitudes and time choices in the simultaneous decision environment, while individual performance and cost-of-time remain significant predictors. This suggests that humans rely on their subjective beliefs and uncertainty attitudes to make prospective time choices in situations with speed-accuracy trade-offs, while these factors seem to play no significant role when the trade-off is solved simultaneous to the actual task. In an additional analysis, we investigate how subjective beliefs and uncertainty attitudes affect participants' payoffs through their time choices. We find that uncertainty aversion and underconfidence are associated with lower payoffs in the prospective high cost-of-time environment.

We derive a second set of results from a structural approach using Bayesian estimation techniques. Complementary to correlating time choices with data on overconfidence and uncertainty aversion, we formulate a Bayesian probabilistic model of solving the speed accuracy trade-off, i.e., the objective function participants are proposed to maximize. In a first step, we show how the proposed functional forms for time-dependent performance, as well as subjective beliefs and uncertainty attitudes reflect the data from the distinct experimental stages. Based on these functions (and their parameters), we can then propose, for each individual, a (probabilistic) *rational* solution to the speed-accuracy trade-off, i.e., a solution that solely depends on a participant's ability and the implemented cost functions as well as a *behavioral* solution, that additionally incorporates a participant's subjective beliefs and uncertainty attitudes into the objective function.

First, the probabilistic models show that both proposed solutions are reasonable benchmarks for participants' time choices across decision environments, validating the overall approach. Yet, individual predictions of *prospective* time choices can by improved by the behavioral model compared to the (more parsimonious) rational model. In contrast, this is not true for *simultaneous* time choices. A Bayesian model comparison that approximates out-of-sample predictive power between the "rational" and "behavioral" model supports these conclusions: For prospective time choices, behavioral predictions are more accurate; yet for simultaneous time choices, rational predictions perform better. The probabilistic model therefore directly corroborates the previous findings from the reduced form analyses.

Overall, our paper and its findings relate to several distinct literatures in economics. The first literature investigates *decision times* in economic choices (see Spiliopoulos & Ortmann, 2018, for a review). We connect to two distinct sub-branches of this literature. The first sub-branch connects decision times with economic decision-making under risk (Kirchler et al., 2017; Kocher et al., 2013; Rubinstein, 2013). This literature so far has produced mixed results: While Rubinstein (2013) finds that higher risk-taking correlates with lower decision times, Kocher et al. (2013) find no impact of time pressure on risk attitudes (for lotteries in the gain domain). In contrast to both, Kirchler et al. (2017) observe that lower decision times decrease risk-taking. While we do not aim to reconcile these mixed results, we contribute a new angle to this discussion: Our results suggest that uncertainty attitudes might not only affect the outcome of decision-making but that they might already influence the endogenous choice of decision time itself.

The second sub-branch of this literature investigates the *allocation* of decision time. Chabris et al. (2009) identify that people allocate decision time according to cost-benefit principles when making value-based choices between smaller-and-sooner versus larger-and-later payments and spend less time on their choices when the differences in value between the options are large. In contrast, Oud et al. (2016) find evidence for "irrational" time allocation, i.e., that people take too much time for choices between food options when the options offer similar value. Hausfeld and Resnjanskij (2018), instead, do not find conclusive evidence for irrational time allocation in lottery choices and propose that decision-makers trade-off decision quality and decision speed when the opportunity cost of time is high. Similarly, Olschewski et al. (2024) find adaptation to the opportunity cost of time in lottery choices. We provide two new perspectives to this discussion: First, instead of studying value-based decision-making or choices in lotteries, we investigate time allocation in a cognitively-demanding task where time is the main input to arrive at an objectively correct solution. Second, we provide evidence that participants seem to act according to rational considerations in a simultaneous decision environment when deciding how much time to spend to solve a problem.

Our study is also related to a literature investigating the origins of the planning fallacy. Kahneman and Tversky (1982) propose that the planning fallacy originates in the human tendency to rely on intuitive "internal judgments" when planning a project. These intuitive judgments neglect information about other similar projects and their completion time. In contrast to this view, Brunnermeier et al. (2008) develop a model where the planning fallacy results from agents' optimal reaction to their distorted subjective probabilities. They propose a theoretical model, review existing empirical evidence, and largely find support for their model. We provide new evidence that planned actions indeed depend on subjective and possibly inaccurate estimates of (performance-based) probabilities and thus support the interpretation by Brunnermeier et al. (2008). The discussion of the origins of the planning fallacy is also related to a recent interest in economics to understand the differences between planned and actual attention. Avoyan et al. (2023) find that planned attention (i.e., a pre-specified time budget for a strategic game) and actual attention (i.e., how long people then look at a specific game) do not coincide. They investigate this disparity and find that salient features of the games (e.g., payoff numbers) affect the planned attention, while their actual strategic complexity determines actual attention. We add to this by showing that planned (time) choices are more likely susceptible to biased, subjective interpretations of the decision problem, whereas actual time choices are more determined by the (difficulty of the) task at hand.

Finally, we relate to economic literature, which investigates the time usage of persons (Aguiar & Hurst, 2007; Aguiar et al., 2012, 2013; Becker, 1965; Goldszmidt et al., 2020; Juster & Stafford, 1991; Stratton, 2012). This literature highlights the importance of the opportunity cost or the value of time for decision-making, e.g., in households' decisions to substitute between market and non-market activities, for workers searching for a job or deciding how many hours of labor to supply. To measure the value of time, this literature often relies on people's observed choices and subsequently uses those measures to assess the possible time-saving benefits of policy interventions (Goldszmidt et al., 2020). Our results suggest that economic agents' perception of their opportunity cost or value of time are likely influenced by behavioral factors, such as overconfidence in their ability to find a job or to earn a certain amount of money given an input of work hours. Our results – interpreted in a broader sense – suggest that measures of the value of time solely based on observed choices may provide a skewed picture of the actual underlying valuation of time.

The remainder of this paper is structured as follows: Section 2 introduces our theoretical framework and derives hypotheses. Section 3 describes the experiment, and Section 4 introduces different measures of performance, subjective beliefs about performance, and uncertainty attitudes and provides empirical evidence on their distribution. The following two sections provide reduced form (section 5) and structural (section 6) results on the relation between the (behavioral) measures, time choices, and payoffs. Section 7 concludes.

2 Theoretical Framework

This section presents a simple theoretical model demonstrating the economics of time choices in a speed-accuracy trade-off. In our model, agents choose how much time they take to solve a given task to maximize a payoff function. We assume that this payoff function contains two components. The first component captures an agent's performance (or accuracy) in a given task which we model as the time-dependent probability $p(t)$ that an agent solves a task correctly. We assume that this probability is concave and strictly increases in time (i.e., $p'(t) > 0$ and $p''(t) \leq 0$). The second component is a reward function $y(t)$, which specifies the time-dependent reward for solving the task. We assume that agents solve the following optimization problem:

$$t^* = \text{argmax}_t \Pi(t) = p(t)y(t) \tag{1}$$

where t is the main choice variable and t^* the optimal amount of time that maximizes payoffs. This general framework does not yet contain a speed-accuracy trade-off without a more restricted definition of $y(t)$. In the real world, time is a costly resource, and the rewards for solving a task are often only paid if it is solved correctly or to a sufficient threshold. Therefore, we assume the following simple reward function:[1]

$$y(t) = \begin{cases} Y - c(t) & \text{if task is solved correctly and } Y > c(t) \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

In this reward function, Y describes a fixed maximally possible reward for solving a task and $c(t)$ the cost of time, which we assume to be concave and strictly increase in time (i.e., $c'(t) > 0$ and $c''(t) \leq 0$). $c(t)$ can thus be understood to encompass both the labor or effort cost of solving a task, as well as the opportunity cost of time. This reward function introduces the central tension: To maximize (expected) payoff, an agent needs to solve the task as fast as possible, as the reward reduces in time, but as accurately as possible, as the reward can only be gained by providing an accurate (i.e., correct) solution. This creates incentives for both fast and accurate solutions, and the optimal action of an agent is to implement the unique time choice t^* that maximizes equation 1.[2]

How does this optimal time choice change when the cost of time $c(t)$ in equation 2 changes? For ease of exposition, assume that two situations exist such that $c_1(t) > c_2(t)\ \forall\ t$. These different costs of time imply different optimal time choices and generate the first general prediction[3]:

Prediction 1: *If the cost of time is high (low), an agent chooses little (more) time to solve the task.*

How does the optimal time choice depend on an agent's performance $p(t)$? Assume that two (otherwise identical) agents i and j differ in their ability irrespective of time, such that $p(t)_i > p(t)_j\ \forall\ t$. Thus agent i has a higher performance than agent j and equation 2 implies that $t_i^* < t_j^*$. This means that the optimal time choice for agent i is lower compared to agent j and generates the second prediction:

Prediction 2: *A more (less) performant agent chooses less (more) time.*

In contrast to the fully optimal decision maker, we now introduce a behavioral agent with two behavioral characteristics: (1) subjective beliefs and (2) uncertainty attitudes. These two characteristics are important drivers of choices in decisions over uncertain events, where objective probabilities are unknown to the decision-maker (see e.g., Fellner, 1961), and the outcome of any choice is inherently uncertain. We follow the previous literature on two-step models that incorporate both behavioral character-

1 We could also assume an accuracy threshold, which needs to be crossed, or time-dependent benefits. We focus on the binary outcome of a correctly or incorrectly solved task for simplicity of exposition.

2 See Appendix A.3.1 for a formal proof of the uniqueness of the maximum.

3 We discuss the generality of all predictions in Appendix A.3.2.

istics in the formulation of overall decision weights in the presence of uncertainty (Fox & Tversky, 1998; Kilka & Weber, 2001; Tversky & Fox, 1995; Wakker, 2004; Wu & Gonzalez, 1999). The first step is a translation of events (i.e., how likely is a correct solution with time t) into subjective probability judgments. The second step is mapping the subjective probabilities into decision weights. The first step captures our notion of over-/underconfidence and the second of uncertainty attitudes.

In the first step, a behavioral agent replaces $p(t)$ with a subjective belief $b(t)$. Importantly, in our task, only two outcomes exist: E a correct solution and $\neg E$ its complement. Therefore, we shorten $b(E|t)$ to $b(t)$ for brevity and define this as the subjective belief of a correct solution conditional on time t.[4] We do not impose any assumptions about the origin, formation, and shape of subjective beliefs, as many mechanisms and specifications are possible.[5].

In the second step, an agent weights the subjective probabilities $b(t)$ by a weighting function $w(\cdot)$, which reflects attitudes towards the time-dependent probabilities with which the rewards for a correct solution can be obtained (c.f. Fox & Tversky, 1998; Kilka & Weber, 2001; Tversky & Fox, 1995). Such probability weighting is a well-established feature in the domains of risk and uncertainty (Abdellaoui et al., 2005; Gonzalez & Wu, 1999; L'Haridon & Vieider, 2019; Li et al., 2018; Trautmann & van de Kuilen, 2015; Tversky & Kahneman, 1992; Wakker, 2010), where agents typically overweight small and underweight large probabilities.[6]

Jointly, both subjective beliefs and probability weighting imply that behavioral agents maximize a modified behavioral version of equation 2:

$$t^B = \text{argmax}_t \Pi^B(t) = w(b(t))y(t) \tag{3}$$

This implies two new predictions. First, consider an agent who overestimates their ability, i.e., $b(t) > p(t)\ \forall\ t$. Maximizing 3 results in a behavioral time choice $t^B < t^*$. This is because the agent overestimates their performance at a given task and thus decides to invest less time. This is Prediction 3:

Prediction 3: *An over(under)estimating agent chooses less (more) time.*

4 Similar to Wakker (2004, p. 237) we do not impose additivity as a condition for $b(t)$, i.e., $b(E|t) + b(\neg E|t) \neq b(S|t)$, where S represents the sample space of outcomes.

5 For example, one mechanism could be general over- or underconfidence, due to an agent's tendency to over-/ underestimate their own ability (Moore & Healy, 2008; Moore & Schatz, 2017). Alternatively, cognitive approaches suggest the potential for insufficient adjustment away from over- or underoptimistic defaults due to limited attention (e.g., Gabaix, 2019), and psychological research demonstrates effects of the difficulty of a task on overconfidence (e.g., Lichtenstein & Fischhoff, 1977)

6 Similar to subjective beliefs, we do not impose any assumptions about the source of probability weighting, but recent evidence suggests that cognitive factors could determine weighting behavior, such as a compression of probabilities towards mental defaults of 50:50 due to cognitive noise (Enke & Graeber, 2023), or a mental coding of probabilities in log-odds (Zhang & Maloney, 2012).

Similarly, consider an agent who consistently underweights subjective probabilities by some weighting function, i.e., $w(b(t)) < b(t)\ \forall\ t$. Compared to an "uncertainty-neutral" agent (i.e., for whom $w(b(t)) = b(t)\ \forall\ t$), this agent's time choice is larger, i.e., $t^B > t^*$. In other words, an uncertainty-averse agent invests more time to increase the probability of success, as they undervalue a given subjective probability $b(t)$. This is Prediction 4:

Prediction 4: *An over(under)weighting agent chooses less (more) time*

The presented theoretical framework and our hypotheses predict that time choices, as solutions to the maximization problem, are not directly affected by the decision environment for otherwise mathematically equivalent trade-offs. However, this might not be the case. A small literature in cognitive science investigates differences between motor-tasks and mathematically equivalent economic lottery tasks (Trommershäuser et al., 2008; Wu et al., 2009). This literature finds that participants can solve motor-task tasks nearly optimally but are affected by probability weighting and thus fail to maximize their payoff in the equivalent lottery choices. This suggests that solutions to maximization problems depend on *how* trade-offs are being solved and that behavioral factors could play a more critical role in deliberate choice environments than when choices are made intuitively.

The exact reasons for this discrepancy are not yet fully explored. One potential explanation relates to the time available to make choices. In typical lottery tasks, people can deliberate and weigh the options before making a choice. In contrast, people have to make choices more intuitively and respond quickly in typical motor tasks. Research in psychology suggests that humans use simpler decision rules and heuristics and change their information acquisition patterns under time pressure (Payne et al., 1996; Rieskamp & Hoffrage, 2008; Wu et al., 2022). This may leave less room for subjective interpretations of the decision problem and lead to seemingly more rational choices. A second possible explanation stems from a literature in psychology that shows that participants choose different amounts of time when planning a task prospectively, compared to choosing time while working on the task. This is known as the "planning fallacy" (Buehler et al., 1994) and describes the phenomenon that humans typically overestimate their future ability and thus underestimate the time required to complete (or reach a particular performance in) a future task (see the review in Buehler & Griffin, 2015). Overall, this suggests that time choices and their determinants likely depend on the decision environment. Subjective considerations, such as probability weighting or assessments of ability, are more likely to affect time choices in environments where time is planned prospectively. These effects should be weaker when time is chosen while working on the task. This leads to an additional and literature-based prediction:

Prediction 5: *Overconfidence and overweighting affect time choices more strongly in prospective decision environments compared to time choices made while solving a task.*

3 The Experiment

We designed an experiment around a "cognitive visual search task" to test our predictions. This task allows us to easily measure the relevant participant-level characteristics and implement a highly salient speed-accuracy trade-off. We test our theoretical predictions in a within-subject design for different decision environments and cost-of-time specifications, which we describe in more detail below.

3.1 Experimental Design

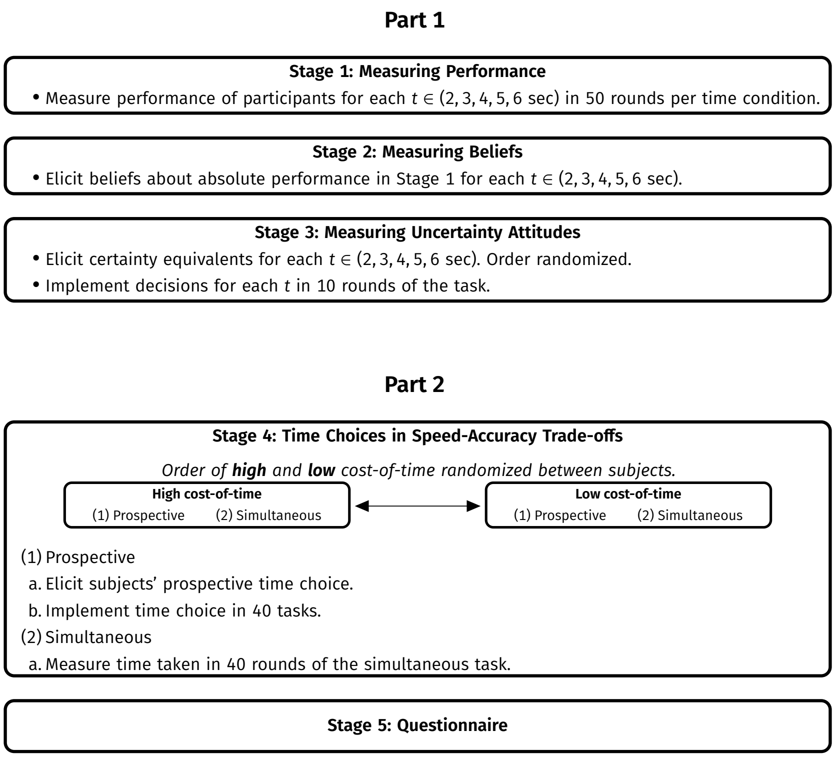


Figure 1. Outline of the Experiment

The experiment consists of two parts (see Figure 1). In the **first part**, we elicit participants' time-dependent performance, subjective beliefs about performance, and uncertainty attitudes. In the **second part**, we introduce the speed-accuracy trade-off and observe participants' time choices in two decision environments and for two cost-of-time specifications. At the beginning of part one and part two, participants have training rounds to familiarize themselves with the task. The experiment concludes with a questionnaire. We first introduce and describe the main task before describing the experiment's structure and the experimental implementation.

Main Task. In the main task of our experiment, participants need to select the two-digit Arabic number with the highest value in a 4×4 table of 16 numbers in a certain amount of time (see Figure 2). The experimental screen shows the remaining time as a decreasing bar over the table and the reward for a correct and incorrect solution below. We sample the numbers in the table such that the task always has similar difficulty across repetitions.[7] Once a participant selects a cell in the table, it is highlighted in yellow. Participants can change their selection as long as there is time available. When the time runs out, the currently selected cell is automatically submitted as the participant's answer.[8]

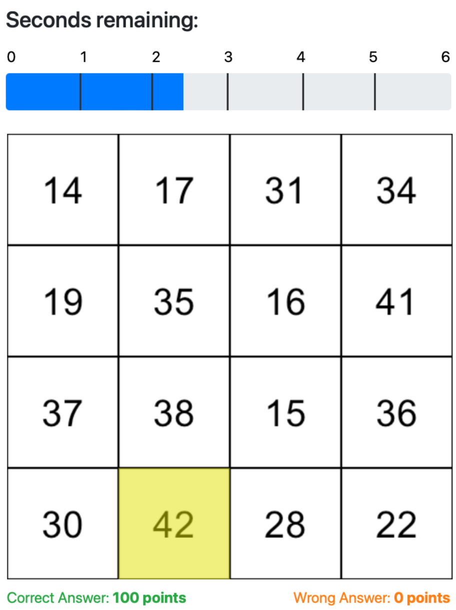


Figure 2. Main Experimental Task

We designed this task to combine the advantages of classical paradigms used to investigate speed-accuracy trade-offs with a more cognitively demanding task that captures relevant aspects of economic decision-making. Similar to classical tasks in cognitive science (such as random-dot kinematograms, motor-control tasks, or goal-directed movement tasks (see Heitz, 2014, for a review), participants can learn our task extremely fast and do many repetitions in a reasonably short amount of time, allowing

7 Accordingly, the 16 values in the table are sampled in the following manner: Firstly, we sample a solution, such that $41 \leq \text{solution} \leq 90$. Secondly, we sample the remaining 15 numbers by simple random sampling without replacement from $[\text{solution} - 31, \text{solution} - 1]$. The 16 values are then randomly placed on the table. See Appendix A.4 for a more thorough explanation of the sampling mechanism of the matrices for each experimental stage.

8 This does not yet implement a speed-accuracy trade-off without time costs. We discuss how we implement the speed-accuracy trade-off in our description of the second part of the experiment.

us to collect multiple data points and get a robust estimate of their time-dependent performance. However, our task is distinct from classical paradigms in one crucial area: Instead of relying on intuition, automatic responses, or hand-eye coordination (requiring very fast time choices within a few milliseconds), our task is cognitively more demanding and requires both working memory capacity and (numerical) cognition. Our task, therefore, requires skills that are essential requirements and determinants of performance on the job in many occupations (Brown et al., 2020; Corgnet et al., 2015; Hanushek et al., 2015).

Stage 1: Performance. In stage one of the experiment, we measure participants' time-dependent performance in the main task. More specifically, we fix the time and reward scheme and measure participants' performance in 2, 3, 4, 5, and 6 seconds in 50 tasks each. Participants get a payoff of 100 points for each correctly solved task and 0 points if they do not select the correct solution before the allocated time has run out. The 250 tasks are divided into five rounds, and each round is divided into five blocks. Each block consists of ten tasks with a constant fixed time (i.e., one block contains ten tasks with either 2, 3, 4, 5, or 6 seconds each). Overall, stage one adheres to the following structure:

$$\underbrace{\underbrace{\text{10 tasks with 6 seconds}}_{\text{Block 1}}\ \underbrace{10\times 5s}_{\text{Block 2}}\ \underbrace{10\times 4s}_{\text{Block 3}}\ \underbrace{10\times 3s}_{\text{Block 4}}\ \underbrace{10\times 2s}_{\text{Block 5}}}_{\text{Round 1}} \quad \underbrace{\underbrace{10\times 6s}_{\text{Block 6}}\dots\underbrace{10\times 2s}_{\text{Block 10}}}_{\text{Round 2}} \quad \dots \quad \underbrace{\dots\ \underbrace{10\times 2s}_{\text{Block 25}}}_{\text{Round 5}}$$

Before the first task in each block, participants see a countdown, followed by a fixation cross in the middle of the screen (see Figure A14). After each block, participants take a small break of ten seconds and an extended break of up to two minutes after each round (i.e., after 50 tasks).

Stage 2: Beliefs. In the second stage, we elicit participants' belief distribution about their performance for each fixed time in stage one (2,3,4,5,6 seconds) using a *ball allocation task* (see Figure A11 for a screenshot of the task).[9] In each task, participants allocate 100 virtual balls into ten bins. Each bin represents an interval of five correctly solved tasks (e.g., the first bin represents between zero and five correctly solved tasks, the second bin between six and ten correctly solved tasks, etc.), and each ball represents one percentage point of the belief distribution. By distributing 100 balls across all bins, subjects report their belief distribution about their performance in stage one. Participants do five ball allocation tasks (one for each fixed time from stage one), which are unannounced, and the instructions are only presented on-screen. We incentivize each

9 This task was first introduced in surveys by Delavande & Rohwedder (2008, 2011) and recently applied in incentivized experiments by Drerup et al. (2017), and Chen and Schildberg-Hörisch (2019).

of the five ball allocation tasks individually according to the randomized quadratic scoring rule (Hossain & Okui, 2013; Schlag & Van Der Weele, 2013) similar to Chen and Schildberg-Hörisch (2019). Accordingly, participants can win a fixed amount of 250 points for each ball allocation task in a binary lottery. The probability of winning the prize increases in the number of balls a participant allocates to the bin that contains the actual number of correctly solved tasks.[10]

We chose to elicit belief distributions, as it is unclear how humans rely on their belief distribution (e.g., on which moments) when asked for a point estimate (Engelberg et al., 2009). Eliciting the full distribution provides a richer data set and allows us to investigate different moments and measures of centrality. The approach to elicit belief distributions instead of point predictions is an increasingly popular feature of recent experimental papers (Bruhin et al., 2018; Chen & Schildberg-Hörisch, 2019; Crosetto & De Haan, 2023; Eyting & Schmidt, 2021).

Stage 3: Uncertainty Attitudes. In the third stage, we elicit participants' certainty equivalents for each fixed time (2,3,4,5,6 seconds) and the same reward scheme as in stage one using choice lists. Participants work on ten tasks for each fixed time in this stage, but they choose the *payment scheme* for these tasks themselves. For each fixed time, participants choose the payment scheme from a table that contains 21 rows (see screenshot A12 in Appendix A.5.3). In each row, participants choose between payment scheme A – which is the same as in stage one (i.e., 100 points for a correct answer and 0 otherwise) – and scheme B – which always yields a fixed reward, regardless of the correctness of their solution. The fixed reward increases by five points from 0 to 100 points in each row. Similar to previous studies (e.g., Enke & Graeber, 2023; Gonzalez & Wu, 1999; Oprea, 2024), we enforce consistency of choices and allow only a single switching point in the entire table, i.e., participants can switch at most once between scheme A and B. In addition, we implement an auto-completion for the choice lists to ease elicitation further: When a participant chooses scheme B in one row, the computer fills all preceding rows with scheme A and subsequent rows with scheme B. Participants can revise the switching point suggested by the computer and have to confirm their final choice. At the beginning of stage three, participants answered five comprehension questions about this mechanism.

After participants fill out the choice lists for all fixed times (order randomized), they solve 50 tasks, 10 for each time. Participants' reward scheme for each time is determined by randomly drawing one row of the associated choice list and implementing

10 We calculate an integer $W = \sum_{j=1}^{10} (b_j - 100 \times \mathbb{1}_j)^2$ for each individual and every ball allocation task. b_j captures the number of balls in bin j, and $\mathbb{1}_j$ is an indicator function that is equal to 1 if bin j contains participants' actual performance. We then draw a random integer (H) from the uniform distribution with the bounds 0 and $20,000$. If W is higher than H, the participant gains a payoff of 250 points and 0 otherwise.

this choice. When participants choose the safe amount in the drawn row, they still see the ten tasks, but their reward remains independent of their answer. We made this design decision to minimize the effect of participants wanting to finish the experiment quicker, not wanting to work on the task, or wanting to relax.[11] Participants see the randomly drawn row, their choice in that row, and the resulting payoff scheme before working on the ten tasks for each time.

Stage 4: Time Choices in Speed-Accuracy Trade-offs. In the fourth stage, we implement a speed-accuracy trade-off in our task and elicit participants' time choices. More specifically, we change the (so far fixed) reward scheme into a time-dependent *reward function*, which reduces the reward for a correct answer the longer a participant chooses to work on a task. Facing this reward function, participants have to solve a speed-accuracy trade-off, where higher time choices simultaneously decrease – due to the cost of time – and increase – due to the higher accuracy or performance – their (expected) reward. We choose the following easily understandable piecewise linear reward function:

$$y(t) = \begin{cases} 150 - \kappa t & \text{if task is solved correctly and } t < \frac{150}{\kappa} \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

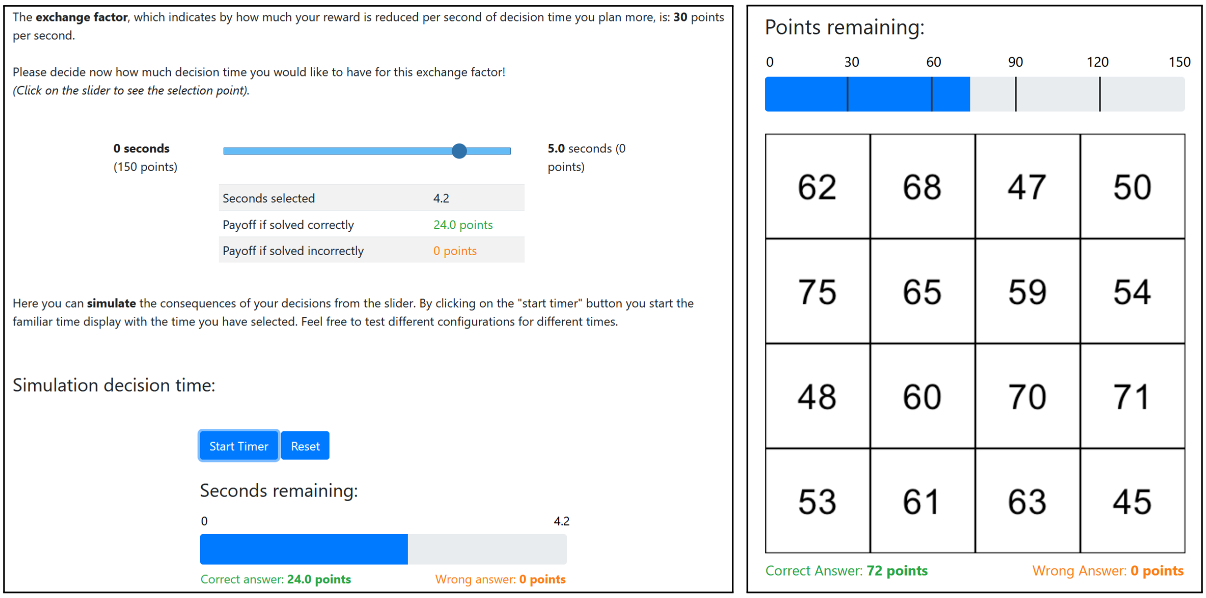
This function is equal to the reward function in equation 2 with a fixed maximum payoff Y of 150 points and a linear function for the cost of time $c(t)$, where each second reduces the reward by κ points.[12]

We implement two cost-of-time parameters κ to test **Prediction 1**. We predicted that in situations where the cost of time is low, participants take relatively more time than in situations where the cost of time is high. We therefore implement a high ($\kappa = 30$) and low ($\kappa = 10$) cost-of-time. In the low cost-of-time setting, the reward is equal to the previous stages (i.e., 100 points) when taking 3.33 seconds to answer correctly and equal to 0 after 15 seconds. In the high cost-of-time setting, these times are shorter, and participants get a reward of 100 for solving the task in 1.67 seconds and 0 if they do not select the correct answer within 5 seconds. We randomize the order of the two cost-of-time settings between participants.

11 In fact, even for the lowest time (2 seconds), only 3% of participants choose the safe reward in all rows. This provides evidence that participants try to optimize their payoffs rather than minimize their time working on the task. Furthermore, in the implementation stage, participants selected an answer in 86.4% of the tasks in the safe payment scheme (B) (versus 97.9% in payoff scheme A). This indicates that choices for B are not driven by the desire to relax.

12 While we could use a more complex reward function (e.g., a logarithmic cost-of-time), we chose a linear function to facilitate participants' understanding of the trade-off.

We introduce two different decision environments that vary how participants choose the time to work on our task. We call the first the "prospective" and the second the "simultaneous" environment.



(a) Prospective **(b)** Simultaneous

Figure 3. Experimental Decision Screens: Prospective and Simultaneous

In the *prospective* environment, participants choose the amount of time for 40 tasks ex-ante before working on the tasks. They enter their choice via a slider, which updates a table where participants see the payoffs from a correct (and incorrect) answer. Additional to the reward table, a "simulation area" below the slider allows participants to simulate their time choice. The simulation area contains a progress bar – similar to all previous tasks – that updates live to their chosen time. Participants can start a timer simulation, where the progress bar simulates the time for one task. We chose this feature to maximize the salience of the trade-off. The decision screen is presented in Figure 3 a).

In the *simultaneous* condition, participants decide on the amount of time for each task while solving the task by choosing when to submit their final answer. We alter the progress bar for this environment to show the remaining points for a correct answer instead of the remaining time. The speed of the progress bar is determined by the cost of time and the maximum amount of points. Participants select an answer by clicking on a cell and submit their answer by clicking on an already selected cell (see Figure 3 b) for a screenshot of the decision screen).

Overall, stage four thus contains four sub-phases (prospective low, prospective high, simultaneous low, and simultaneous high) with 40 tasks per sub-phase. Participants first work on the prospective task before working on the simultaneous task within the same cost-of-time condition.

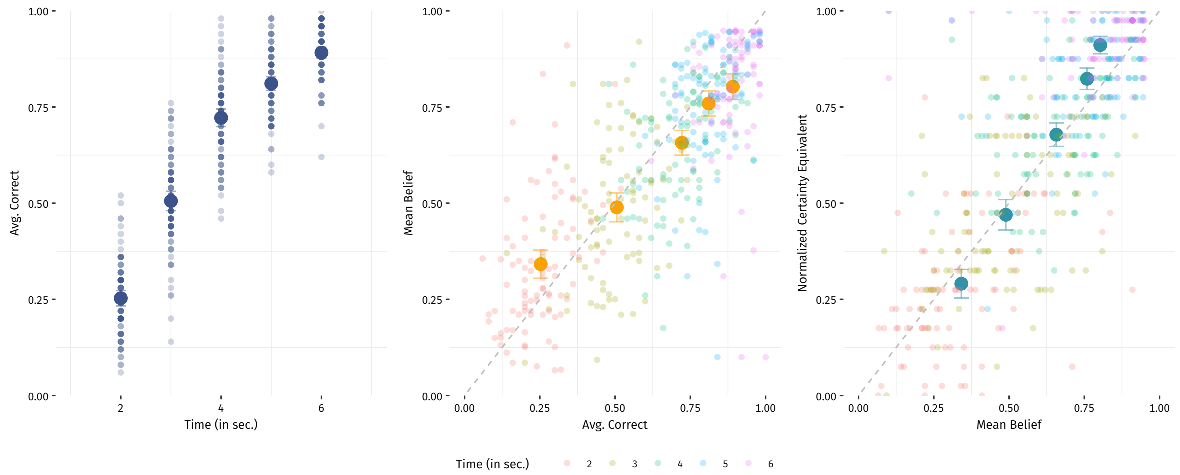
Stage 5: Questionnaire and Additional Measures. We collect additional participant-level data in stage five. First, we measure participants' reaction time via a modified version of our main task. Here, participants need to identify a single "X" among 15 "0"s in the familiar 4x4 table (see screenshot A13). The maximum reward they can earn is 50 points, and the cost-of-time is 10 points per second. Like in the simultaneous environment, participants must select and submit their selection with one mouse click each. In total, participants solve 30 reaction-time-tasks. Secondly, we collect survey measures of risk and time preferences according to the Global Preference Survey (GPS) module (Falk et al., 2023), subjective fatigue levels during the week and right after the study using visual analog scales (Radbruch et al., 2003), competition preferences (Fallucchi et al., 2020), and participants' basic socio-demographic information. Furthermore, we elicit subjectively perceived time pressure during the tasks in the prospective and simultaneous environment.

3.2 Implementation

We pre-registered the experiment in June 2021 (AEA RCT Registry No. 7748) and subsequently conducted sessions at the MABELLA laboratory a the University of Mainz in June and July 2021. Participants were invited using ORSEE (Greiner, 2015), and the experiment was programmed in oTree (Chen et al., 2016). 91 participants, all with (corrected to) normal vision, in 15 sessions participated in the study. Each session lasted between 1:45 and two hours. Participants earned 23.70€ on average (min: 18.90€; max: 30.40€), which includes a 5€ show-up fee. To limit outside influences on participants' time choices inside the experiment (e.g., wanting to leave the lab earlier), we instructed participants that they would have to wait until everybody in their session had finished the experiment and would only receive payment afterward. The experimental currency was called points during the experiment, and the exchange rate was 100 points = 0.20€. In each experimental stage, 30% of the tasks were randomly selected for payoff. After arriving at the lab, we assigned each participant a random seat in the laboratory, where they received printed instructions about the experiment. We instructed participants only to read the relevant instructions for each stage. Each stage at the computer ended with a prompt for participants to read the next part of the instructions. The elicitation of beliefs was unannounced and explained on screen, not in the printed instructions. Participants could contact the experimenter via a chatbox or raise their hands if they had questions. The translated instructions are available in Appendix A.5.1.

4 Experimental Measures and Descriptives

This section briefly describes the measures and descriptive data on the three components we predicted to impact participants' time choices: participants' performance, their beliefs, and their uncertainty attitudes (see Figure 4).[13]



(a) Performance **(b)** Beliefs **(b)** Uncertainty Attitudes

Figure 4. Descriptive Results: Performance, Beliefs and Uncertainty Attitudes This graph plots individual and average (over individuals) datapoints for average correct solution in stage 1 of the experiment by available decision time (a), the mean of participants' belief distribution from the ball allocation task and their true average correct solution (b), as well as their normalized certainty equivalent from the multiple price lists given their mean belief (c). We color-code beliefs (b) and normalized certainty equivalents (c) by the respective time.

4.1 Performance

We measure time-dependent performance for each participant based on the number of correct solutions for each of the five fixed times (2,3,4,5,6 seconds) in stage one of the experiment. A first – aggregate – measure is the mean performance of each participant, i.e., the fraction of correct solutions across all time conditions (μ^i). On average, participants answer 63.6% of the 250 tasks correctly across all fixed times. A less aggregate approach is to calculate five measures of mean performance, one for each fixed time (μ^i_t). As expected, participants' performance is worst in 2 seconds (25.3% correct solutions) and increases with more time (3 sec: 50.6%; 4 sec: 72.2%; 5 sec:

13 Figure A3 in Appendix A.2 provides the empirical cumulative distributions based on the raw data.

81.1% and 6 sec: 89.1%).[14] Panel (a) of Figure 4 further reveals a considerable degree of individual heterogeneity in time-dependent performance.

4.2 Beliefs

We measure participants' subjective beliefs about their performance based on the data from the ball allocation task in stage two. We follow a similar approach to Engelberg et al. (2009) and Delavande & Rohwedder (2008, 2011) to provide a parsimonious description of subjective beliefs. First, we fit a distribution on the data from each ball allocation task (2 sec., ..., 6) and obtain the distribution's moments and measures of centrality. More specifically, we fit a two-parameter beta distribution by maximum likelihood if a participant allocates probability mass (i.e., balls) into more than one bin and an isosceles trapezoid distribution if a participant allocates all probability mass into only one bin. We subsequently use the mean of the belief distribution as our measure of participants' subjective beliefs for the analysis. The mean – in contrast to the mode or median – has the advantage that it provides a measure based on the entire distribution of elicited beliefs.[15]

Panel (b) of Figure 4 plots the mean belief to the average number of correctly solved tasks (separated by the available time), both on an aggregate and individual level. On average, participants' mean belief is 0.34 with 2 seconds, 0.49 with 3, 0.65 with 4, 0.75 with 5 and 0.8 with 6 seconds, indicating slight overweighting of lower average performance, yet underweighting of larger average performance. On an individual level, we match the mean belief in a given time to the average performance in that time and again observe a considerable amount of individual differences.

In addition, we can construct a parsimonious measure of over- and underconfidence: We apply a similar approach to Chen and Schildberg-Hörisch (2019) and com-

14 Parametric and non-parametric tests (i.e., t-tests, Mann-Whitney-U tests, and Kolmogorov-Smirnov tests) confirm that an increase in the available time leads to significant (all pairwise comparisons $p < 0.001$) differences (increases) in performance in terms of the mean, mean rank and across the entire distribution

15 Engelberg et al. (2009) and Kröger and Pierrot (2019) investigate which measure of centrality (i.e., the mean, mode, or median) of elicited belief distributions of professional forecasters most strongly correlates with their point predictions. Engelberg et al. (2009) finds no significant differences, while Kröger and Pierrot (2019) suggest that the mode or the mean might fit the data better than a specific quantile (i.e., the median). While reassuring, the implications for our setting are limited as we inspect retrospective beliefs about own performance rather than beliefs about uncertain future events. Regardless, we replicate our principle analysis with the median and the mode of the belief distributions and report the results in the Appendix. We find that estimation results of the most parsimonious model with the median (see Table A7 to A10) and the mode (Table A11 to A14) closely match our main results. While all estimates are numerically similar, minor differences exist in standard errors and p-values. Overall, we conclude that the main results are largely robust to alternative measures for subjective beliefs.

pare participants' mean subjective beliefs to their estimated 95% performance interval.[16] We define a participant to have well-calibrated beliefs for time $t \in (2, \ldots, 6)$ if the mean subjective belief for time t is within the confidence interval, and we assign a value of 0 to the measure of overconfidence. When the subjective belief is above or below the confidence interval, we subtract the value of the closest bound. The resulting measure is negative for underconfident and positive for overconfident agents and describes by how many percentage points participants over- or underestimate their performance. On average, participants slightly overestimate their performance with 2 seconds (by 4.2pp.) and underestimate it for all other fixed times (3 sec: -0.01pp.; 4 sec: -2.6pp.; 5 sec: -2.7pp. and 6 sec: -4.4pp.), matching the aggregate data from panel (b) of Figure 4. Consequently, the mean mean of these five time-dependent measures reveals that that participants slightly underestimate their ability on average (by 1.2pp.; t-test of mean $= 0$: $p = 0.082$).

4.3 Uncertainty Attitudes

Finally, we construct the measure of participants' uncertainty attitudes from the data gathered in the multiple price lists in stage three of the experiment. We define the normalized certainty equivalent $NCE_{t,i}$ for each participant i and time t as the midpoint of the interval between the rows of the multiple price lists where participants switched from payoff scheme A (100 points for a correct solution, 0 otherwise) to payoff scheme B (sure payoff). If a subject always chooses payoff scheme A (B), we code their NCE with 1 (0).[17] Assuming linear utility, the $NCE_{t,i}$ correspond to the implied probability weight (L'Haridon & Vieider, 2019).

However, the normalized certainty equivalents do not have a straightforward interpretation by themselves. In the literature on risk and uncertainty, normalized certainty equivalents are usually obtained for – and compared to – objective probabilities. In contrast, we elicited them for a specific reward scheme and a given amount of time t to work on our task. In line with the two-step model outlined in Section 2, we, therefore, relate the NCE_t^i data to participants' *subjective beliefs*. Specifically, we calculate the difference between the NCE and the mean of participants' belief distribution for each time

16 We define upper and lower 95% confidence bounds of performance by an approach similar to Chen and Schildberg-Hörisch (2019) and calculate 95% Wilson score intervals for the share of correct solutions for each fixed time and each participant. While Chen and Schildberg-Hörisch (2019) rely on Wald-type approximations, we use Wilson score intervals, as Brown et al. (2001) provide evidence that standard Wald-type approximations are often severely biased in the case of binary outcome data. This is especially the case when the outcome is close to 0 or 1, which is true for the performance of many participants with two or six seconds. In these cases, Brown et al. (2001) suggests using Wilson score intervals. These upper and lower confidence estimates provide a more robust performance measure.

17 This occurred in 6.6% (=30) of choices across all 455 multiple price lists.

t. This provides a measure of over-/ underweighting, which is positive for uncertainty-averse and negative for uncertainty-seeking agents. On average, participants slightly overweight subjective beliefs with 2 (by 5.0pp.) and 3 seconds (by 1.9pp.) and underweight it for all other fixed times (4 sec: -2.1pp.; 5 sec: -6.2pp.; 6 sec: -10.3pp.). We define the mean of these five time-dependent measures as our measure of average uncertainty aversion and find that our experimental sample is, on average, slightly uncertainty-seeking (by 2.3pp.; t-test of mean $= 0$: $p = 0.055$).

5 Reduced Form Results

We first summarize participants' time choices in the second stage of the experiment. Subsequently, we conduct regression analyses to test our experimental hypotheses about the relationship between our experimental measures and their predicted effects on time choices.

5.1 Time Choices

Figure 5 plots participants' time choices in both decision environments and for both cost-of-time parameters. For the prospective task, we use participants' time choice directly and rely on the mean time choice for the simultaneous task. We formulate three observations based on the raw time choice data.

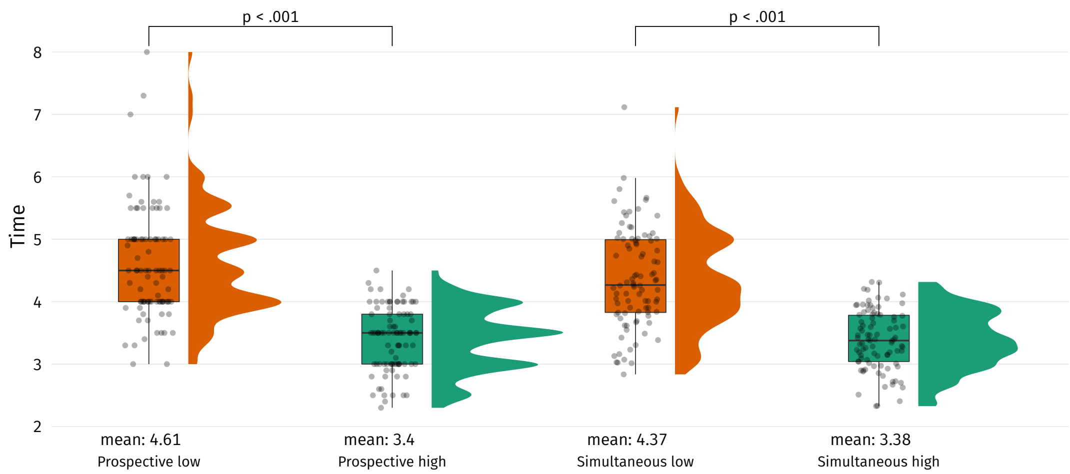


Figure 5. Time Choices across Environments and Cost   This graph shows participants' time choices in the prospective task and mean time decision in the simultaneous task for both cost-of-time environments. The means are calculated for each cost-of-time and decision situation. The brackets and p-values signify comparisons of two outcomes using two-sided paired t-tests

Firstly, irrespective of the decision environment (i.e., prospective or simultaneous), participants react to the two cost-of-time parameters in the direction predicted by our theoretical framework. 95.6% of participants choose more time (1.20 seconds longer) in the low cost-of-time situation compared to the high cost-of-time situation in the prospective environment.[18] In the simultaneous choice environment, all participants have a higher average response time (by 0.99 seconds) for the low cost-of-time setting. These differences confirm that participants choose significantly (both t-tests: $p < 0.001$) more time in the low cost-of-time condition compared to the high cost-of-time condition.

Result 1: *Consistent with prediction 1, participants take more (less) time when the cost-of-time is low (high).*

Secondly, both time choices in the simultaneous environment are strongly correlated (Spearman's $\rho = 0.79, p < 0.001$) as well as the average response times in the prospective environment (Spearman's $\rho = 0.53, p < 0.001$). Conversely, the correlation between the same cost-of-time condition and across decision environments is smaller (high cost-of-time: Spearman's $\rho = 0.26, p = 0.012$; low cost-of-time: Spearman's $\rho = 0.40, p < 0.001$). This indicates that participants' time choices correlate more strongly within the same decision environment than within the same cost-of-time condition.

Thirdly, the raw data shows that participant-level heterogeneity exists even within a single condition. For example, the inter-quartile range in the two high cost-of-time conditions is 1 (*prospective*) and 1.16 (*simultaneous*) seconds and 0.8 and 0.74 in the two low cost-of-time conditions. This heterogeneity in time choices could result from individual differences in performance, beliefs, or uncertainty attitudes – the hypothesized channels introduced in Section 2.

We investigate our theoretical predictions in a regression framework, where the dependent variable is the time choice. Table 1 presents regression results for the two decision environments and cost-of-time parameters. We estimate one OLS model for each decision environment and each cost-of-time condition and one pooled model with individual random effects for each decision environment. We use the most parsimonious measures of overconfidence and uncertainty attitudes in our main specification, i.e., the average overestimation and average uncertainty aversion. In addition, we include participants' average performance to control for the effect of ability differences and a dummy for the order of the cost-of-time conditions to control for order effects.

Prospective Decision Environment. We present the estimation results for the prospective decision environment in columns 1, 2, and 3. As predicted by our theoretical framework, higher average overconfidence reduces the time participants choose. More specifically, a 10pp. overestimation (i.e., an agent who believes to solve 10pp. more problems

18 2.2% choose the same time, and only 2.2% a (slightly) lower time. Both individuals who chose a lower time deviated from their previous choice only by 0.1 second.

Table 1. Time choices

	Prospective			Simultaneous		
	Linear models		Panel	Linear models		Panel
	(1)	(2)	(3)	(4)	(5)	(6)
Cost of time	*High*	*Low*	*Both*	*High*	*Low*	*Both*
Average Time	3.40	4.61	4.01	3.38	4.37	3.88
Average Overconfidence (10pp.)	-0.262***	-0.476**	-0.369***	-0.061	0.076	0.007
	(0.088)	(0.236)	(0.135)	(0.079)	(0.140)	(0.094)
Average Uncertainty Aversion (10pp.)	0.114**	0.274*	0.194**	0.004	-0.115	-0.055
	(0.052)	(0.142)	(0.082)	(0.045)	(0.086)	(0.059)
Average Performance (10pp.)	-0.142**	-0.448***	-0.295***	-0.374***	-0.607***	-0.490***
	(0.060)	(0.107)	(0.067)	(0.058)	(0.094)	(0.068)
High first	-0.022	-0.255	-0.138	-0.034	-0.094	-0.064
	(0.108)	(0.180)	(0.121)	(0.086)	(0.134)	(0.099)
Low time cost			1.202***			0.991***
			(0.080)			(0.053)
Random Effects			Yes			Yes
Unique Obs	91	91	91	91	91	91
Num.Obs.	91	91	182	91	91	182
$R^2_{\text{Adj.}}$	0.062	0.207	0.574	0.401	0.426	0.702

Note: Linear OLS regressions in columns 1,2,4, and 5. Random effects panel models in columns 3 and 6. The dependent variable is the time selected in the prospective environment and the mean submission time in the simultaneous environment. Heteroscedasticity robust standard errors for the linear models and clustered (on the individual level) standard errors in the panel models. *Average Uncertainty Aversion* and *Average Overconfidence* are the measures described in Section 4, *Average Performance* is the average performance, *Low time cost* is a dummy for the low cost-of-time condition, *High first* is a dummy for the order of the two cost-of-time conditions. *(10pp.)* indicates that a unit change in the variable corresponds to a 10 percentage points change. * p < 0.1, ** p < 0.05, *** p < 0.01

than they do) is associated with a 0.26 seconds ($p = 0.004$) lower time choice in the high cost-of-time environment and a 0.48 seconds ($p = 0.047$) lower time choice in the low cost-of-time environment and a 0.37 seconds ($p = 0.007$) lower time choice in the combined panel model.

The uncertainty aversion results mirror the overestimation results. As predicted, a higher average uncertainty aversion is associated with a higher time choice. More specifically, a 10pp. higher uncertainty aversion is associated with a 0.11 seconds ($p = 0.03$) higher time choice in the high cost-of-time environment and a 0.27 seconds ($p = 0.057$) higher time choice in the low cost-of-time environment and a 0.19 seconds ($p = 0.018$) higher time choice in the combined panel model.

Finally, higher performance is associated with a lower time choice. More specifically, the coefficient on average performance indicates that a 10pp. increase in average performance is associated with choosing 0.14 seconds less in the low cost of time ($p = 0.021$), 0.45 seconds less in the high cost of time ($p < 0.001$) and 0.30 seconds ($p < 0.001$) in the panel model. Furthermore, the estimated coefficient on the difference in time choice between the high and the low cost-of-time settings in the panel model indicates that participants take roughly 1.2 seconds longer when the cost-of-time is low, providing additional support for **Result 1**. We summarize our results in the prospective environment as follows:

Result 2a: *A higher average performance is associated with a lower time choice in the prospective decision environment.*

Result 3a: *A higher average overestimation is associated with a lower time choice in the prospective decision environment.*

Result 4a: *A higher average uncertainty aversion is associated with a higher time choice in the prospective decision environment.*

Simultaneous Decision Environment. Conversely, in the simultaneous decision environment (columns 4, 5, and 6), all estimates for overconfidence and average uncertainty aversion are smaller and insignificant. The coefficients for average performance are larger than in the prospective decision environment and remain significant. They indicate that a 10pp. increase in average performance is associated with choosing 0.37 seconds less in the low cost of time ($p < 0.001$), 0.6 seconds less in the high cost of time ($p < 0.001$) and 0.49 seconds ($p < 0.001$) in the panel model. The estimated coefficient for the low time cost dummy in the panel model indicates that participants take roughly 0.99 seconds longer ($p < 0.001$) than in the high cost of time environment. We, therefore, stipulate the following results for the simultaneous decision environment:

Result 2b: *A higher average performance is associated with a lower time choice in the simultaneous decision environment.*

Result 3b: *We do not find support for prediction 3 (i.e., that overestimation is associated with a lower time choice) in the simultaneous decision environment.*

Result 4b: *We do not find support for prediction 4 (i.e., that uncertainty aversion is associated with a higher time choice) in the simultaneous decision environment.*

Result 5: *We find that overestimation and uncertainty aversion are associated with time choices in the prospective but not in the simultaneous decision environment.*

Other than the hypothesized inherent difference between decision environments, another potential reason for the missing effect of the behavioral factors could be that participants learn throughout the forty tasks in the simultaneous environment and adapt their time choices. To test this, we re-estimate our regression in the simultaneous environment and use three alternative measures for time choices: (i) the average submission time of the first ten tasks, (ii) the submission time of only the first task, and (iii) the submission time in task ten. We show the results in Table A6 in Appendix A.2. We do not find evidence of any effect of the behavioral factors for any of the alternative measures, and our results are qualitatively similar to the main results in Table 1.

Controlling the main regression for individual-level characteristics (survey measures of time, risk and competition preferences, gender, age, perceived time pressure, fatigue, and the anticipation of more intensive work in the second part of the experiment) does not affect the main regression coefficients in a meaningful way (see Table A2 in Appendix A.2). Only age has a small negative and significant coefficient in the panel model for the prospective condition, while all other individual-level characteristics are small and insignificant. We, therefore, conclude that the estimates for our main measures of interest (overconfidence and uncertainty aversion) are robust to controlling for fatigue or depletion effects, perceived time pressure in the second part of the experiment, the anticipation of more intensive work, or other individual characteristics.[19]

Finally, using alternative specifications for performance, such as the average performance for each fixed time (Table A3) or the estimated structural performance parameters (Table A4) does not substantially change our coefficients of interest.

Overall, the reduced form results support behavioral predictions 3 and 4 in the prospective decision environment but not in the simultaneous environment, supporting prediction 5. This suggests that our participants rely on their beliefs and uncertainty attitudes when solving speed-accuracy trade-offs in prospective time planning situations. Conversely, these behavioral measures do not predict their time choices when working on the task.

19 In Appendix A.1.2, we further investigate whether self-reported effort in part two of the experiment is correlated with participants' time choices and do not find any evidence to support this claim.

5.2 Payoffs

The previous analysis on time choices has revealed that overconfidence and uncertainty aversion predict time choices in the prospective decision environment but not in the simultaneous decision environment. What these analyses so far neglected is if these effects translate into consequences for participants, i.e., if more "behavioral" time choices actually lead to lower payoffs (and can be appropriately interpreted as deviations from "rational" choices). One challenge here is that payoffs – given the time-sensitive reward scheme – depend on time choices, which in turn are determined by participants' performance, their beliefs and uncertainty attitudes as established above. To model the impact of these behavioral factors on *payoffs*, we therefore can not use a standard OLS setup, but have to employ a *path analysis*.[20] A path analysis allows us to (i) investigate how time choices and participants' average performance predict payoffs and (ii) analyze the indirect effects of the behavioral factors on payoffs *through* time choices.

We specify an over-identified recursive path model with two endogenous variables (see Figure A4). The first endogenous variable is participants' time choice which – according to our theoretical model and equal to the specification in Table 1 – is associated with overconfidence, uncertainty attitudes, performance, and the dummy for the order of the decision environment. The second endogenous variable is participants' payoff. We model the payoff to be affected by time choices, the general performance measure, and the order dummy. The results are displayed in Table 2.[21] The results for the effect of overconfidence and uncertainty aversion on time choice are qualitatively similar to the results obtained in Table 1 and confirm that those predict time choices.

Furthermore, the estimates show that time choices affect payoffs significantly in the high cost-of-time but not in the low cost-of-time condition. In the high cost-of-time condition, a 1-second higher time choice is associated with a reduction in payoff by 7.5 points ($p < 0.001$) in the prospective and by 11.2 points ($p < 0.001$) in the simultaneous

20 Path analysis allows for the estimation of simultaneous equations and multiple endogenous variables. Akin to mediation analysis, it allows for a straightforward estimation of indirect effects. The models are estimated using maximum likelihood, and their assumptions are similar to classical linear regression, including common assumptions of independence of error terms, but extended to all (intermediate) variables and their disturbances (see Kline (2011) for an extensive discussion of the different assumptions).

21 We additionally estimate a full model where we allow overconfidence and uncertainty aversion to affect both time choices and payoffs. Theoretically, an argument for including these paths might be due to "motivational aspects" of (over)confidence as demonstrated by Chen and Schildberg-Hörisch (2019). However, our theoretical framework does not allow for this effect. The results (presented in Table A5 in Appendix A.2) are qualitatively similar to the parsimonious model, and the additional paths seem to play no role empirically. The modification indices for the two paths between overconfidence and uncertainty aversion and payoffs in the reduced model are below 2, indicating that their effect is insignificant and their inclusion would not improve the fit of the model.

Table 2. Effects of overconfidence and uncertainty aversion on time decisions and payoffs

	Prospective		Simultaneous	
	High (1)	*Low* (2)	*High* (3)	*Low* (4)
Regression Slopes				
Time Choice				
Average Overconfidence (10pp.)	-0.26***	-0.48**	-0.06	0.08
	(0.10)	(0.23)	(0.08)	(0.14)
Average Uncertainty Aversion (10pp.)	0.11**	0.27**	0.00	-0.11
	(0.05)	(0.14)	(0.04)	(0.08)
Average Performance (10pp.)	-0.14**	-0.45***	-0.37***	-0.61***
	(0.06)	(0.10)	(0.05)	(0.09)
High first	-0.02	-0.25	-0.03	-0.09
	(0.11)	(0.17)	(0.08)	(0.13)
Payoff				
Time Choice	-7.47***	-0.25	-11.20***	-0.59
	(1.10)	(1.41)	(1.11)	(1.44)
Average Performance (10pp.)	6.20***	9.18***	5.27***	8.39***
	(0.69)	(1.33)	(0.60)	(1.55)
High first	-0.75	-3.86**	0.10	0.08
	(0.96)	(1.78)	(0.83)	(1.65)
Intercepts				
Time Choice	4.32***	7.60***	5.77***	8.27***
	(0.35)	(0.67)	(0.37)	(0.60)
Payoff	12.43*	26.95**	35.04***	35.23**
	(6.43)	(13.08)	(6.54)	(15.61)
Indirect Effects on Payoff				
Average Overconfidence (10pp.)	1.96**	0.12	0.69	-0.04
	(0.80)	(0.71)	(0.87)	(0.24)
Average Uncertainty Aversion (10pp.)	-0.85**	-0.07	-0.04	0.07
	(0.41)	(0.39)	(0.50)	(0.21)
Average Performance (10pp.)	1.06**	0.11	4.19***	0.36
	(0.44)	(0.62)	(0.72)	(0.91)
Total Effects on Payoffs				
Average Performance (10pp.)	7.26***	9.29***	9.46***	8.75***
	(0.88)	(1.18)	(0.81)	(1.05)
CFI	1.00	1.00	1.00	1.00
TLI	1.00	1.04	1.02	1.03
RMSEA	0.02	0.00	0.00	0.00

Note: Path analysis estimated by maximum likelihood. The recursive, reduced and thus over-identified model has two endogenous variables: *time choice* and *payoff*. *Time choice* has a dual role and has an effect on *payoff*. The exogenous variables are *Average Uncertainty Aversion* and *Average Overconfidence* as described in Section 4, *Average Performance* as the average performance, *High first* is a dummy for the order of the two cost-of-time conditions. *(10pp.)* indicates that a unit change in the variable corresponds to a 10 percentage points change. Bootstrapped ($n = 1000$) standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

environment. Similarly, participants who have a higher average performance in the task earn a higher payoff irrespective of their time choice across all decision environments (all $p < 0.001$). Finally, we observe a negative coefficient for the high-first environment in the prospective low cost-of-time environment. This implies that participants who first encountered the high environment earn less in the prospective low environment; however, this effect does not seem to be driven by time choices.

We now turn to the indirect effects of behavioral factors on payoffs through time choices. The results show that overconfidence and uncertainty aversion significantly affect payoffs through time choices only in the prospective high cost-of-time environment. More specifically, a 10pp. increase in overconfidence is associated with a 2 points ($p < 0.01$) higher payoff – an increase by 7.5% of the average payoff in this decision and cost-of-time environment. The finding is explained by the fact that overconfidence decreases time choices, which in turn increases payoffs. Conversely, this implies that underconfident agents (who select more time) have a lower payoff. For uncertainty aversion, the estimates imply that an increase of 10pp. is associated with a 0.9 points ($p = 0.034$) lower payoff – a reduction in payoff by 3.3%. In all other decision environments, the behavioral factors do not significantly affect payoffs through time choices.

Overall the results of the path analysis confirm that overconfidence and uncertainty aversion significantly predict time choices in the prospective environment. However, they only have an indirect effect on payoffs in the high cost-of-time environment where underconfidence and uncertainty aversion are associated with longer time choices and, in turn, lower payoffs.

6 Structural Estimations

We can also adopt a more structural approach to analyzing participants' time choices, which yields several additional insights. Beyond the reduced-form results, individual structural estimates allow us to assess whether participants aimed to optimize their time choices to maximize payoffs in accordance the theoretical model (i.e., taking into account their performance, beliefs, and uncertainty attitudes) in a formally more pre-specified way (compared to the standard linear regression setup). This approach enables us then to not only correlate time choices with measures of beliefs and uncertainty attitudes, but also to *predict* time choices based on the observed data and assumptions on functional forms. This, in turn, allows for proper model comparisons between different models of time choice that take model fit and complexity into account.

6.1 Performance, Belief and Probability Weighting Function

We start by looking at the individual forms of equations 1 and 3, i.e.,

$$t_i^* = \text{argmax}_t \Pi_i(t) = p(t)_i y(t) \tag{5}$$

and

$$t_i^B = \text{argmax}_t \Pi_i^B(t) = w(b(t))_i y(t) \tag{6}$$

The aim of the structural approach is to be able to make justifiable individual-specific assumptions on (and predictions for) $p(t)_i$ and $w(b(t))_i$. This, in turn, allows to construct a "rational", t_i^*, and "behavioral", t_i^B, benchmark for the solution of the trade-off for each person i. To be able to construct these benchmarks, we first need to formulate both objective functions $\Pi_i(t)$ and $\Pi_i^B(t)$. The former requires us to specify $p(t)_i$. For this, we follow the "workhorse" model from the literature on speed-accuracy trade-offs in neuroscience and psychology (see Dean et al., 2007; Dosher, 1976; McElree & Carrasco, 1999; Reed, 1973):

$$p(t)_i = \beta_i(1 - e^{-(t-\alpha_i)/\lambda_i)}) \tag{7}$$

where β_i describes the asymptotic performance level, α_i the x-axis onset, and λ_i the steepness of the function (see Dean et al., 2007). While other functional forms are principally plausible, a model comparison in Figure A6 in the appendix shows that this functional form is superior in (out-of-sample) predictive power to alternative models of time-dependent performance in stage 1, more specifically to a three-parameter probit and logit model. Based on estimates for the three parameters $\beta_i, \alpha_i, \lambda_i$ we can calculate t_{ic}^* for both cost-of-time conditions c for each individual i.

To obtain *behavioral* predictions for the optimal time choice t_{ic}^B (and specify $\Pi^B(t)_i$ in turn), we additionally need $w(b(t))_i$, which – in line with the two-step models described in the theoretical section – consists of $b(t)_i$ and $w(b(t))_i$. For both $b(t)_i$ and $w(b(t))_i$, we follow the literature on belief and probability weighting and estimate a two parameter weighting function. For example, Tversky and Fox (1995) and Fox and Tversky (1998) estimate a two-parameter weighting function for subjective beliefs and empirically show the canonical inverse s-shape known from lottery domains. Wu and Gonzalez (1999) support this finding and demonstrate that a two-parameter weighting function fits subjective beliefs well across multiple considered domains. We follow these approaches and use the two-parameter weighting function proposed by Goldstein and Einhorn (1987) and Gonzalez and Wu (1999), separately for both for beliefs and uncertainty attitudes.[22] The belief weighting function, in turn, reads:

$$b(t)_i = \frac{\delta_i^b p(t)_i^{\gamma_i^b}}{\delta_i^b p(t)_i^{\gamma_i^b} + (1 - p(t)_i)^{\gamma_i^b}} \tag{8}$$

In this equation, δ_i^b describes the elevation and γ_i^b the curvature of the belief weighting function, and $p(t)_i$ the time-dependent performance in time t according to equation 7. Elevation and curvature equal to one imply a linear relationship between subjective beliefs and performance and, thus, unbiased or well-calibrated beliefs.

As stated, we "concatenate" the belief weighting function with an additional two-parameter weighting function for $w(b(t))$ that captures uncertainty attitudes:

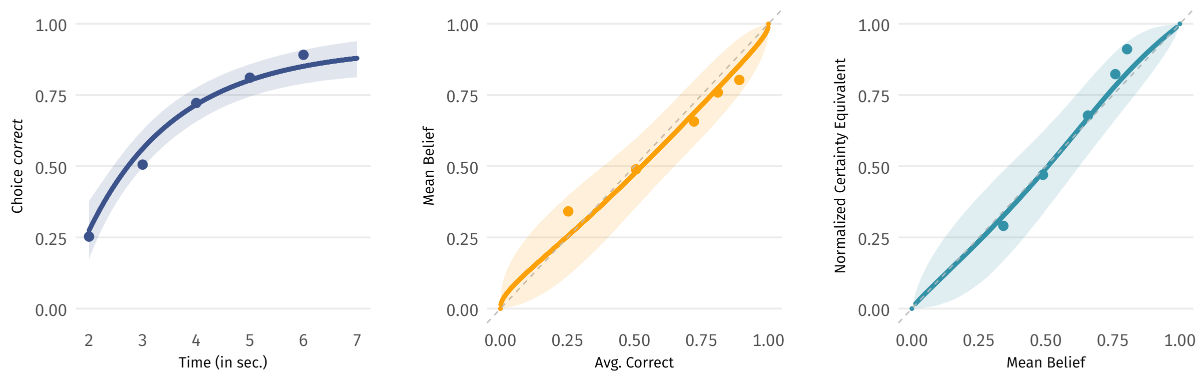
$$w(b(t)) = \frac{\delta^w b(t)^{\gamma^w}}{\delta^w b(t)^{\gamma^w} + (1 - b(t))^{\gamma^w}} \tag{9}$$

where δ^W describes the elevation and γ^W the curvature of the "probability" weighting function capturing uncertainty attitudes.

We fit a Bayesian probabilistic model with Numpyro (Bingham et al., 2019; Phan et al., 2019) to obtain the (posterior) probability of the individual parameter vector $\boldsymbol{\theta}_i = (\beta_i, \alpha_i, \lambda_i, \delta^b, \gamma^b, \delta^w, \gamma^w)$. Where necessary, we chose generic, weakly-informative priors (see Section A.2.1). Bayesian models offer more flexibility compared to traditional maximum likelihood methods and easily propagate uncertainty from a previous stage in the model to later sections. Further, excluding specific participants due to numerical issues during estimation becomes unnecessary, as the prior is given a larger weight for participants with less informative data.

Figure 6 shows the fitted functions of $p(t)$, $b(t)$ and $w(b(t))$. Several insights can be gained from the structural estimations: First, the structural models (i.e., the chosen functional forms) are able to capture average behavior of subjects in the performance stage (panel a), as well as for data on their mean beliefs (b) and uncertainty attitudes (c). The *estimation uncertainty* around the performance predictions is relatively small, which is perhaps not surprising given the extensive length of stage 1. In contrast, both the predictions of the beliefs and uncertainty attitudes weighting function remain much more uncertain. Consider for example β_i, i.e., the asymptotic level of performance, which is on average $0.921\,[0.838 - 0.996]$. In contrast, the elevation parameter of the belief weighting function is on average $1\,[0.543 - 1.490]$, i.e., there is more uncertainty around the value of this parameter (see also sd column). The same applies to the remaining parameters of the belief and uncertainty attitudes weighting

22 Again, see Figures A7 and A8 for model comparisons with alternative weighting functions. Overall (across domains), the proposed functional form is slightly superior to a Prelec two-parameter weighting function as well as a Baseline model without any belief or probability weighting.



(a) Performance

(b) Beliefs

(c) Uncertainty Attitudes

	mean	sd	median	hdi 2.5%	hdi 97.5%	$\hat{R}$
Asymptotic Level Performance β_i	0.921	0.046	0.926	0.838	0.996	1
Steepness Performance λ_i	1.762	0.340	1.747	1.117	2.430	1
x-axis onset Performance α_i	1.374	0.213	1.402	0.950	1.742	1
Elevation Beliefs δ_i^b	1.000	0.246	0.982	0.543	1.490	1
Curvature Beliefs γ_i^b	0.996	0.261	0.972	0.522	1.513	1
Elevation NCE δ_i^w	1.098	0.309	1.075	0.525	1.708	1
Curvature NCE γ_i^w	1.201	0.333	1.177	0.585	1.858	1

(d) Posterior Parameters Table

Figure 6. Structural Predictions: Performance, Beliefs and Uncertainty Attitudes Average and predicted choices for Performance **(a)**, Beliefs **(b)**, and Uncertainty Attitudes **(c)**. **(d)** Estimated parameter values of equation 9 based on 1000 posterior samples (+ 1000 warmup) per each of four chains. Parameters are averages over individuals. Mean, median and sd refer to the mean, median and standard deviation of the posterior distribution samples. HDI 2.5% and HDI 97.5% indicate the borders of the 95% highest-density interval (HDI). $\hat{R}$ is a diagnostic of convergence of the Markov chains Markov chains ($\hat{R} = 1$ indicating convergence).

function. With most beliefs and uncertainty attitudes related parameters being close to 1, the structural estimates confirm the conclusions drawn from the raw data in Figure 4, that – on average – neither the beliefs nor uncertainty attitudes deviate strongly from the "well-calibrated" case. However, note that these values remain *averages* over the individual data, conflating potential individual heterogeneity.

6.2 Structural Predictions of Time Choices

Equipped with the estimates of the individual parameters, we can now turn to modeling time choices. Given the individual parameter vector $\boldsymbol{\theta}_i = (\beta_i, \alpha_i, \lambda_i, \delta_i^b, \gamma_i^b, \delta_i^w, \gamma_i^w)$, we can calculate both t_{ic}^* (where $\delta_i^b = \gamma_i^b = \delta_i^w = \gamma_i^w = 1$) and t_{ic}^b. More specifically, the probabilistic model builds a regression model from the individual predictions, i.e., $t_{ice} \sim \mathcal{N}(t^{B/*}, \sigma^{B/*})$ where t_{ice} is the implemented time choice of individual i in the cost regime $c \in H, L$ (high and low) and environment $e \in (P, S)$ (prospective and simultaneous). $\sigma^{B/*}$ is a participant and environment-invariant variance parameter that indicates the standard deviation of the prediction error (in either the rational or behavioral model). The probabilisitic model jointly estimates $\boldsymbol{\theta}_i$ and $\sigma^{B/*}$ and conditions $\boldsymbol{\theta}_i$ on the data observed in the previous stages of the experiment (i.e., the performance stage, the ball allocation task as well as the multiple price lists).

However, a particular challenge for estimating the model lies in its "optimization step" that actually calculates both t_i^B and t_i^* given $\boldsymbol{\theta}_i$: Every sample from the posterior requires to optimize functions 5 and 6 for the individual parameter values. This is computationally very expensive and renders the estimation of the model highly demanding. To circumvent this issue, we follow an approach similar in objective to the one by Straub et al. (2024):[23] Instead of optimizing based on each sample every time, we *approximate* $t_i^{*/B} \approx \hat{f}(\boldsymbol{\theta}_i)$ during sampling with a linear model. More specifically, based on a "training" data set of different parameter values of $\boldsymbol{\theta}$ and the corresponding optimal time choice $t^{*/B}$, we fit a 8-degree polynomial regression that predicts the optimal solution (i.e., time choice) based on the parameter values. We fit a polynomial regression for the rational and behavioral time choice separately with corresponding R^2 values of 1 and 0.9998, which highlights the successful approximation of optimal time choices using this approach (see Figure A10). During sampling, the linear approximations (which remain differentiable) thus substitute analytically-obtained optimal time choices. The two models (for the rational and behavioral benchmark) jointly estimate both $\boldsymbol{\theta}_i$ and $\sigma^{B/*}$ based on the data from all stages of the experiment.

Table 3. Average predicted rational and behavioral time choices

	mean	median	sd	hdi 2.5%	hdi 97.5%	$\hat{R}$
Rational Prediction:						
Low Cost	4.622	4.634	0.24	4.147	5.072	1
High Cost	2.825	2.837	0.1	2.624	3.004	1
Behavioral Prediction:						
Low Cost	4.652	4.642	0.336	4.012	5.32	1
High Cost	2.966	2.978	0.252	2.463	3.442	1

Note: The table contains the average (over individuals) summary of the time prediction posterior for the rational and behavioral prediction, including mean, sd and median as well as the 95% HDI interval and the $\hat{R}$ statistic.

Table 3 contains the average time choices according to the rational and behavioral prediction. The rational prediction is, on average, $t_L^* = 4.622\,[4.147 - 5.072]$ (sec.) in

23 Note that Straub et al. (2024) use a neural network to amortize Bayesian actor models in a sensorimotor task to approximate the optimal motor response given a (non-)quadratic cost function; For our problem, simpler polynomial regressions remain sufficient.

the low-cost and $t_H^* = 2.825\,[2.624 - 3.004]$ in the high-cost regime, whereas the behavioral prediction amounts to $t_L^B = 4.652\,[4.012 - 5.32]$ and $t_H^B = 2.966\,[2.463 - 3.442]$. Based on the posterior samples, we can calculate that $P(t_L^B > t_L^*) = 0.642$, $P(t_H^B > t_H^*) = 0.501$, i.e., that only for the high cost there is slight evidence for a larger behavioral benchmark compared to the rational one. The behavioral prediction is more uncertain (see sd column), which is unsurprising given that uncertainty in the parameters of the belief and probability weighting function propagates into uncertainty in the corresponding behavioral time prediction. Recall that the average implemented time choices are $\bar{t}_{L,P} = 4.61$, $\bar{t}_{L,S} = 4.37$, $\bar{t}_{H,P} = 3.4$, $\bar{t}_{H,S} = 3.38$ (all in sec.; see Figure 5). Both the rational and behavioral benchmark thus *underestimate* implemented time choices in the high-cost regime, while the predictions are well in line with implemented time choices in the low-cost of time (for both environments).

However, similar to before, this data masks potential individual heterogeneity. Therefore, we plot implemented and predicted time choices – both rational and behavioral – for each subject in Figure 6:

We start by focussing on the first column, which plots implemented time choices in the prospective environment versus the rational (top) and behavioral (bottom) benchmark for each individual. The rational benchmark positively correlates with plannes time choices ($\rho = 0.76$) and shows how this benchmark already is already reasonable. One caveat, however, remains in that especially in the high cost regime, the rational benchmark is less able to accommodate individual differences in planned time choices. The behavioral benchmark improves upon these predictions: Both the overall correlation with time choices is higher ($\rho = 0.84$) and the predictions in the high-cost regime are more varied between individuals. This is first tentative evidence that the behavioral model improves predictions for prospective time choices.

For simultaneous time choices, consider the second column: There, the rational time choices exhibit a high positive correlation with implemented choices ($\rho = 0.82$) which is similar to the (marginally-smaller) correlation of behavioral time choices ($\rho = 0.81$) in the bottom panel. In turn, both the rational and behavioral benchmark seem to offer predictions of similar overall quality at first glance.[24]

Comparing the correlations within-benchmark and between-environments (i.e., within rows), the correlations indicate that the rational model is an overall better benchmark for simultaneous compared to prospective time choices, while the behavioral model yields better predictions for prospective time choices. Or, in other words, the behavioral model – which is the more complex model – improves predictions by

24 Note that, if we only consider simultaneous time choices in the high cost environment, the correlation between time choices and the behavioral benchmark may visually appear larger, but remain close to identical with $\rho = 0.6482$ for the behavioral predictions and $\rho = 0.6479$ for the rational predictions.

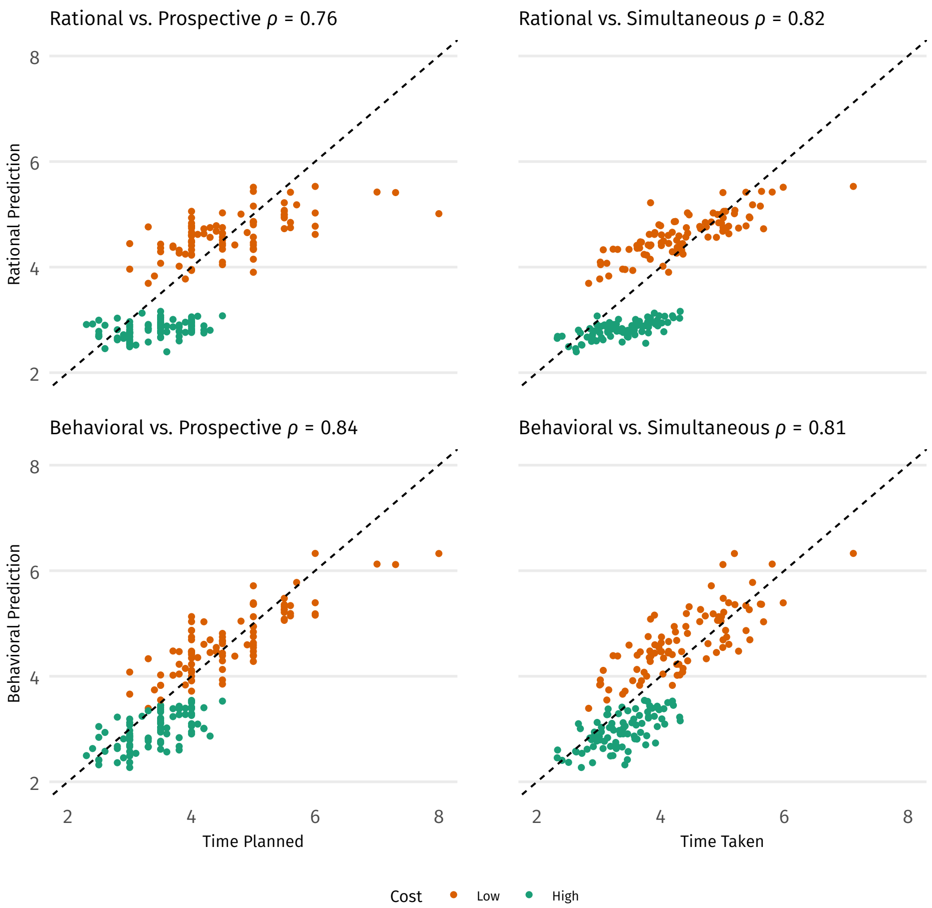
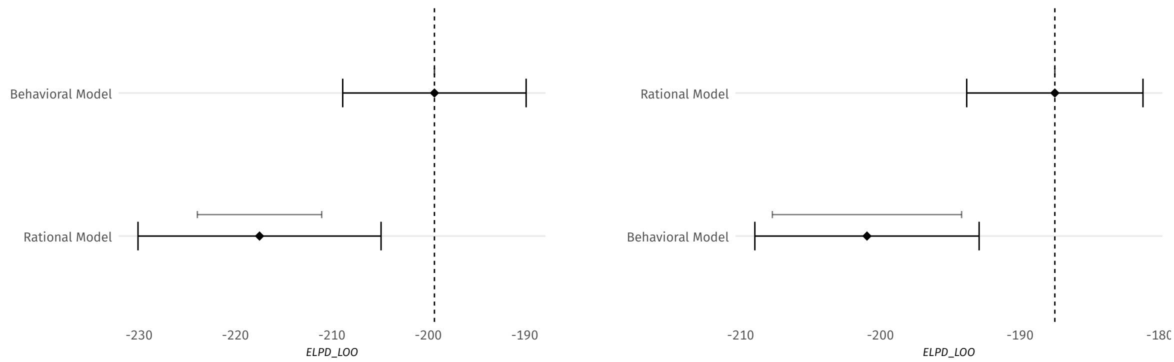


Figure 7. Rational, Behavioral and Implemented Time Choices This figure plots individual predictions (i.e., means of individual posterior distributions) for t^* (first row) and t^b (second row) for both prospective (first column) and simultaneous time choices (second column). ρ values are rank correlation coefficients between predicted and implemented choices.

the more parsimonious rational model only for prospective and not for simultaneous time choices. This, in turn, is similar to the results from the (reduced-form) regression analyses outlined above.

However, instead of simply comparing point-estimates of correlations, we can also take a more principled approach and perform a model comparison that accounts for model complexity and uncertainty: Fig 8 depicts $ELPD_{LOO}$ values which measure the goodness of fit of a model minus a model complexity penalty and provide a computationally less demanding approximation to leave-one-out out-of-sample prediction accuracy (Vehtari et al., 2017), while accommodating model complexity (via penalizing high posterior variance).

The model comparison corroborates the previous finding: For prospective time choices (panel a) the behavioral model $ELPD_{LOO} = -199.374$ is higher compared to the rational model $ELPD_{LOO} = -217.512$. The reverse is true in the simultaneous time



(a) Prospective Time Choices

(b) Simultaneous Time Choices

Figure 8. Model Comparison Time Choices $ELPD_{LOO}$ refers to the expected log predictive density based on pareto-smoothed importance sampling leave-one-out cross-validation (PSIS-LOO-CV, in short LOO); A larger $ELPD_{LOO}$ indicates better model fit. Error bars show the standard error of the respective $ELPD_{LOO}$ value and the standard error of the $\Delta ELPD_{LOO}$ value, the $ELPD_{LOO}$ difference to the best model. Model comparison done via the `arviz`-package (Kumar et al., 2019).

choices (panel b), with $ELPD_{LOO} = -187.516$ for the rational model and $ELPD_{LOO} = -200.963$ for the behavioral model.[25] [26]

Result 6: *The probabilistic models indicates that a "behavioral" model – compared to a "rational" model – improves time choice predictions in the prospective but not simultaneous decision environment.*

7 Discussion and Conclusion

In this paper, we investigated the influence of subjective beliefs and uncertainty attitudes on time choices in a speed-accuracy trade-off in a cognitively demanding task. Based on a simple theoretical framework, we designed an experiment that allows for the incentive-compatible measurement of performance, beliefs about performance, and uncertainty attitudes toward working on a task. We implemented a simple speed-accuracy trade-off by reducing the reward participants obtain for a correct solution the more time they choose. We design a rich choice environment and elicit time choices in both a low and high cost-of-time condition as well as two distinct decision environments, choosing time prospectively and simultaneously.

25 A cost-specific model comparison in Figure A9 shows that the differences between rational and behavioral model is largely driven by the difference in the model fit in the low cost environment, which in turn fits to the near-identical correlations in the high cost environment described above.

26 Note, further, that the standard errors of the $ELPD_{LOO}$ values are relatively large, which cautions against interpreting too much from these relatively moderate differences (which in turn fits to the modest correlation differences from Figure 7).

We show that overconfidence and uncertainty attitudes affect time choices in prospective decision-making in the predicted direction: Overconfident agents take less time, while uncertainty-averse agents take more time. This leads to lower payoffs for uncertainty-averse and underconfident agents. In contrast, we find no evidence for the influence of overconfidence and uncertainty aversion in the simultaneous decision environment. This finding is in line with results from the previous literature, which highlights different determinants for planned and actual choices.

In summary, this paper provides novel and relevant results about human behavior in cognitively-demanding tasks governed by speed-accuracy trade-offs. At the same time, our results suggest many open questions and avenues for future research. While the results of our pre-registered experiment provide suggestive evidence for an association between behavioral measures and prospective time choices, we do not claim that these results are causal. It would be interesting to investigate treatments that try to manipulate (or de-bias) beliefs by providing feedback to participants about their actual performance or their supposed uncertainty attitudes. These treatments should affect time choices in prospective environments but not in simultaneous ones. While our experiment featured a rich choice environment, it seems further worthwhile to investigate time choices under more realistic circumstances, i.e., more complex reward schemes and tasks with more extended time frames. This will contribute to a better understanding of how time choices are made in different settings and how they may – ultimately – be improved.

A Appendix

A.1 Robustness Analyses

A.1.1 Learning Effects. One potential problem for our measures of performance could arise if participants improve throughout the first stage of the experiment. To investigate potential learning effects, we estimate average marginal effects from a probit model on the performance data in stage one. The dependent variable is whether a participant selects the correct solution and the independent variables are the round number, a third-degree polynomial of available time, as well as participant fixed effects.[27] Table A1 presents the estimation results. The coefficient on the round variable is very close to 0 and insignificant ($p = 0.34$), indicating that no significant learning takes place. The average marginal effect suggests that the mean participant performance increases slightly (by 1.5pp. over all 250 tasks) but insignificantly ($p = 0.322$). We thus conclude that participants do not learn throughout stage one and that ability, and thus performance, is stable.

A.1.2 Intensive Margin of Effort. While performance might be stable in the fixed-time environment of stage one of the experiment, participants might (anticipate to) work more or less intensely during stage four and thus choose a higher or lower time. We conduct two analyses to investigate this. The first analysis is based on a self-reported survey item elicited at the end of the experiment. We asked participants to compare the intensity, with which they searched for the solution between stage one and stage four on a slider from 0 (higher intensity in stage one) and 10 (higher intensity in stage four). The median answer is 5, and the mean 5.5, indicating that participants on average report to work with similar intensity in the two stages. We additionally asked participants who selected a value smaller than four or larger than seven whether they anticipated the change in their effort intensity while making their time decisions. Twenty-three participants reported working more intensively in stage four and that they anticipated this while making their time selection. We check whether participants' self-reported measure of effort intensity correlates with the time they select in stage four and find no significant correlation between the two variables for either high or low cost of time in either the prospective or the simultaneous condition[28], as well as insignificant and small effects of the survey variable when included in the main regression (c.f. Table A2). Furthermore, we find no differences in terms of mean or mean rank for time choice, performance, and payoff between participants that indicate

27 Using different polynomials for time and a higher degree polynomial for the round does not change the estimates significantly.

28 Spearmans ρ: simultaneous high ($\rho = -0.5, p = 0.63$); low ($\rho = -0.06, p = 0.55$); prospective high ($\rho = -0.02, p = 0.88$); low ($\rho = -0.006, p = 0.96$)

Table A1. Learning in stage one

	Dependent Variable: *Correct solution* (1)
Raw Regression Estimates	
Round	0.000
	(0.000)
Time	1.591***
	(0.222)
$Time^2$	-0.216***
	(0.059)
$Time^3$	0.012**
	(0.005)
Average Marginal Effects	
Round	0.000
	(0.000)
Time	1.577***
	(0.0028)
Individual fixed effects	X
Observations	22750

Note: Generalized linear effects panel logit model, where the dependent variable is whether a participant answers the task correctly. The independent variables are the round in stage 1, a third-degree polynomial of the available time to answer the task, and participant fixed effects. Heteroscedasticity robust standard errors clustered on the individual level. The upper part of the table contains the raw regression estimates and the lower the calculated average marginal effects of the variables. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

to have worked more intensely in stage four and those that do not (all non-paired t-test and Mann-Whitney-U tests for all cost-of-time and decision environments $p > 0.25$). This indicates that participants who report having worked more intensely in stage four have not selected a significantly lower time, performed better, or earned a higher payoff in stage four.

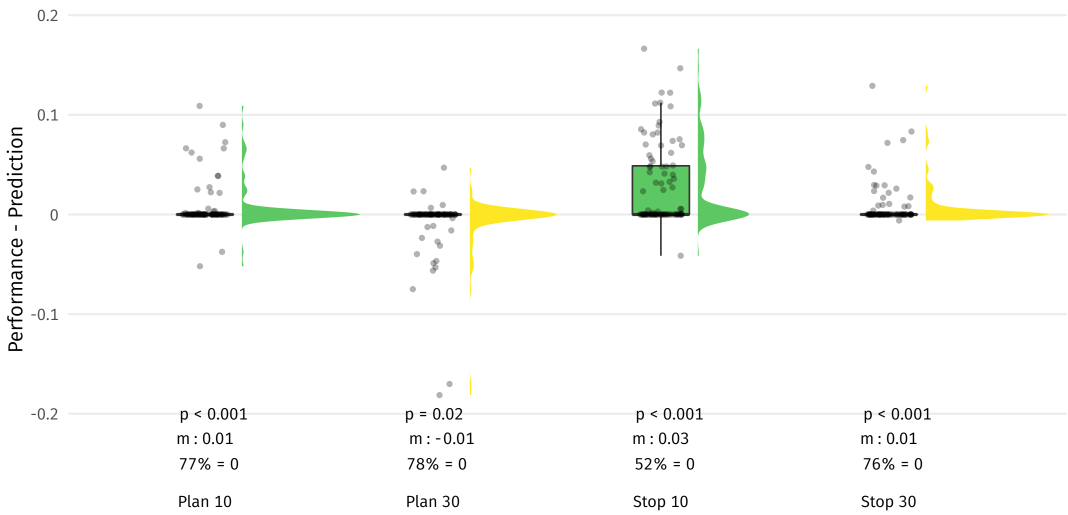


Figure A1. Deviations Time Decisions and Confidence Intervals This graph shows how far away participants' actual performance in stage five of the experiment is from the closest 95% confidence bound. The value is 0 if the performance lies within the predicted confidence interval. p reports the p-value of a test that the mean is equal to 0, m reports the mean, and the final row reports the number of observations where the actual performance is contained in the estimated 95% confidence bound around the predicted performance.

The second analysis compares the actual performance of participants in stage one and stage four. We test whether participants' performance in stage four is contained in the predicted 95%-confidence bound of the performance function estimated on the data from stage one. This is true for 70.6% of participants' (average) performance across all environments in stage four. In all but the simultaneous condition with a high cost-of-time, participants are slightly better than the prediction. Figure A2 displays the density of the difference between the predicted performance and the actual performance in the prospective and the simultaneous environment for both cost-of-time conditions. Figure A1 the differences between participants' performance and the closest confidence bound when their actual performance is outside the confidence interval. On average, participants' performance is significantly[29] larger than their confidence interval in all but the prospective condition with a high cost of time. However, participants' mean distance from the closest confidence bounds is between -1 and +3 percentage points.

29 Using t-test of the mean being equal to 0. See Figure A1 for the p-values.

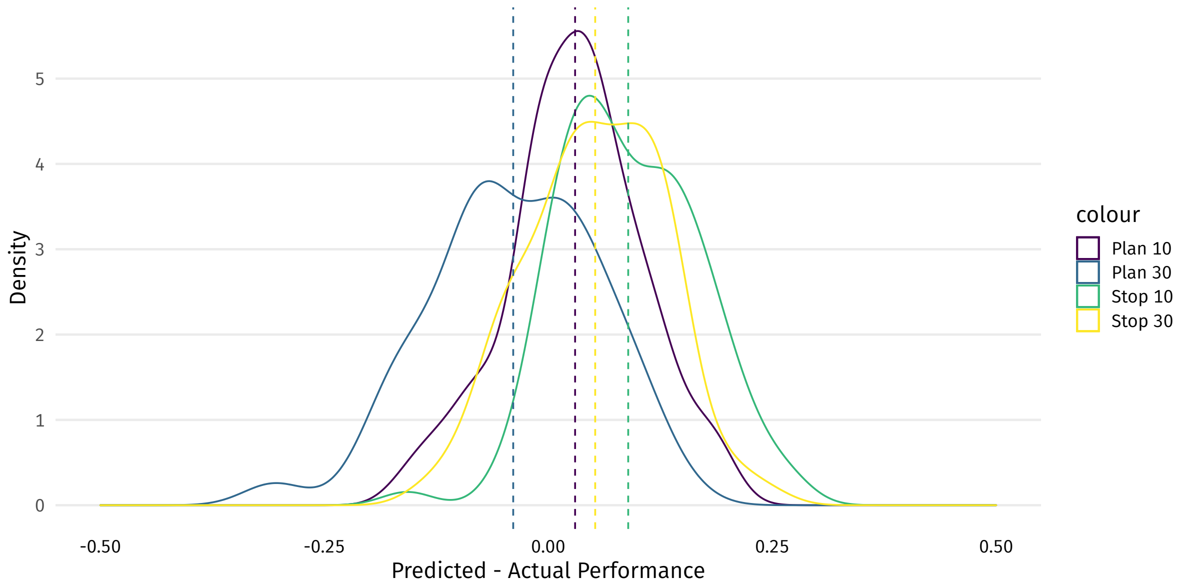


Figure A2. Time Decisions: Robustness Analysis This graph plots density curves of the deviation between predicted performance and actual performance across both decisions environments and cost-of-time parameters.

Overall, we conclude that the estimated performance function from stage one is a reasonable approximation of roughly 70% of participants' performance in stage four. Thus, in 30% of the decisions in stage four, our structural performance estimate based on the data from stage one does not predict performance well. Importantly, we find that changes in participants' self-reported effort intensity do not correlate significantly with the time decisions. Therefore, while performance, and thus our estimates of the structurally estimated benchmarks, might be slightly biased, the reduced-form analysis of the selected time seems largely unaffected.

A.2 Additional Figures and Tables

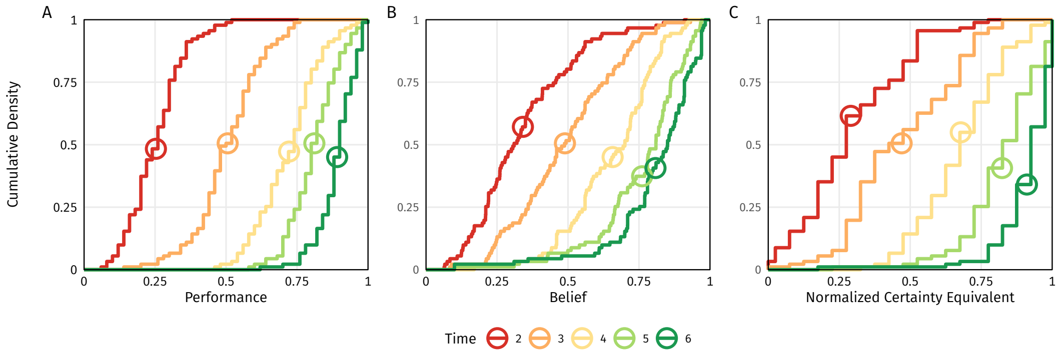


Figure A3. Empirical Cumulative Distribution Functions Panel A shows the empirical cumulative distribution function (ECDF) of mean performance for all participants. Colors indicate the fixed times in part 1 of the experiment. Panel B shows the ECDF of the mean beliefs, and Panel C the ECDF of the normalized certainty equivalents. The circles indicate the mean of the respective ECDFs.

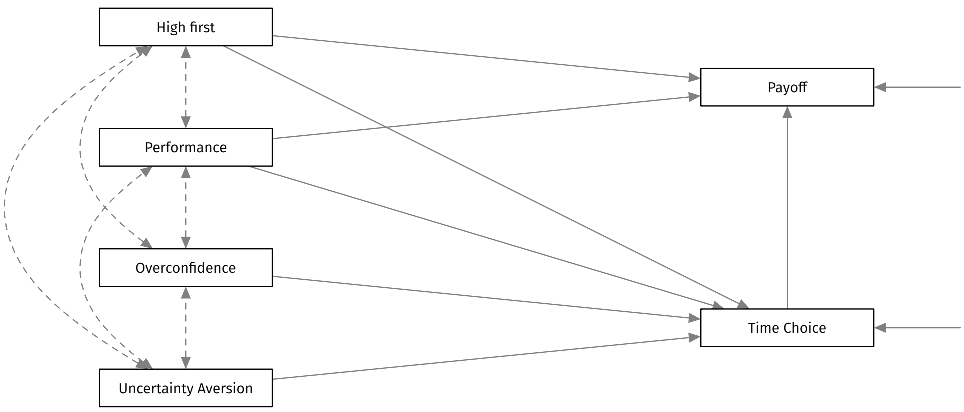


Figure A4. Symbolic Representation of Path Analysis Model This graph shows the path analysis model graphically. The arrows indicate the direction of the relationship. Estimated intercepts and variances are not displayed. The two endogenous variables *Time* and *Payoff* are on the right side of the graph, and the exogenous variables *High first*, *Performance*, *Overconfidence*, and *Uncertainty Aversion* on the left.

A.2.1 Probabilistic Model.

Priors.

$$
\begin{aligned}
\beta_i &\sim \mathcal{N}^+(0.5, 1) \\
\alpha_i &\sim \mathcal{N}^+(0, 1) \\
\lambda_i &\sim \mathcal{N}^+(0, 1)
\end{aligned}
\qquad
\begin{aligned}
\delta_i^b &\sim \mathcal{N}^+(1, 0.5) \\
\gamma_i^b &\sim \mathcal{N}^+(1, 0.5) \\
\delta_i^w &\sim \mathcal{N}^+(1, 0.5) \\
\gamma_i^w &\sim \mathcal{N}^+(1, 0.5)
\end{aligned}
\qquad
\begin{aligned}
\sigma^b &\sim \mathcal{N}^+(0, 1) \\
\sigma^w &\sim \mathcal{N}^+(0, 1) \\
\sigma^B &\sim \mathcal{N}^+(0, 1) \\
\sigma^* &\sim \mathcal{N}^+(0, 1)
\end{aligned}
$$

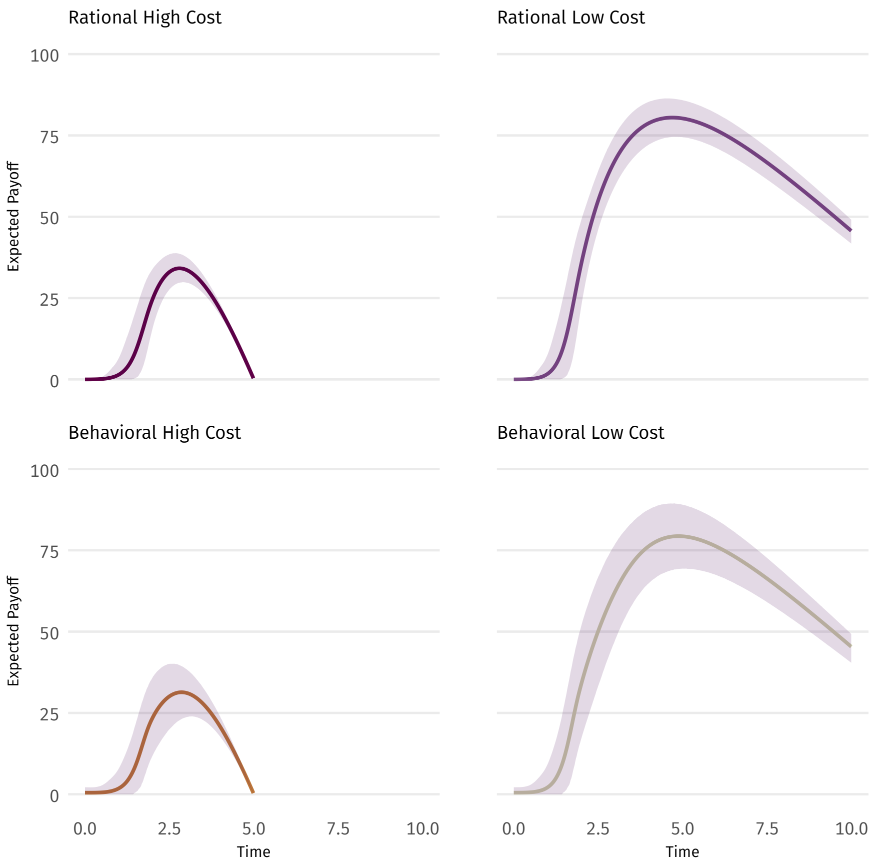
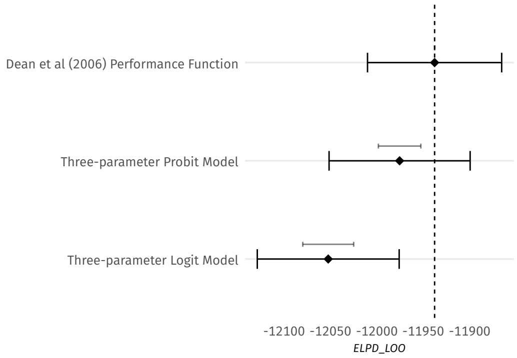


Figure A5. Rational and Behavioral Objective Functions This plot depicts the average (of individuals') rational (first row) and behavioral (second row) objective function, for both high (first column) and low (second column) cost, including 95 % HDI.

Model	Choice Function
Dean et al (2006)	$p(t) = \beta(1 - e^{-(t-\alpha)/\lambda})$
Probit Model	$p(t) = \Phi\left(\beta_0 + \beta_1 \times t + \beta_2 \times t^2\right)$
Logit Model	$p(t) = \frac{1}{1+e^{-(\beta_0+\beta_1 \times t+\beta_2 \times t^2}}$

(a) Candidate Models Time-dependent Performance

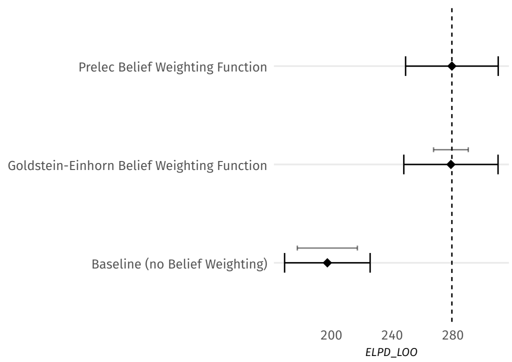


(b) $ELPD_{LOO}$ values

Figure A6. Model Comparison Correct Choices Stage 1 $ELPD_{LOO}$ refers to the expected log predictive density based on pareto-smoothed importance sampling leave-one-out cross-validation (PSIS-LOO-CV, in short LOO); A larger $ELPD_{LOO}$ indicates better model fit. Error bars show the standard error of the respective $ELPD_{LOO}$ value and the standard error of the $\Delta ELPD_{LOO}$ value, the $ELPD_{LOO}$ difference to the best model. Model comparison done via the `arviz`-package (Kumar et al., 2019).

Model	Choice Function
Prelec Belief Weighting	$b(t) = e^{-\delta^b(-\ln p(t))\gamma^b}$
Goldstein-Einhorn Belief Weighting	$b(t) = \frac{\delta^b p(t)^{\gamma^b}}{\delta^b p(t)^{\gamma^b}+(1-p(t))^{\gamma^b}}$
Baseline (no Belief Weighting)	$b(t) = p(t)$

(a) Candidate Models Belief Weighting

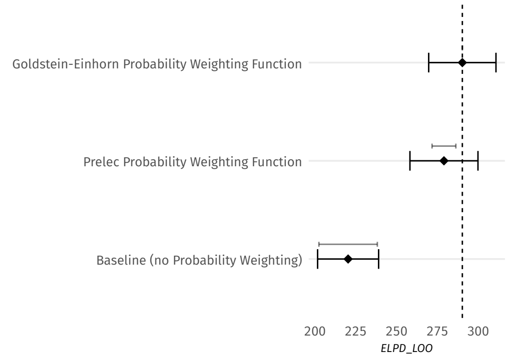


(b) $ELPD_{LOO}$ values

Figure A7. Model Comparison Belief Weighting $ELPD_{LOO}$ refers to the expected log predictive density based on pareto-smoothed importance sampling leave-one-out cross-validation (PSIS-LOO-CV, in short LOO); A larger $ELPD_{LOO}$ indicates better model fit. Error bars show the standard error of the respective $ELPD_{LOO}$ value and the standard error of the $\Delta ELPD_{LOO}$ value, the $ELPD_{LOO}$ difference to the best model. Model comparison done via the `arviz`-package (Kumar et al., 2019).

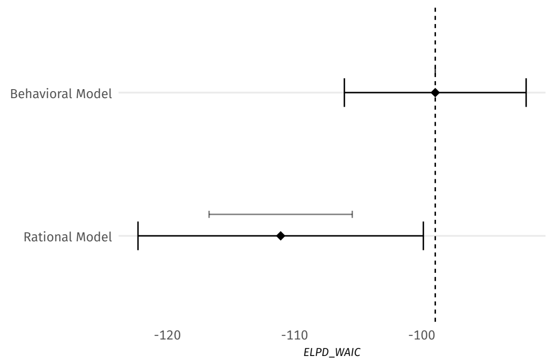
Model	Choice Function
Goldstein-Einhorn Probability Weighting	$w(t) = \frac{\delta^w b(t)^{\gamma^w}}{\delta^w b(t)^{\gamma^w} + (1-b(t))^{\gamma^w}}$
Prelec Probability Weighting	$w(t) = e^{-\delta^w(-\ln b(t))^{\gamma^w}}$
Baseline (no Probability Weighting)	$w(t) = b(t)$

(a) Candidate Models Probability Weighting

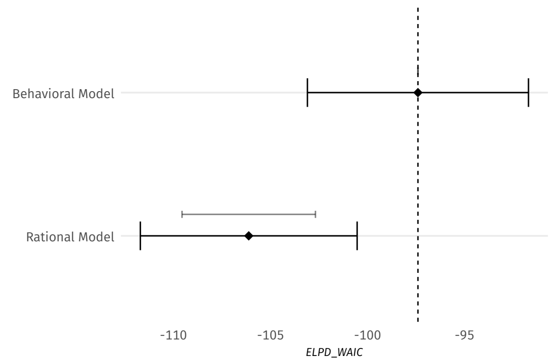


(b) $ELPD_{LOO}$ values

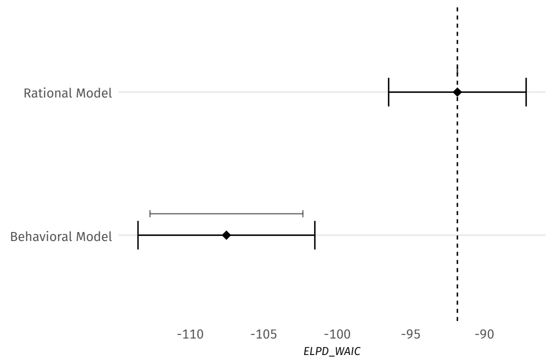
Figure A8. Model Comparison Probability Weighting $ELPD_{LOO}$ refers to the expected log predictive density based on pareto-smoothed importance sampling leave-one-out cross-validation (PSIS-LOO-CV, in short LOO); A larger $ELPD_{LOO}$ indicates better model fit. Error bars show the standard error of the respective $ELPD_{LOO}$ value and the standard error of the $\Delta ELPD_{LOO}$ value, the $ELPD_{LOO}$ difference to the best model. Model comparison done via the `arviz`-package (Kumar et al., 2019).



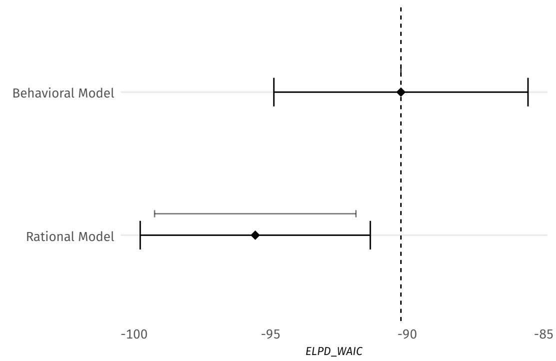
(a) Prospective Time Choices: Low Cost



(b) Prospective Time Choices: High Cost

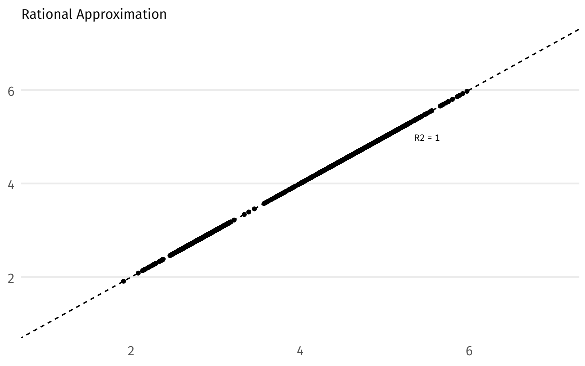


(c) Simultaneous Time Choices: Low Cost

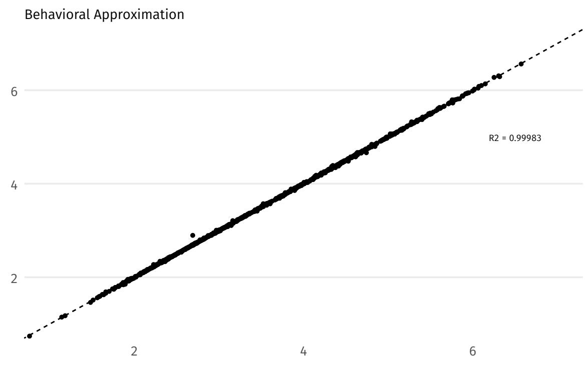


(c) Simultaneous Time Choices: High Cost

Figure A9. Model Comparison Time Choices $ELPD_{WAIC}$ refers to the expected log predictive density based on the widely-applicable information criterion (WAIC) (Watanabe, 2013); A larger $ELPD_{WAIC}$ indicates better model fit. Error bars show the standard error of the respective $ELPD_{WAIC}$ value and the standard error of the $\Delta ELPD_{WAIC}$ value, the $ELPD_{WAIC}$ difference to the best model. Model comparison done via the `arviz`-package (Kumar et al., 2019).



(a) Rational Approximation



(b) Behavioral Approximation

Figure A10. Rational and Behavioral Approximation Predictions of 8-degree linear polynomial models with 495 (rational) and 12870 (behavioral) coefficients. Plot includes 1,000 random samples from data set, R^2 value based on full sample.

A.2.2 Additional Regressions.

Table A2. Time choice and individual characteristics

	Prospective			Simultaneous		
	Linear models		Panel	Linear models		Panel
	(1)	(2)	(3)	(4)	(5)	(6)
Cost of time	*High*	*Low*	*Both*	*High*	*Low*	*Both*
Average Time	3.40	4.61	4.01	3.38	4.37	3.88
Average Overconfidence (10pp.)	-0.252**	-0.543**	-0.397***	-0.054	0.093	0.019
	(0.096)	(0.241)	(0.131)	(0.087)	(0.160)	(0.100)
Average Uncertainty Aversion (10pp.)	0.127*	0.309*	0.218**	0.001	-0.114	-0.057
	(0.064)	(0.157)	(0.086)	(0.052)	(0.110)	(0.068)
Average Performance (10pp.)	-0.094	-0.450***	-0.272***	-0.351***	-0.583***	-0.467***
	(0.082)	(0.148)	(0.088)	(0.062)	(0.122)	(0.076)
GPS Risk	-0.099	-0.110	-0.104	-0.045	0.005	-0.020
	(0.066)	(0.115)	(0.067)	(0.046)	(0.100)	(0.059)
GPS Patience	-0.028	-0.039	-0.033	-0.047	-0.005	-0.026
	(0.058)	(0.091)	(0.057)	(0.042)	(0.083)	(0.051)
Fatigue	-0.012	-0.011	-0.012	0.000	-0.034	-0.017
	(0.022)	(0.037)	(0.024)	(0.015)	(0.027)	(0.017)
Intensive Work anticipated	-0.013	0.001	-0.006	-0.031	0.023	-0.004
	(0.133)	(0.214)	(0.138)	(0.095)	(0.160)	(0.111)
Time Pressure	0.000	-0.002	-0.001	-0.002	-0.003	-0.002
	(0.002)	(0.004)	(0.003)	(0.002)	(0.004)	(0.002)
Competition	0.055	0.096	0.075	-0.003	0.022	0.010
	(0.064)	(0.111)	(0.069)	(0.047)	(0.081)	(0.053)
Female	0.149	-0.070	0.040	0.048	0.003	0.026
	(0.156)	(0.229)	(0.151)	(0.110)	(0.162)	(0.110)
Age	-0.033	-0.065	-0.049**	-0.009	-0.001	-0.005
	(0.020)	(0.041)	(0.024)	(0.016)	(0.028)	(0.019)
High first	-0.114	-0.336	-0.225*	-0.073	-0.101	-0.087
	(0.115)	(0.209)	(0.130)	(0.096)	(0.142)	(0.102)
Low time cost			1.202***			0.991***
			(0.080)			(0.053)
Random Effects			Yes			Yes
Unique Obs	91	91	91	91	91	91
Num.Obs.	91	91	182	91	91	182
$R^2_{\text{Adj.}}$	0.061	0.191	0.575	0.371	0.389	0.697

Note: Linear OLS regressions in columns 1,2,4, and 5. Random effects panel models in columns 3 and 6. The dependent variable is the time selected in the prospective environment and the mean submission time in the simultaneous environment. Heteroscedasticity robust standard errors for the linear models and clustered (on the individual level) standard errors in the panel models. *Average Uncertainty Aversion* and *Average Overconfidence* are the measures described in Section 4, *Average Performance* is the average performance, *GPS Risk, GPS Patience, Fatigue, Intensive Work anticipated, Time Pressure, Competition, Female, and Age* the individual survey measures elicited in stage 5, *Low time cost* is a dummy for the low cost-of-time condition, *High first* is a dummy for the order of the two cost-of-time conditions. *(10pp.)* indicates that a unit change in the variable corresponds to a 10 percentage points change. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A3. Time choice with individual performance

	Prospective			Simultaneous		
	Linear models		Panel	Linear models		Panel
	(1)	(2)	(3)	(4)	(5)	(6)
Cost of time	*High*	*Low*	*Both*	*High*	*Low*	*Both*
Average Time	3.40	4.61	4.01	3.38	4.37	3.88
Average Overconfidence (10pp.)	-0.291***	-0.489**	-0.390***	-0.041	0.153	0.056
	(0.100)	(0.225)	(0.128)	(0.074)	(0.135)	(0.087)
Average Uncertainty Aversion (10pp.)	0.134**	0.294**	0.214***	0.004	-0.129	-0.063
	(0.051)	(0.145)	(0.080)	(0.047)	(0.089)	(0.059)
Performance in 2 sec.	-1.510*	-2.118	-1.814**	-1.844**	-1.660	-1.752**
	(0.838)	(1.381)	(0.873)	(0.765)	(1.103)	(0.809)
Performance in 3 sec.	0.653	0.507	0.580	-0.449	-1.411	-0.930
	(0.742)	(1.098)	(0.740)	(0.777)	(1.193)	(0.838)
Performance in 4 sec.	-0.492	-1.768	-1.130	-1.041	-2.996***	-2.018***
	(0.847)	(1.412)	(0.853)	(0.718)	(1.133)	(0.771)
Performance in 5 sec.	0.933	0.486	0.709	0.182	1.390	0.786
	(1.072)	(1.875)	(1.231)	(0.878)	(1.264)	(0.927)
Performance in 6 sec.	-1.655	-2.190	-1.922	-0.387	-0.282	-0.334
	(1.234)	(2.349)	(1.470)	(1.076)	(1.568)	(1.147)
High first	-0.034	-0.264	-0.149	-0.033	-0.033	-0.033
	(0.113)	(0.181)	(0.116)	(0.092)	(0.142)	(0.103)
Low time cost			1.202***			0.991***
			(0.080)			(0.053)
Random Effects			Yes			Yes
Num.Obs.	91	91	182	91	91	182
Unique Obs	91	91	91	91	91	91
$R^2_{\text{Adj.}}$	0.072	0.196	0.575	0.410	0.457	0.706

Note: Linear OLS regressions in columns 1,2,4, and 5. Random effects panel models in columns 3 and 6. The dependent variable is the time selected in the prospective environment and the mean submission time in the simultaneous environment. Heteroscedasticity robust standard errors for the linear models and clustered (on the individual level) standard errors in the panel models. *Average Uncertainty Aversion* and *Average Overconfidence* are the measures described in Section 4, *Performance in X sec.* is the average performance in X seconds, *Low time cost* is a dummy for the low cost-of-time condition, *High first* is a dummy for the order of the two cost-of-time conditions. *(10pp.)* indicates that a unit change in the variable corresponds to a 10 percentage points change.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A4. Time choice and performance estimates

	Prospective			Simultaneous		
	Linear models		Panel	Linear models		Panel
	(1)	(2)	(3)	(4)	(5)	(6)
Cost of time	*High*	*Low*	*Both*	*High*	*Low*	*Both*
Average Time	3.40	4.61	4.01	3.38	4.37	3.88
Average Overconfidence (10pp.)	-0.300***	-0.516**	-0.408***	-0.065	0.091	0.013
	(0.082)	(0.240)	(0.131)	(0.087)	(0.150)	(0.101)
Average Uncertainty Aversion (10pp.)	0.152***	0.309**	0.230***	0.007	-0.134	-0.064
	(0.045)	(0.146)	(0.078)	(0.052)	(0.098)	(0.066)
Performance: Steepness	0.099	0.547***	0.323***	0.477***	0.843***	0.660***
	(0.096)	(0.206)	(0.118)	(0.125)	(0.194)	(0.143)
Performance: Asymptotic level	-2.635**	-3.687	-3.161**	-2.041***	-1.570	-1.805**
	(1.137)	(2.610)	(1.527)	(0.717)	(1.221)	(0.783)
Performance: X-axis onset	0.514***	1.127***	0.821***	0.709***	1.106***	0.907***
	(0.194)	(0.398)	(0.239)	(0.176)	(0.224)	(0.175)
High first	-0.066	-0.276	-0.171	-0.028	-0.045	-0.036
	(0.105)	(0.179)	(0.116)	(0.091)	(0.137)	(0.102)
Low time cost			1.202***			0.991***
			(0.080)			(0.053)
Random Effects			Yes			Yes
Num.Obs.	91	91	182	91	91	182
Unique Obs	91	91	91	91	91	91
$R^2_{\text{Adj.}}$	0.129	0.214	0.579	0.343	0.414	0.697

Note: Linear OLS regressions in columns 1,2,4, and 5. Random effects panel models in columns 3 and 6. The dependent variable is the time selected in the prospective environment and the mean submission time in the simultaneous environment. Heteroscedasticity robust standard errors for the linear models and clustered (on the individual level) standard errors in the panel models. *Average Uncertainty Aversion* and *Average Overconfidence* are the measures described in Section 4, *Steepness Perf., Asymptotic level Perf., and X-axis onset Perf.* are the three estimated parameters from the performance fit,*Low time cost* is a dummy for the low cost-of-time condition, *High first* is a dummy for the order of the two cost-of-time conditions. *(10pp.)* indicates that a unit change in the variable corresponds to a 10 percentage points change. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A5. Effects of overconfidence and uncertainty aversion on time decisions and payoffs

	Prospective		Simultaneous	
	High (1)	*Low* (2)	*High* (3)	*Low* (4)
Regression Slopes				
Time Choice				
Average Overconfidence (10pp.)	-0.26***	-0.48**	-0.06	0.08
	(0.09)	(0.24)	(0.08)	(0.14)
Average Uncertainty Aversion (10pp.)	0.11**	0.27**	0.00	-0.11
	(0.05)	(0.14)	(0.04)	(0.08)
Average Performance (10pp.)	-0.14**	-0.45***	-0.37***	-0.61***
	(0.06)	(0.10)	(0.06)	(0.09)
High first	-0.02	-0.25	-0.03	-0.09
	(0.10)	(0.17)	(0.08)	(0.13)
Payoff				
Time Choice	-7.29***	-0.39	-11.20***	-0.84
	(1.19)	(1.37)	(1.13)	(1.46)
Average Overconfidence (10pp.)	0.91	-1.41	0.49	1.53
	(1.12)	(1.92)	(0.94)	(2.09)
Average Uncertainty Aversion (10pp.)	0.15	-0.06	-0.49	-1.07
	(0.63)	(1.20)	(0.40)	(1.26)
Average Performance (10pp.)	6.27***	9.02***	5.37***	8.49***
	(0.73)	(1.40)	(0.64)	(1.59)
High first	-0.96	-3.58**	0.05	-0.15
	(1.03)	(1.76)	(0.88)	(1.83)
Intercepts				
Time Choice	4.32***	7.60***	5.77***	8.27***
	(0.38)	(0.68)	(0.38)	(0.62)
Payoff	11.56	28.24**	34.37***	35.77**
	(7.23)	(13.53)	(6.70)	(15.66)
Indirect Effects on Payoff				
Average Overconfidence (10pp.)	1.91**	0.18	0.69	-0.06
	(0.76)	(0.72)	(0.89)	(0.28)
Average Uncertainty Aversion (10pp.)	-0.83**	-0.11	-0.04	0.10
	(0.40)	(0.38)	(0.49)	(0.22)
Average Performance (10pp.)	1.04**	0.17	4.19***	0.51
	(0.45)	(0.61)	(0.72)	(0.91)
Total Effects on Payoffs				
Average Overconfidence (10pp.)	2.82**	-1.22	1.18	1.47
	(1.16)	(1.94)	(1.41)	(2.07)
Average Uncertainty Aversion (10pp.)	-0.68	-0.17	-0.53	-0.98
	(0.66)	(1.21)	(0.60)	(1.24)
Average Performance (10pp.)	7.31***	9.19***	9.56***	9.00***
	(0.91)	(1.21)	(0.80)	(1.17)
CFI	1.00	1.00	1.00	1.00
TLI	1.00	1.00	1.00	1.00
RMSEA	0.00	0.00	0.00	0.00

Note: Path analysis estimated by maximum likelihood. The recursive fully specified and thus just-identified model has two endogenous variables: *time choice* and *payoff*. *Time choice* has a dual role and is allowed to have an effect on *payoff*. Payoff is the average payoff for each participant calculated based on their time choice and performance in the respective tasks in stage five. The exogenous variables are *Average Uncertainty Aversion* and *Average Overconfidence* as described in Section 4, *Average Performance* as the average performance, *High first* is a dummy for the order of the two cost-of-time conditions. *(10pp.)* indicates that a unit change in the variable corresponds to a 10 percentage points change. Bootstrapped ($n = 1000$) standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01

Table A6. Time choices in the simultaneous condition

	Rounds 1 - 10			Round 1			Round 10		
	Linear models		Panel	Linear models		Panel	Linear models		Panel
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Cost of time	*High*	*Low*	*Both*	*High*	*Low*	*Both*	*High*	*Low*	*Both*
Average Overconfidence (10pp.)	0.033	-0.012	0.018	0.066	0.146	0.113	-0.119	-0.022	-0.063
	(0.052)	(0.090)	(0.113)	(0.100)	(0.208)	(0.142)	(0.132)	(0.149)	(0.131)
Average Uncertainty Aversion (10pp.)	0.026	0.016	-0.034	0.051	-0.092	-0.076	0.096	-0.070	-0.042
	(0.032)	(0.063)	(0.077)	(0.067)	(0.134)	(0.095)	(0.073)	(0.085)	(0.082)
Average Performance (10pp.)	-0.001	-0.064	-0.523***	0.021	0.006	-0.477***	-0.009	-0.103	-0.547***
	(0.030)	(0.058)	(0.082)	(0.072)	(0.132)	(0.101)	(0.082)	(0.098)	(0.092)
High first	0.033	0.215**	0.060	0.034	0.251	0.078	-0.215*	0.221	-0.061
	(0.051)	(0.088)	(0.115)	(0.130)	(0.209)	(0.153)	(0.126)	(0.171)	(0.141)
Low time cost			1.042***			0.680***			0.928***
			(0.073)			(0.122)			(0.125)
Random Effects			Yes			Yes			Yes
Unique Obs	91	91	91	91	91	91	91	91	91
Num.Obs.	91	91	182	91	91	182	91	91	182
$R^2_{\text{Adj.}}$	0.004	0.041	0.593	-0.019	-0.012	0.248	0.018	-0.002	0.343

Note: Linear OLS regressions in columns 1,2,4,5,7 and 8. Random effects panel models in columns 3, 6 and 9. The dependent variable is the mean submission time in the first 10 rounds (columns 1-3), the submission time in round 1 (columns 4-6), and the submission time in round 10 (columns 7-9) in the simultaneous environment. Heteroscedasticity robust standard errors for the linear models and clustered (on the individual level) standard errors in the panel models. *Average Uncertainty Aversion* and *Average Overconfidence* are the measures described in Section 4, *Average Performance* is the average performance, *Low time cost* is a dummy for the low cost-of-time condition, *High first* is a dummy for the order of the two cost-of-time conditions. *(10pp.)* indicates that a unit change in the variable corresponds to a ten percentage points change. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A7. Time choices: beliefs median

	Prospective			Simultaneous		
	Linear models		Panel	Linear models		Panel
	(1)	(2)	(3)	(4)	(5)	(6)
Cost of time	*High*	*Low*	*Both*	*High*	*Low*	*Both*
Average Time	3.40	4.61	4.01	3.38	4.37	3.88
Average Overconfidence (10pp.)	-0.340***	-0.619*	-0.480***	-0.049	0.038	-0.005
	(0.119)	(0.331)	(0.176)	(0.075)	(0.127)	(0.084)
Average Uncertainty Aversion (10pp.)	0.084	0.225	0.155*	0.004	-0.114	-0.055
	(0.052)	(0.142)	(0.081)	(0.046)	(0.089)	(0.061)
Average Performance (10pp.)	-0.139**	-0.447***	-0.293***	-0.372***	-0.606***	-0.489***
	(0.059)	(0.106)	(0.065)	(0.058)	(0.093)	(0.068)
High first	-0.027	-0.256	-0.141	-0.042	-0.095	-0.068
	(0.103)	(0.175)	(0.116)	(0.084)	(0.133)	(0.097)
Low time cost			1.202***			0.991***
			(0.080)			(0.053)
Random Effects			Yes			Yes
Unique Obs	91	91	91	91	91	91
Num.Obs.	91	91	182	91	91	182
$R^2_{\text{Adj.}}$	0.107	0.238	0.581	0.398	0.426	0.702

Note: Linear OLS regressions in columns 1,2,4, and 5. Random effects panel models in columns 3 and 6. The dependent variable is the time selected in the prospective condition and the average submission time in the simultaneous condition. Heteroscedasticity robust standard errors for the linear models and clustered (on the individual level) standard errors in the panel models. *Average Uncertainty Aversion* and *Average Overconfidence* are the measures described in Section 4, *Average Performance* is the average performance, *Low time cost* is a dummy for the low cost-of-time condition, *High first* is a dummy for the order of the two cost-of-time conditions. (10pp.) indicates that a unit change in the variable corresponds to a 10 percentage points change. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A8. Time choice and individual characteristics: beliefs median

	Prospective			Simultaneous		
	Linear models		Panel	Linear models		Panel
	(1)	(2)	(3)	(4)	(5)	(6)
Cost of time	*High*	*Low*	*Both*	*High*	*Low*	*Both*
Average Time	3.40	4.61	4.01	3.38	4.37	3.88
Average Overconfidence (10pp.)	-0.336***	-0.690**	-0.513***	-0.033	0.045	0.006
	(0.118)	(0.315)	(0.162)	(0.082)	(0.156)	(0.095)
Average Uncertainty Aversion (10pp.)	0.095	0.249	0.172**	0.003	-0.117	-0.057
	(0.064)	(0.153)	(0.083)	(0.053)	(0.113)	(0.070)
Average Performance (10pp.)	-0.092	-0.447***	-0.269***	-0.346***	-0.583***	-0.464***
	(0.079)	(0.145)	(0.086)	(0.064)	(0.120)	(0.075)
GPS Risk	-0.095	-0.102	-0.098	-0.047	0.006	-0.021
	(0.065)	(0.115)	(0.066)	(0.047)	(0.102)	(0.060)
GPS Patience	-0.013	-0.015	-0.014	-0.044	0.005	-0.020
	(0.059)	(0.088)	(0.055)	(0.043)	(0.083)	(0.052)
Fatigue	-0.011	-0.007	-0.009	-0.001	-0.035	-0.018
	(0.020)	(0.035)	(0.022)	(0.015)	(0.025)	(0.017)
Intensive Work anticipated	0.000	0.024	0.012	-0.034	0.029	-0.003
	(0.131)	(0.214)	(0.137)	(0.096)	(0.162)	(0.112)
Time Pressure	0.000	-0.002	-0.001	-0.002	-0.003	-0.002
	(0.002)	(0.004)	(0.002)	(0.002)	(0.003)	(0.002)
Competition	0.045	0.077	0.061	-0.002	0.023	0.010
	(0.061)	(0.107)	(0.066)	(0.048)	(0.081)	(0.053)
Female	0.138	-0.085	0.027	0.051	-0.008	0.021
	(0.149)	(0.223)	(0.146)	(0.111)	(0.162)	(0.111)
Age	-0.034*	-0.067*	-0.051**	-0.008	-0.002	-0.005
	(0.020)	(0.039)	(0.023)	(0.016)	(0.028)	(0.019)
High first	-0.111	-0.330	-0.220*	-0.080	-0.095	-0.087
	(0.111)	(0.210)	(0.129)	(0.095)	(0.141)	(0.100)
Low time cost			1.202***			0.991***
			(0.080)			(0.053)
Random Effects			Yes			Yes
Unique Obs	91	91	91	91	91	91
Num.Obs.	91	91	182	91	91	182
$R^2_{\text{Adj.}}$	0.104	0.228	0.582	0.367	0.391	0.697

Note: Linear OLS regressions in columns 1,2,4, and 5. Random effects panel models in columns 3 and 6. The dependent variable is the time selected in the prospective environment and the mean submission time in the simultaneous environment. Heteroscedasticity robust standard errors for the linear models and clustered (on the individual level) standard errors in the panel models. *Average Uncertainty Aversion* and *Average Overconfidence* are the measures described in Section 4, *Average Performance* is the average performance, *GPS Risk, GPS Patience, Fatigue, Intensive Work anticipated, Time Pressure, Competition, Female, and Age* the individual survey measures elicited in stage 5, *Low time cost* is a dummy for the low cost-of-time condition, *High first* is a dummy for the order of the two cost-of-time conditions. *(10pp.)* indicates that a unit change in the variable corresponds to a 10 percentage points change. * p < 0.1, ** p < 0.05, *** p < 0.01

Table A9. Time choice with individual performance: beliefs median

	Prospective			Simultaneous		
	Linear models		Panel	Linear models		Panel
	(1)	(2)	(3)	(4)	(5)	(6)
Cost of time	*High*	*Low*	*Both*	*High*	*Low*	*Both*
Average Time	3.40	4.61	4.01	3.38	4.37	3.88
Average Overconfidence (10pp.)	-0.361***	-0.629**	-0.495***	-0.033	0.097	0.032
	(0.108)	(0.312)	(0.159)	(0.067)	(0.122)	(0.077)
Average Uncertainty Aversion (10pp.)	0.103**	0.244*	0.174**	0.004	-0.126	-0.061
	(0.051)	(0.146)	(0.080)	(0.049)	(0.092)	(0.062)
Performance in 2 sec.	-1.539*	-2.157	-1.848**	-1.853**	-1.668	-1.760**
	(0.818)	(1.440)	(0.885)	(0.762)	(1.103)	(0.809)
Performance in 3 sec.	0.534	0.285	0.410	-0.443	-1.441	-0.942
	(0.711)	(1.155)	(0.731)	(0.776)	(1.197)	(0.839)
Performance in 4 sec.	-0.332	-1.428	-0.880	-1.064	-2.903**	-1.984**
	(0.810)	(1.447)	(0.849)	(0.706)	(1.139)	(0.767)
Performance in 5 sec.	0.865	0.372	0.618	0.176	1.412	0.794
	(1.012)	(1.835)	(1.179)	(0.874)	(1.266)	(0.926)
Performance in 6 sec.	-1.529	-2.153	-1.841	-0.313	-0.433	-0.373
	(1.119)	(2.368)	(1.438)	(1.035)	(1.523)	(1.097)
High first	-0.041	-0.268	-0.155	-0.037	-0.027	-0.032
	(0.109)	(0.177)	(0.112)	(0.091)	(0.141)	(0.101)
Low time cost			1.202***			0.991***
			(0.080)			(0.053)
Random Effects			Yes			Yes
Num.Obs.	91	91	182	91	91	182
Unique Obs	91	91	91	91	91	91
$R^2_{\text{Adj.}}$	0.113	0.223	0.581	0.409	0.456	0.706

Note: Linear OLS regressions in columns 1,2,4, and 5. Random effects panel models in columns 3 and 6. The dependent variable is the time selected in the prospective environment and the mean submission time in the simultaneous environment. Heteroscedasticity robust standard errors for the linear models and clustered (on the individual level) standard errors in the panel models. *Average Uncertainty Aversion* and *Average Overconfidence* are the measures described in Section 4, *Performance in X sec.* is the average performance in X seconds, *Low time cost* is a dummy for the low cost-of-time condition, *High first* is a dummy for the order of the two cost-of-time conditions. *(10pp.)* indicates that a unit change in the variable corresponds to a 10 percentage points change.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A10. Time choice and performance estimates: beliefs median

	Prospective			Simultaneous		
	Linear models		Panel	Linear models		Panel
	(1)	(2)	(3)	(4)	(5)	(6)
Cost of time	*High*	*Low*	*Both*	*High*	*Low*	*Both*
Average Time	3.40	4.61	4.01	3.38	4.37	3.88
Average Overconfidence (10pp.)	-0.365***	-0.647**	-0.506***	-0.051	0.047	-0.002
	(0.098)	(0.324)	(0.163)	(0.081)	(0.129)	(0.089)
Average Uncertainty Aversion (10pp.)	0.126***	0.261*	0.194**	0.007	-0.140	-0.066
	(0.047)	(0.148)	(0.078)	(0.055)	(0.103)	(0.071)
Performance: Steepness	0.098	0.550***	0.324***	0.473***	0.843***	0.658***
	(0.094)	(0.207)	(0.118)	(0.126)	(0.194)	(0.143)
Performance: Asymptotic level	-2.444**	-3.390	-2.917*	-2.004***	-1.443	-1.723**
	(1.108)	(2.567)	(1.491)	(0.724)	(1.225)	(0.786)
Performance: X-axis onset	0.511***	1.126***	0.819***	0.706***	1.095***	0.901***
	(0.184)	(0.387)	(0.229)	(0.176)	(0.229)	(0.178)
High first	-0.069	-0.273	-0.171	-0.035	-0.042	-0.039
	(0.101)	(0.175)	(0.112)	(0.089)	(0.136)	(0.100)
Low time cost			1.202***			0.991***
			(0.080)			(0.053)
Random Effects			Yes			Yes
Num.Obs.	91	91	182	91	91	182
Unique Obs	91	91	91	91	91	91
$R^2_{\text{Adj.}}$	0.163	0.242	0.585	0.339	0.417	0.697

Note: Linear OLS regressions in columns 1,2,4, and 5. Random effects panel models in columns 3 and 6. The dependent variable is the time selected in the prospective environment and the mean submission time in the simultaneous environment. Heteroscedasticity robust standard errors for the linear models and clustered (on the individual level) standard errors in the panel models. *Average Uncertainty Aversion* and *Average Overconfidence* are the measures described in Section 4, *Steepness Perf., Asymptotic level Perf., and X-axis onset Perf.* are the three estimated parameters from the performance fit,*Low time cost* is a dummy for the low cost-of-time condition, *High first* is a dummy for the order of the two cost-of-time conditions. *(10pp.)* indicates that a unit change in the variable corresponds to a 10 percentage points change. * p < 0.1, ** p < 0.05, *** p < 0.01

Table A11. Time choices: beliefs mode

	Prospective			Simultaneous		
	Linear models		Panel	Linear models		Panel
	(1)	(2)	(3)	(4)	(5)	(6)
Cost of time	*High*	*Low*	*Both*	*High*	*Low*	*Both*
Average Time	3.40	4.61	4.01	3.38	4.37	3.88
Average Overconfidence (10pp.)	-0.235***	-0.502*	-0.369***	-0.028	0.058	0.015
	(0.070)	(0.261)	(0.128)	(0.058)	(0.100)	(0.067)
Average Uncertainty Aversion (10pp.)	0.075	0.179	0.127	0.000	-0.132	-0.066
	(0.053)	(0.141)	(0.081)	(0.045)	(0.088)	(0.060)
Average Performance (10pp.)	-0.132**	-0.433***	-0.283***	-0.369***	-0.597***	-0.483***
	(0.058)	(0.102)	(0.063)	(0.058)	(0.093)	(0.068)
High first	-0.038	-0.268	-0.153	-0.044	-0.097	-0.070
	(0.103)	(0.173)	(0.114)	(0.083)	(0.130)	(0.095)
Low time cost			1.202***			0.991***
			(0.080)			(0.053)
Random Effects			Yes			Yes
Unique Obs	91	91	91	91	91	91
Num.Obs.	91	91	182	91	91	182
$R^2_{\text{Adj.}}$	0.092	0.257	0.583	0.397	0.435	0.703

Note: Linear OLS regressions in columns 1,2,4, and 5. Random effects panel models in columns 3 and 6. The dependent variable is the time selected in the prospective environment and the mean submission time in the simultaneous environment. Heteroscedasticity robust standard errors for the linear models and clustered (on the individual level) standard errors in the panel models. *Average Uncertainty Aversion* and *Average Overconfidence* are the measures described in Section 4, *Average Performance* is the average performance, *Low time cost* is a dummy for the low cost-of-time condition, *High first* is a dummy for the order of the two cost-of-time conditions. *(10pp.)* indicates that a unit change in the variable corresponds to a 10 percentage points change. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A12. Time choices and individual characteristics: beliefs mode

	Prospective			Simultaneous		
	Linear models		Panel	Linear models		Panel
	(1)	(2)	(3)	(4)	(5)	(6)
Cost of time	*High*	*Low*	*Both*	*High*	*Low*	*Both*
Average Time	3.40	4.61	4.01	3.38	4.37	3.88
Average Overconfidence (10pp.)	-0.230***	-0.541**	-0.386***	-0.019	0.064	0.023
	(0.077)	(0.246)	(0.116)	(0.064)	(0.130)	(0.078)
Average Uncertainty Aversion (10pp.)	0.087	0.200	0.144*	-0.003	-0.141	-0.072
	(0.066)	(0.156)	(0.085)	(0.052)	(0.115)	(0.070)
Average Performance (10pp.)	-0.084	-0.432***	-0.258***	-0.344***	-0.575***	-0.460***
	(0.080)	(0.144)	(0.086)	(0.064)	(0.120)	(0.075)
GPS Risk	-0.098	-0.103	-0.100	-0.047	0.008	-0.020
	(0.065)	(0.116)	(0.066)	(0.047)	(0.100)	(0.059)
GPS Patience	-0.012	-0.005	-0.009	-0.044	0.006	-0.019
	(0.060)	(0.083)	(0.053)	(0.042)	(0.082)	(0.051)
Fatigue	-0.010	-0.003	-0.007	-0.001	-0.033	-0.017
	(0.021)	(0.035)	(0.022)	(0.015)	(0.025)	(0.017)
Intensive Work anticipated	-0.016	0.003	-0.006	-0.034	0.031	-0.002
	(0.131)	(0.219)	(0.139)	(0.096)	(0.163)	(0.113)
Time Pressure	0.000	-0.003	-0.002	-0.002	-0.003	-0.003
	(0.002)	(0.004)	(0.002)	(0.002)	(0.003)	(0.002)
Competition	0.046	0.072	0.059	-0.003	0.022	0.009
	(0.062)	(0.107)	(0.066)	(0.047)	(0.080)	(0.053)
Female	0.146	-0.084	0.031	0.051	-0.010	0.020
	(0.150)	(0.226)	(0.148)	(0.110)	(0.162)	(0.110)
Age	-0.031	-0.061	-0.046*	-0.007	0.001	-0.003
	(0.020)	(0.041)	(0.024)	(0.017)	(0.028)	(0.019)
High first	-0.122	-0.341	-0.231*	-0.081	-0.096	-0.089
	(0.112)	(0.212)	(0.130)	(0.094)	(0.141)	(0.100)
Low time cost			1.202***			0.991***
			(0.080)			(0.053)
Random Effects			Yes			Yes
Unique Obs	91	91	91	91	91	91
Num.Obs.	91	91	182	91	91	182
$R^2_{\text{Adj.}}$	0.084	0.241	0.582	0.368	0.402	0.698

Note: Linear OLS regressions in columns 1,2,4, and 5. Random effects panel models in columns 3 and 6. The dependent variable is the time selected in the prospective environment and the mean submission time in the simultaneous environment. Heteroscedasticity robust standard errors for the linear models and clustered (on the individual level) standard errors in the panel models. *Average Uncertainty Aversion* and *Average Overconfidence* are the measures described in Section 4, *Average Performance* is the average performance, *GPS Risk, GPS Patience, Fatigue, Intensive Work anticipated, Time Pressure, Competition, Female, and Age* the individual survey measures elicited in stage 5, *Low time cost* is a dummy for the low cost-of-time condition, *High first* is a dummy for the order of the two cost-of-time conditions. *(10pp.)* indicates that a unit change in the variable corresponds to a 10 percentage points change.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A13. Time choice with individual performance: beliefs mode

	Prospective			Simultaneous		
	Linear models		Panel	Linear models		Panel
	(1)	(2)	(3)	(4)	(5)	(6)
Cost of time	*High*	*Low*	*Both*	*High*	*Low*	*Both*
Average Time	3.40	4.61	4.01	3.38	4.37	3.88
Average Overconfidence (10pp.)	-0.270***	-0.542**	-0.406***	-0.019	0.097	0.039
	(0.068)	(0.265)	(0.127)	(0.056)	(0.098)	(0.064)
Average Uncertainty Aversion (10pp.)	0.095*	0.203	0.149*	0.004	-0.131	-0.064
	(0.051)	(0.145)	(0.080)	(0.050)	(0.093)	(0.062)
Performance in 2 sec.	-1.601*	-2.270	-1.936**	-1.858**	-1.667	-1.762**
	(0.833)	(1.439)	(0.885)	(0.766)	(1.117)	(0.817)
Performance in 3 sec.	0.603	0.308	0.456	-0.431	-1.448	-0.940
	(0.699)	(1.200)	(0.748)	(0.781)	(1.222)	(0.851)
Performance in 4 sec.	-0.210	-0.997	-0.604	-1.063	-2.736**	-1.900**
	(0.855)	(1.439)	(0.848)	(0.757)	(1.204)	(0.827)
Performance in 5 sec.	0.936	0.493	0.715	0.182	1.394	0.788
	(1.025)	(1.765)	(1.148)	(0.879)	(1.268)	(0.929)
Performance in 6 sec.	-1.794	-2.811	-2.302	-0.327	-0.623	-0.475
	(1.152)	(2.327)	(1.411)	(1.094)	(1.606)	(1.162)
High first	-0.056	-0.288	-0.172	-0.039	-0.031	-0.035
	(0.108)	(0.173)	(0.108)	(0.090)	(0.141)	(0.101)
Low time cost			1.202***			0.991***
			(0.080)			(0.053)
Random Effects			Yes			Yes
Num.Obs.	91	91	182	91	91	182
Unique Obs	91	91	91	91	91	91
$R^2_{\text{Adj.}}$	0.106	0.247	0.584	0.408	0.459	0.706

Note: Linear OLS regressions in columns 1,2,4, and 5. Random effects panel models in columns 3 and 6. The dependent variable is the time selected in the prospective environment and the mean submission time in the simultaneous environment. Heteroscedasticity robust standard errors for the linear models and clustered (on the individual level) standard errors in the panel models. *Average Uncertainty Aversion* and *Average Overconfidence* are the measures described in Section 4, *Performance in X sec.* is the average performance in X seconds, *Low time cost* is a dummy for the low cost-of-time condition, *High first* is a dummy for the order of the two cost-of-time conditions. *(10pp.)* indicates that a unit change in the variable corresponds to a 10 percentage points change. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A14. Time choice and performance estimates: beliefs mode

	Prospective			Simultaneous		
	Linear models		Panel	Linear models		Panel
	(1)	(2)	(3)	(4)	(5)	(6)
Cost of time	*High*	*Low*	*Both*	*High*	*Low*	*Both*
Average Time	3.40	4.61	4.01	3.38	4.37	3.88
Average Overconfidence (10pp.)	-0.280***	-0.540**	-0.410***	-0.030	0.084	0.027
	(0.062)	(0.262)	(0.125)	(0.065)	(0.113)	(0.076)
Average Uncertainty Aversion (10pp.)	0.113**	0.216	0.165**	0.004	-0.148	-0.072
	(0.047)	(0.146)	(0.078)	(0.052)	(0.100)	(0.068)
Performance: Steepness	0.085	0.527**	0.306***	0.470***	0.829***	0.649***
	(0.093)	(0.204)	(0.115)	(0.125)	(0.192)	(0.142)
Performance: Asymptotic level	-2.610**	-3.609	-3.110**	-2.035***	-1.602	-1.819**
	(1.183)	(2.719)	(1.563)	(0.736)	(1.110)	(0.756)
Performance: X-axis onset	0.496***	1.090***	0.793***	0.701***	1.066***	0.883***
	(0.183)	(0.372)	(0.218)	(0.177)	(0.233)	(0.179)
High first	-0.082	-0.289*	-0.186*	-0.038	-0.050	-0.044
	(0.099)	(0.172)	(0.108)	(0.088)	(0.134)	(0.098)
Low time cost			1.202***			0.991***
			(0.080)			(0.053)
Random Effects			Yes			Yes
Unique Obs	91	91	91	91	91	91
Num.Obs.	91	91	182	91	91	182
$R^2_{\text{Adj.}}$	0.160	0.261	0.587	0.339	0.421	0.698

Note: Linear OLS regressions in columns 1,2,4, and 5. Random effects panel models in columns 3 and 6. The dependent variable is the time selected in the prospective environment and the mean submission time in the simultaneous environment. Heteroscedasticity robust standard errors for the linear models and clustered (on the individual level) standard errors in the panel models. *Average Uncertainty Aversion* and *Average Overconfidence* are the measures described in Section 4, *Steepness Perf., Asymptotic level Perf., and X-axis onset Perf.* are the three estimated parameters from the performance fit,*Low time cost* is a dummy for the low cost-of-time condition, *High first* is a dummy for the order of the two cost-of-time conditions. *(10pp.)* indicates that a unit change in the variable corresponds to a 10 percentage points change. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

A.3 Additional Theory

A.3.1 Uniqueness of the Maximum at t^*. To prove that t^* is unique, start with the objective function and the reward function:

$$t^* = \text{argmax}_t \Pi(t) = p(t)y(t)$$

$$y(t) = \begin{cases} Y - c(t) & \text{if task is solved correctly and } Y > c(t) \\ 0 & \text{otherwise} \end{cases}$$

We define t_b as t where $Y = c(t)$ and t_0 as t where $t = 0$. Thus $[t_0, t_b]$ is the relevant interval for the maximization problem.
We assume that performance $p(t)$ and the cost of time $c(t)$ are positive, concave, and increasing functions, i.e.,

$$p(t) > 0,\ p'(t) > 0,\ p''(t) \leq 0,\ \forall t \in [t_0, t_b]$$

$$c(t) > 0,\ c'(t) > 0,\ c''(t) \leq 0,\ \forall t \in [t_0, t_b]$$

Thus, the overall reward function $y(t)$ is characterized by:

$$y(t) > 0,\ y'(t) < 0,\ y''(t) \leq 0,\ \forall t \in [t_0, t_b]$$

To determine whether $\Pi(t)$ has a unique maximum, we make the following observations

- $p(t), y(t)$ are non-negative in $[t_0, t_b]$
- $p(t_0) = 0$ and $y(t_b) = 0 \implies p(t_0)y(t_0) = p(t_b)y(t_b)$
- $p'(t)y'(t) < 0$ in $[t_0, t_b]$.

We can then apply Rolle's theorem since $\Pi(t_0) = \Pi(t_b)$, which states that there exists at least one stationary point t^{stat}, where $\Pi'(t^{stat}) = 0$.
The necessary condition for t^{stat} to be a maximum is that $\Pi''(t^{stat}) < 0$. The second derivative

$$\Pi''(t) = p''(t)y(t) + 2p'(t)y'(t) + p(t)y''(t)$$

is negative in $[t_0, t_b]$, since $p''(t)y(t) \leq 0$, $p'(t)y'(t) < 0$ and $p(t)y''(t) \leq 0$. Thus we have a local maximum at t^{stat}. This maximum is a unique maximum since $\Pi''(t)y(t) \leq 0$ everywhere in $[t_0, t_b]$, and $\Pi(t)$ is thus a concave function which can only have one unique maximum. Thus, the maximum at t^{stat} is a unique global maximum, which we call t^*.

A.3.2 Generality of Predictions 1-4. In this section, we discuss the generality of predictions 1-4, while relying on the assumptions from Section A.3.1.

Prediction 1. We define $\text{argmax}_t \Pi_1(t) = t_1^*$ and $\text{argmax}_t \Pi_2(t) = t_2^*$ and investigate if $t_1^* < t_2^*$ when $c_1(t) > c_2(t)\ \forall\ t$.
We rewrite

$$c_1(t) \; = \; c_2(t) + d_c(t)$$

where $d_c(t) > 0\ \forall\ t$ describes the difference between the two cost functions. This implies that

$$\Pi_1(t) \; = \; p(t)(m - c_2(t)) \quad \text{and} \quad \Pi_2(t) \; = \; p(t)(m - (c_2(t) + d_c(t))$$

combining the two yields

$$\Pi_1(t) - \Pi_2(t) \; = \; -p(t)d_c(t)$$

and taking the first derivative with respect to t

$$\Pi_1'(t) \; = \; \Pi_2'(t) - (p(t)d_c(t))'$$

$t_1^* < t_2^*$ requires the first derivative $\Pi_1'(t)$ *evaluated at* t_2^* to be negative (as both t_1^* and t_2^* are unique (see proof above)) and thus

$$\Pi_2'(t_2^*) - p'(t_2^*)d_c(t_2^*) - p(t_2^*)d_c'(t_2^*) \; < \; 0 \tag{10}$$

By definition $\Pi_2'(t_2^*) = 0$, such that the inequality reduces to $p'(t_2^*)d_c(t_2^*) > -p(t_2^*)d_c'(t_2^*)$. Remember that by definition $p(t) > 0$, $p'(t) > 0$, and $d(t) > 0$. Therefore, the inequality is true in the following three cases:

if1 $d_c'(t_2^*) > 0$. This is the case where the change in the difference between cost conditions evaluated at t_2^* is positive, i.e., where $c_1(t_2^*)$ and $c_2(t_2^*)$ “drift apart”.
if2 $d_c'(t_2^*) = 0$. This is the case when the difference between the cost conditions does not change at t_2^*.
if3 $d_c'(t_2^*) < 0$ and $\frac{p'(t_2^*)}{p(t_2^*)} > -\frac{d_c'(t_2^*)}{d_c(t_2^*)}$. This means that the (normalized) increase in performance at t_2^* is still larger than the decrease in the cost conditions. Intuitively, this condition implies that the rate of change in the difference between the cost function is not more extreme that the rate of increase in performance.

In the case of linear cost functions (i.e., as implemented in the experiment), Prediction 1 applies as $d_c'(t) > 0\ \forall\ t$.

Prediction 2. We again define $\text{argmax}_t \Pi_i(t) = t_i^*$ and $\text{argmax}_t \Pi_j(t) = t_j^*$ and discuss if $t_i^* < t_j^*$ when $p_i(t) > p_j(t)\ \forall\ t$.
Prediction 2 implies that

$$\Pi_i(t) \;=\; (p(t) + d_p(t))(m - c(t)) \;=\; \Pi_j(t) + d_p(t)(m - c(t))$$

and thus,

$$\Pi_i'(t) \;=\; \Pi_j'(t) + (d_p(t)(m - c(t))'$$

$t_i^* < t_j^*$ requires the first derivative $\Pi_i'(t)$ *evaluated at* t_j^* to be negative. This implies the inequality $\frac{d_p'(t_j^*)}{d_p(t_j^*)} < \frac{c'(t_j^*)}{m-c(t_j^*)}$. This inequality is satisfied in the following three cases:

1. $d_p'(t_j^*) < 0$ (difference between performance shrinks),
2. $d_p'(t_j^*) = 0$ (constant) and
3. $d_p'(t_j^*) > 0$ and $\frac{c'(t_j^*)}{m-c(t_j^*)} > \frac{d_p'(t_j^*)}{d_p(t_j^*)}$

If we assume the functional form proposed for performance in this experiment (equation 7), and that differences in performance originate in a shift in α (x-axis onset), i.e., holding steepness and asymptotic level constant, we define:

$$d(t) \;=\; \beta\left(1 - e^{-(t-\alpha)/\lambda}\right) - \beta\left(1 - e^{-(t-(\alpha+\zeta))/\lambda}\right)$$

where ζ is the shift in the x-axis onset. Then the first derivative is clearly negative, i.e.

$$d'(t) \;=\; -\frac{\beta\left(e^{\zeta/\lambda} - 1\right)e^{(\alpha-t)/\lambda}}{\lambda} \;<\; 0$$

Prediction 3-4. We combine the discussions of predictions 3 and 4, which are similar to the previous discussion in Prediction 2. We define
$\text{argmax}_t \Pi^b(t) = t^b$ and $\text{argmax}_t \Pi(t) = t^*$ and discuss if $t^b < t^*$ when $w(b(t)) > p(t)\ \forall\ t$.
The relevant inequality is

$$\Pi^b(t)' \;=\; \Pi'(t) + (d^b(t)(m - c(t))'$$

where $d^b(t) = w(b(t)) - p(t)$ and $d^b(t) > 0\ \forall\ t$.
This inequality is satisfied once:

1. $d^b(t^*)' < 0$ (difference between subjective performance shrinks),
2. $d^b(t^*)' = 0$ (constant) and
3. $d^b(t^*)' > 0$ and $\frac{c'(t^*)}{m-c(t^*)} > \frac{d^b(t^*)'}{d^b(t^*)}$

We assume that $d^b(t)$ is similar to $d_p(t)$, i.e., that behavioral differences between agents originate in a constant shift of the subjective performance function. In this case, the prediction holds. For more complex functional form assumptions (e.g., as in equations 8 and 9), the assessment of cases 1-3 strongly depends on the chosen parameter values. Overall, we thus conclude that predictions 1 and 2 generally hold for the linear cost function in this experiment and the proposed functional form for performance. Predictions 3 and 4 hold in case of certain restrictions on the functional form, but alternative functional forms and certain parameter values might generate opposite predictions.

A.4 Task Generation and Sampling

The tables for the tasks are generated to have similar difficulty across all stages. All participants see the same tables; however, *when* the tasks are presented within one stage is different for participants. The general procedure to sample the number in the matrix for a single task is as follows:

1. a solution between 41 and 90 is randomly chosen with a uniform probability
2. 15 other numbers are randomly chosen without replacement from the interval $[\text{solution}-31, \text{solution}-1]$.

Thus, the non-solution numbers are always within a close range of the solution, ensuring similar difficulty across all tasks. Additionally, all numbers have double digits.

Stage 1: 250 tasks. In the main task, 250 tables are generated, with 50 tables for each of the fixed times (2,3,4,5,6 seconds). All possible solutions from the interval $41, 90$ are used for each fixed time. This ensures that the distribution of solutions is the same across all possible fixed time settings. The order of the tables in the blocks is randomized, so all participants see the same tables for each fixed time but in a different order.

Stage 3: 50 tasks. In the implementation of stage 2, the endogenous choice of reward schemes determines the number of tables that participants have to solve. Since we were not interested in comparing performance across the different reward schemes, we generated 50 tables, one for each possible solution. The order (and thus assignment to the times) is randomized. Participants thus see different tables for different times.

Stage 4: 160 tasks. For stage four, we need 40 tasks for each cost of time and choice environment combination. We generate tables similar to stage 1. However, we only sampled 40 solutions instead of all 50. Thus, the tables have similar difficulty to stage 1, as deterministically changing either the upper or lower interval and applying any other deterministic rule to select the solutions could have resulted in a biased performance estimate. All participants see the same 40 tables within a single environment but in a different order.

A.5 Experimental Material

A.5.1 Experimental instructions (translated).

General explanation about the study

We would like to welcome you to the study. Thank you for your participation.

All of the information you have provided is treated as confidential and not passed on to third parties. Furthermore, the leaders of the study are not able to match your answers to your identity. The data are used exclusively for scientific purposes.

During this study you can make money, depending on your answers. Therefore, it is very important that you read the explanations very carefully. In case you have any difficulties in understanding the instructions, please feel free to write a chat message to the study director. We will explain to you beforehand exactly what the study looks like.

During the study you are not allowed to communicate with other participants or use your mobile phone. In addition, we would like to point out that you may only use the functions on the computer that are intended for the course of the study. Not following these rules will result in exclusion from the study and all payments.

Please note that you can only complete today's study after all study participants have reached the end of the study. After this you will receive an overview of your payout and an explicit request to leave the room and collect your payment.

Payment

For arriving punctually for the study, you will receive a separate participation fee of 5.00€. In addition to this, depending on your answers, you can still earn more money. The study is divided into several sections, within each of which you will have make several choices. In each of these sections, you can earn points based on your answers. These points are registered in your personal points account. Your private points account will be displayed at the end of this study.

At the end of the study, the points you have earned are converted into euros, rounded to the nearest 10 cents and paid out to you **in cash**, for which the following rule applies

1000 points = 2,00 Euro
(100 points = 20 Cent).

Throughout the following pages we will explain the exact nature of the study.

Overview of today's study

The study consists of several **sections**. At the beginning of a new section, you will see the

1

following STOP sign on your screen. STOP If you see the STOP sign on your screen, please read the instructions for the relevant section. If you have read and understood the instructions for the next section, please click on the "Next" (Weiter) button. Weiter

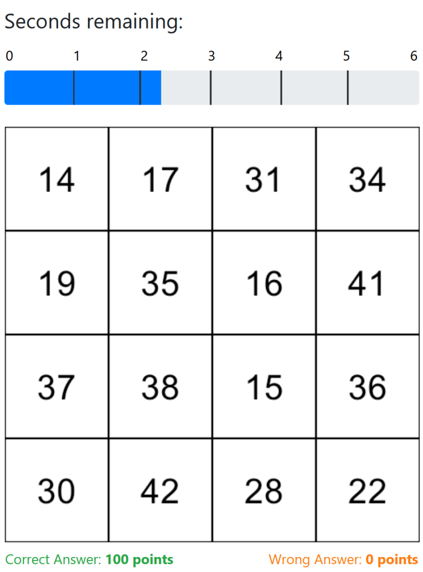
If you have questions while reading the instructions or something is not clear to you, please click on the chat icon in the lower right corner of the screen. A window will open in which you can chat with the heads of the study and ask your questions.

DANGER! Do not click on "Next" now, first read the general explanation and the explanations for the first exercise section.

General explanations: Your answers

In this experiment, you will make the same type of decision repeatedly, with a specific amount of time to make each decision. You have different amounts of time to make decisions in different parts of the study. At the beginning of each section, you will be given detailed information on the amount of time you will have on each specific question.

A central component of this study are the so-called **table questions**:



On **every** table question in this section your task is the following:

Within the available time find the highest value in the table shown and click on it.

Exactly one of the 16 fields always contains the correct answer. You choose your answer by clicking on a box. Your currently selected answer will be highlighted in yellow. You can change your answer as often as you like until the time in which you have to complete the task has expired. The total time that you have for each answer is displayed at the top of the table screen and the remaining time is displayed as a running bar above the table. When the time for each task is over, your currently selected answer will be submitted. If you haven't selected any field when the time has elapsed, your answer will be considered incorrect. After each table question there is an automatic short pause before the next screen is displayed.

Your answer is correct if you clicked on the box with the highest number in the table before the time runs out. You will receive points for each correct answer. How many points you receive is shown in detail in the description for each individual section. Your task is to give as many correct answers as possible in order to earn as many points as possible. At the end of the study, you will receive feedback on how many table questions you solved correctly.

Please note: You will see a new table on each table screen. All tables are the same size and appear in the same place on your screen. Each table contains 16 numbers between 10 and 90. Each number can **only appear once** within a single table. Each table will only appear once in this study. This means you won't see a table twice.

To clarify the task with using an example: Look at the table below and think about what the correct solution is.

50	44	37	42
29	39	26	41
36	51	49	35
25	20	33	24

In this case, the correct answer is "51" as this is the highest number in the table. **Your task would be to find this number and click on the box marked with "51" before the time runs out.**

Practice section - practice rounds for the task

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The study starts with an exercise section. This consists of an interactive example **(phase 1)** and a short exercise session **(phase 2).** The exercise section should make it easier for you to make the best possible decisions later. Please note the following:

You cannot earn any points in the practice section.

Practice Phase 1 is an interactive version of the example on page 3. Practice Phase 2 has a total of 3 rounds, each with 2 table questions. Here you should get to know the main task. Within one round you have the same amount of time to make a decision for each task. The remaining time is displayed as a running bar above the table.

There is a short 10-second break between each lap to relax. During the break you will be shown how much time you have for each individual table screen in the following round. Before the first table question of any given round is shown, you will see a short countdown from 3. After that you will see a screen showing a cross for 4 seconds. This cross is right in the middle of the upcoming decision table. **Move your mouse to the center of the cross to have a good starting position for the task at hand.**

Overview of exercise phase 2:

Round	***1***	***2***	***3***
Table questions	2	2	2
Selection time in seconds	10	7	5

If you have understood the instructions for the exercise section and you have no further questions, please press Weiter **to start the exercises. If you have any questions, please use the chat window.**

Section 1 - Description

Section 1 is the first section where you can earn points. The tasks in section 1 are the same that we have just explained and that you learned about in the practice section. In Section 1, you will have to submit an answer for a total of 250 table questions. These 250 table questions are divided into 5 identical blocks. Each block contains 5 rounds and each individual round contains 10 tables. Below is a table that describes one of the 5 blocks in more detail.

One block:

Round	*1*	*2*	*3*	*4*	*5*
Table Screens	10	10	10	10	10
Selectiontime in seconds	6	5	4	3	2

Within each round you have the same amount of time to solve every single table screen: In the first round you solve 10 table questions while enjoying 6 seconds for each, in the second round you solve 10 table screens with only 5 seconds for each and so on. When a block ends, a new block begins. In this, you have 6 seconds each in the first lap. Before starting the first block, you will see a full overview of all 5 blocks and all laps in Section 1 on the screen.

At the beginning of each new round you have a short break and the time of the next round is announced to you. You can take a longer break of up to 2 minutes between blocks. As in the exercise part, each new lap begins with a countdown and the cross on the screen, which should make it easier for you to find the center of the screen.

Section 1 – Payout

An important difference to the practice section is your payout. **In Section 1, you can earn points with your answers.** Your payout is calculated as follows:

At the beginning of section 1, the computer will randomly select 30 percent (equivalent to 75 table screens) of all 250 table screens for the payout. We call these 75 tables **the payment-relevant tables**. Each of the 250 table screens has the same probability of being selected by the computer as relevant for payment.

Neither the head of the study nor the study participant knows which tables are selected by the computer or can influence this decision. Of course, when you submit your answers for the table questions, you do not yet know which of the 75 payment tables are that will be chosen by chance. You should therefore solve each table as correctly as possible, since you have to assume that each one can be relevant for your payout.

You will receive **100 points** for each **correctly completed payment-related table**. These points will be credited directly to your points account.

If you do not correctly solve a payment-related table, *i.e.*, you have not selected a number or a number other than the highest when the time has elapsed, you will receive **0 points**. Your payout for the 75 payment-relevant tables is summarized in the following table.

Payout for each correctly competed payment-related table	Payout for each not correctly competed payment-related table
100 points	**0 points**

The payouts for a correctly and incorrectly answered payment-relevant table are shown again under *each* table on the table screen. So you do not yet know which of the tables are relevant to payment when you are editing.

At the end of the study, we will tell you how many of the payment-related tables you have solved correctly and how many points you have thus earned in total in section 1 of the study.

An example:
Imagine you solved 180 of the 250 tables correctly. It so happens that you have solved 60 of the 75 payment-eligible tables randomly selected by the computer correctly. You would get 100 points for each of the 60 payment-relevant tables. Your total payout for Section 1 of the study would be 100 * 60 = 6000 points.

If you have understood the instructions for section 1 and you have no further questions, please click on Weiter **to start with section 1. If you have any questions, please use the chat.**

Section 2 - Description

Section 2 consists of **two phases**. First, we will explain the second phase to you.

Procedure phase 2

In the second phase, you will make a decision for every 10 tables in 5 rounds. Your task is the **same as in section 1**. You must again identify the highest number on a table within the available decision time. Each round contains 10 tables with one of the decision timeframes already known to you (10 instances of 6 seconds, 10 of 5 seconds, 10 of 4 seconds, 10 of 3 seconds and 10 of 2 seconds). Note that **the order** of the rounds (and thus the decision times) is now determined **at random**.

***Exemplary* overview section 2 (phase 2):**

Round	*1*	*2*	*3*	*4*	*5*
Table Screens	10	10	10	10	10
Selectiontime in seconds *(This random order is only used as an exaple)*	4	2	3	5	6

Procedure phase 1

In phase 1, your decisions will determine the ***payout*** *for a correctly or incorrectly answered table in phase 2*. For each of the 5 decision times in phase 2 (6 seconds, 5 seconds, 4 seconds, 3 seconds and 2 seconds) you will fill out a so-called decision table.

The decision table:
In **each** decision table you make decisions for exactly one decision time. This is highlighted in yellow and displayed above each decision table (20 seconds in the example below). **This is important to note because the order of the decision tables is determined at random, as is the order of the later rounds (see above for an example).**

Each decision table contains **21 decisions in 21 rows**. In each row of the decision table you have to chose between two options.

A decision table:

20 seconds Decision Time					
	Payout scheme A				Payout scheme B
	If correct:	If wrong:			If correct or wrong:
1.	100 points	0 points	○	○	0 points
2.	100 points	0 points	○	○	5 points
3.	100 points	0 points	○	○	10 points
4.	100 points	0 points	○	○	15 points
5.	100 points	0 points	○	○	20 points
6.	100 points	0 points	○	○	25 points
7.	100 points	0 points	○	○	30 points
8.	100 points	0 points	○	○	35 points
9.	100 points	0 points	○	○	40 points
10.	100 points	0 points	○	○	45 points
11.	100 points	0 points	○	○	50 points
12.	100 points	0 points	○	○	55 points
13.	100 points	0 points	○	○	60 points
14.	100 points	0 points	○	○	65 points
15.	100 points	0 points	○	○	70 points
16.	100 points	0 points	○	○	75 points
17.	100 points	0 points	○	○	80 points
18.	100 points	0 points	○	○	85 points
19.	100 points	0 points	○	○	90 points
20.	100 points	0 points	○	○	95 points
21.	100 points	0 points	○	○	100 points

On the left-hand side of a decision table, the **payout scheme A** is in each row. This is identical to the payout scheme you have already seen in Section 1: In payout scheme A, you receive **100 points** for each correct answer on a table screen within the specified decision time (in the example 20 seconds). No answer or one wrong answer means **0 points**.

On the right side of the table you can see a fixed amount that increases by 5 points in each row. This is **payout scheme B**. In payout scheme B, you receive the number of points specified in the row for each table screen that you edit for the respective decision time (in the example 20 seconds), **regardless of whether you answer correctly or incorrectly in the respective decision time**.

We assume that you prefer the left column (payout scheme A) at the beginning of each decision table, but that you want to switch to payout scheme B, *i.e.*, the right column, from a certain point onwards.

In order to make your decision for the respective decision time, please click on the **right** selection field at the point in which you would like to switch to payment scheme B or the **left** selection field if you prefer payment scheme A once more. All other lines are filled in automatically by the computer. You can adjust your decision at any time. When you have finally made your decision, confirm your selection for this decision time by clicking on the "Next" button.

After you have filled in all the decision tables, *a row of the decision table is randomly selected by the computer* for **each decision time**. Each row has the same probability of being selected by the computer. The computer then checks whether you have chosen payment scheme A or payment scheme B in the line drawn. **Your decision in this line then determines the payout scheme for the 10 tables of the respective decision time in phase 2.** If you have selected the left column **(payout scheme A)** in the drawn line, you will make a decision on 10 tables. With each correct answer **100 points** are credited to your points account and **0 points** for each incorrect answer. If you have opted for the right column **(payment scheme B),** however, you will also solve 10 tables, but you will receive the payment in the drawn line for each task, regardless of whether your answer is correct or incorrect.

After you have completed all *decision tables*, you have completed phase 1 of this section and phase 2 follows. As already described, in phase 2 of this section you will be shown 10 tables per *decision time* (see page 7). As a result, for each ***decision time*** *(6 seconds, 5 seconds, ..., 2 seconds) you have to carefully consider which payment scheme (A or B) would be preferable.*

Section 2 – Payout

As in Section 1, 30% of the tables from Section 2 are randomly selected as being payable. You will receive the payout according to the payout scheme you have chosen for this table.

Two examples:

- The computer has selected a table with a decision time of 5 seconds as relevant for payment. Assuming you had chosen payout scheme A here. This means that you will get **100 points** if you have identified the correct answer in this table and **0 points** if not.

- In another table with 6 seconds that was randomly selected as being relevant for payment, however, you decided on payout scheme B. You will now receive the specified payout (number of points in the right column from the relevant row) regardless of whether you have identified the correct solution or not.

A few practice questions at the beginning of Section 2 should help you determine whether you have understood the explanation for this section correctly.

If you have understood the instructions for section 2 and you have no further questions, please click on Weiter **to start with section 2. If you have any questions, please use the chat.**

<u>Section 3 - Description</u>

Section 3 consists of **3 phases**. In phases 2 and 3 you will again make a decision on the tables already familiar to you. **In section 3, you can now determine the decision time for all table screens yourself.**

Phase	Phase 1	Phase 2	Phase 3
Number table screens	_	40	40
Selectiontime in seconds	_	determined in phase 1	own decision per table screen
Payout for correctly competed table screens	_	determined in phase 1	maximum 150, **every second reduced by the exchange rate**

Procedure phase 1 and phase 2

First we describe **phase 1 of the third section**: In this phase you *plan* the decision time for *phase 2*, in which you make another decision for 40 tables. Phase 1 and 2 are thus directly connected to each other.

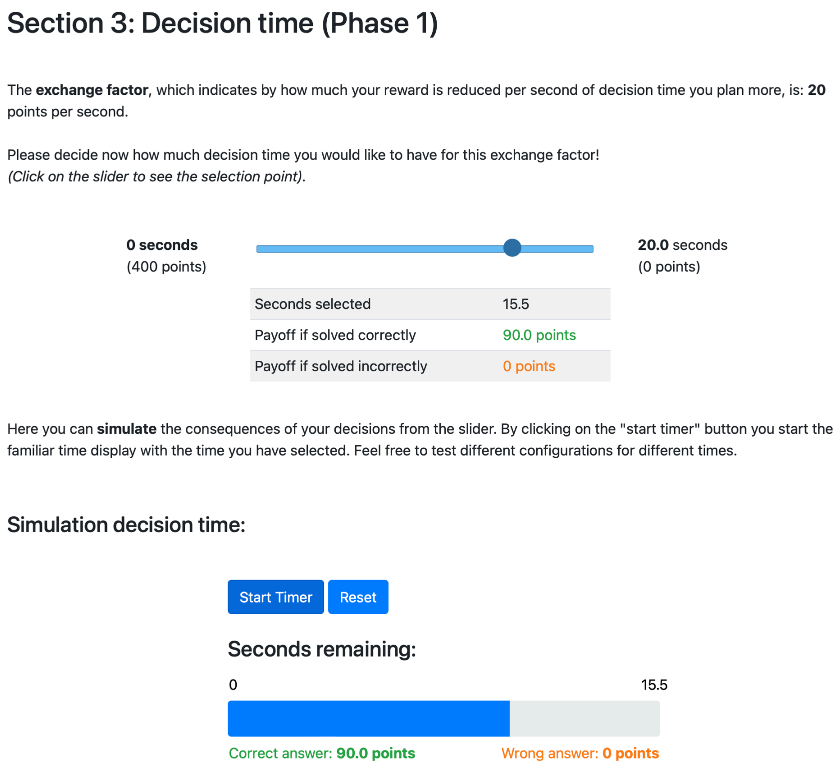
The planning of your decision time in phase 1 takes place on a *time screen*:

The time screen:

You will see a slider on the time screen. With the help of this slider you can choose between a **longer decision time** and a **higher payout**. There is an "exchange rate" between the decision time and the payout for a correct answer on a table screen. **This means that the payout for a correctly solved table screen is reduced by the exchange rate for every additional second**

of decision time you give yourself. You would get the maximum payout if you opted for a 0-second decision time and managed to correctly solve the table screen in phase 2 in 0 seconds. The exact exchange rate will be given to you at the beginning of phase 1.

Example for a time screen:



In the first line you can see the **exchange rate**. In the example, this is **20 points per second**. This means that for every second of decision time, the payout for a correctly solved table screen is reduced by 20 points. The maximum payout here is an example of 400 points. In this example, the exchange rate and the maximum possible payout result in a maximum possible decision time of 20 seconds.

In the example, the slider is positioned so that 15.5 seconds is selected as the decision time. This reduces the payout for a correctly solved table from 400 points to 90 points. This means that there are 15.5 seconds of decision time for each of the 10 tables in phase 2 of the third section. If the correct solution is selected and clicked within these 15.5 seconds, **90 points** are earned in this example. If the answer is wrong, you earn **0 points**.

You can adjust the slider for selecting the decision time **as often as you like**. A click on the "Next" button confirms your entry.
The time screen also offers the possibility to **simulate** the consequences of the selected decision time. It should help to get a feeling for how long the respective periods are.

After you have made your decisions in **phase 1**, **phase 2** follows. Here you will make a decision on 40 of the now-familiar tables. The decision time as well as the payout for a correctly solved table screen is the **one that you set yourself in phase 1 using the slider**.

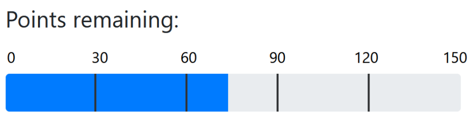
Procedure phase 3

In the third phase, you will again make a decision on a total of **40** tables. **Similar to phase 1, you also have a choice in phase 3 concerning the decision time and the maximum payout of the table screens.**

In phase 3, however, you do not plan in advance (as in phase 1), but rather you decide when you want to stop looking for the right solution **while** solving each table. The number of points that you can earn with your decisions on the table depends on **how much time you take to make a decision on the respective table**. The more time you spend on each screen, the fewer points you will earn with a correct answer. The **exchange** rate between the decision time and the payment for a correct answer is **identical to phase 1**. This means that the reward for a correct answer is reduced by the exchange rate for every second in which you search for a solution.

Below you can see an example of a table screen from Section 3. With the exception of **2 differences**, this is exactly the same as in all previous sections of the experiment.

Tables in section 3:



62	68	47	50
75	65	59	54
48	60	70	71
53	61	63	45

Correct Answer: **72 points** Wrong Answer: **0 points**

The first difference concerns the *time display*. In phase 3, the points you can earn with a correct answer depend directly on how much time you take to make your decision. Therefore, the time display has been **replaced by a point display**. The points display always shows you exactly how many points you would get if you made your decision at exactly this point in time and your answer was correct. If your answer is not correct, you will receive 0 points as before. How many points you get for a correct answer is shown below the table again. The value below the table shows how many points you will receive if you make your decision at that *very moment*.

In the example on page 13, the maximum payout is 150 points. On the sample screen, time has already been spent looking for the right solution. For a correct solution you would receive **92.5 points** in the example if you identified the correct solution at exactly this point in time and transmitted it to the computer.

The second difference to the previous table screens is that you have to confirm your answer in phase 3. Only **when you confirm your answer** does the point display stop at its current value and your decision is transmitted to the computer. *Choosing* a number as an answer is initially the same as before: you click on the number that you want to choose. As before, this is highlighted in yellow. To **confirm your answer, click the currently selected number**

again. The **second click** on a number confirms it, the **decision time is stopped** and your decision and the current decision time are transmitted to the computer.

You can change your decision by clicking on another unselected solution until the time has run out or you have confirmed an answer. At the beginning of phase 3, you can familiarize yourself with the changed procedure (display of points; confirmation of the answer) in a few rounds of practice. For practice purposes, the maximum reward and exchange rate are identical to phase 1 (and phase 3). The display below the table shows the current values for practice purposes, but these are shown in gray to indicate that **you cannot earn any money in the practice rounds**.

Section 3 – Payout

The payout in section 3 follows a similar principle as in section 1. The computer will randomly select for the payout 30 percent out of the 40 tables from phase 2 and the 40 table screens from phase 3. These are the **tables relevant to payment**. Each of the 40 tables has an equal chance of being selected by the computer.

In phase 2 you will receive the number of points **for each correctly solved payment-relevant table that you have set yourself on your time screen.** In phase 3 you will receive the number of points for **each correctly resolved payment-relevant table that was displayed on the points display at the time of your confirmed decision.**

Overview payout section 3:

Phase:	**2**	**3**
payment-relevant tables	12 of 40	12 of 40
Payout for each correctly solved payment-relevant table:	**Set by your choices on the time screen**	**Points displayed on the scoreboard at the time you confirm your decision**
Payout for each NOT correctly solved payment-relevant table:	**0 points**	**0 points**

Please note: After phases 1, 2, and 3, the entire section 3 is repeated again. This means that you will be going through all of the stages in Section 3 all over again. These are phases 4 to 6. These phases are exactly the same as phases 1 to 3. Only the exchange rate will be different in the second run of section 3. We will inform you of the exchange rate at the beginning of phase 4. You can earn money in phases 4 to 6 in the same way as in the first run of the third section. The instructions are therefore identical and you have another opportunity to earn points for your points account.

If you have understood the instructions for section 3 and you have no further questions, please click on Weiter **to start with section 3. If you have any questions, please use the chat.**

A.5.2 On-screen instructions for the belief elicitation.

This part of the study is about estimating as accurately as possible how many table screens you have solved correctly. Please read this page **very carefully**.
The screen on which you will submit your estimate of how many tasks you solved correctly looks like this:

— screenshot of empty task here —

The decision time for which you should provide an estimate is displayed at the top of the page (in this example 20 seconds) and highlighted in yellow. The example above thus relates to an estimate of the number of correctly solved tables in 20 seconds.
As a reminder: in the last section, you encountered 50 tasks for each decision time.
You will provide your assessment for each decision time individually as follows:
The decision screen has **10 columns**. Each column represents a certain number of correctly solved tables. The first column represents 0-5 correctly solved tables, the second column represents 6-10 correctly solved tables, and the last column represents 46-50 correctly solved tables.
Your task now is to distribute 100 balls in these columns. Each ball represents 1% probability. For example, if you put 50 balls in the second column, this means that you assume that you have correctly solved between 6 and 10 of the total of 50 tables with a probability of 50% within the time indicated above the table. If, for example, you place 23 balls in the ninth column, this means that you assume with a probability of 23% that you have correctly solved between 41 and 45 of the total 50 tables. **The more likely you think it is that a column contains the number of tables you solved correctly, the more balls you should place in that column.**
To place balls in a column, please enter the corresponding number in the input field above the column or click on the column. At the bottom left, you will see the number of remaining balls to be distributed among the columns. You can change the number of balls in a column until you press the "Next" button.
The task is finished when you have distributed exactly 100 balls among the 10 columns and are satisfied with the resulting probability distribution. This means that the distribution of balls in the columns reflects your estimation of how many tables you solved correctly. If this is the case, then press the "Next" button at the bottom left.
Overall, the more accurate your estimate - that is, the more balls you have placed in the correct column and the fewer balls you have placed in the columns that do not apply - the more likely you are to win the 250 points.
(Only) For those who are interested in the exact payout scheme: After you have distributed all 100 balls in the 10 columns, a number A is calculated as follows:

$$A = \sum_{i=1}^{10}(\text{Balls in column}_i - 100 \times I_i)^2,$$

where i=1, ...10 denotes the different columns and I_i is equal to 1 for the column containing the number of table screens actually solved correctly and 0 otherwise. Thus, the larger the number A, the more your estimate deviates from the correctly solved table screens.
Then a number X is randomly drawn from the interval [0,20,000]. If $A < X$, you get the additional 250 points. If $A > X$, you will not get any additional points.

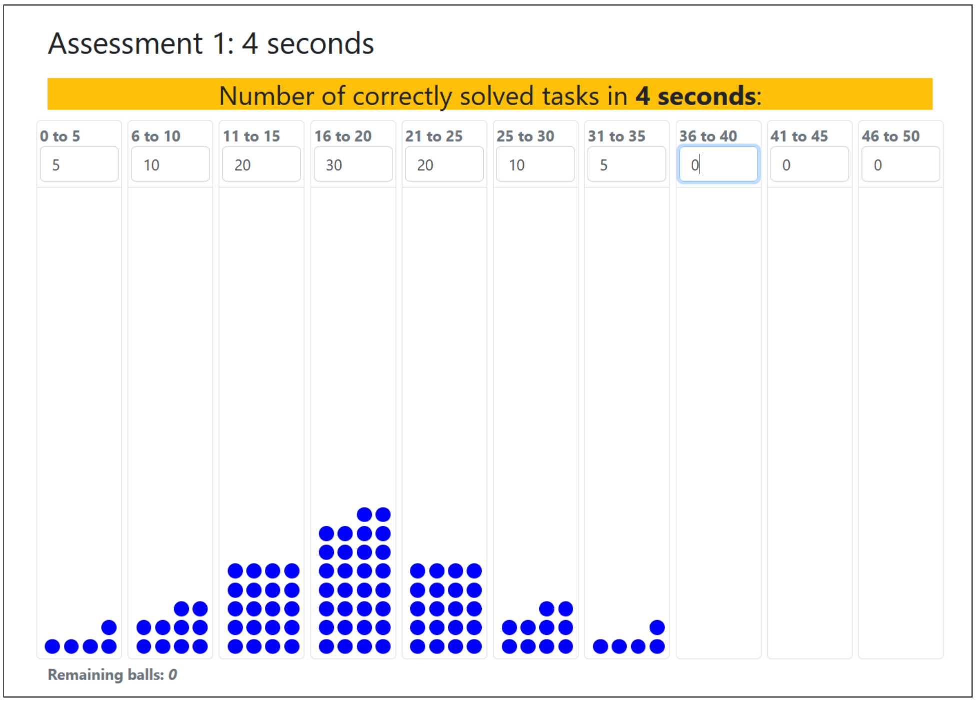


Figure A11. Belief Elicitation

A.5.3 Experimental screenshots.

4 seconds Decision Time					
	Payout scheme A				**Payout scheme B**
	If correct:	**If wrong:**			**If correct or wrong:**
1.	100 points	0 points	◉	○	0 points
2.	100 points	0 points	◉	○	5 points
3.	100 points	0 points	◉	○	10 points
4.	100 points	0 points	○	◉	15 points
5.	100 points	0 points	○	◉	20 points
6.	100 points	0 points	○	◉	25 points
7.	100 points	0 points	○	◉	30 points
8.	100 points	0 points	○	◉	35 points
9.	100 points	0 points	○	◉	40 points
10.	100 points	0 points	○	◉	45 points
11.	100 points	0 points	○	◉	50 points
12.	100 points	0 points	○	◉	55 points
13.	100 points	0 points	○	◉	60 points
14.	100 points	0 points	○	◉	65 points
15.	100 points	0 points	○	◉	70 points
16.	100 points	0 points	○	◉	75 points
17.	100 points	0 points	○	◉	80 points
18.	100 points	0 points	○	◉	85 points
19.	100 points	0 points	○	◉	90 points
20.	100 points	0 points	○	◉	95 points
21.	100 points	0 points	○	◉	100 points

Figure A12. Uncertainty Aversion Elicitation

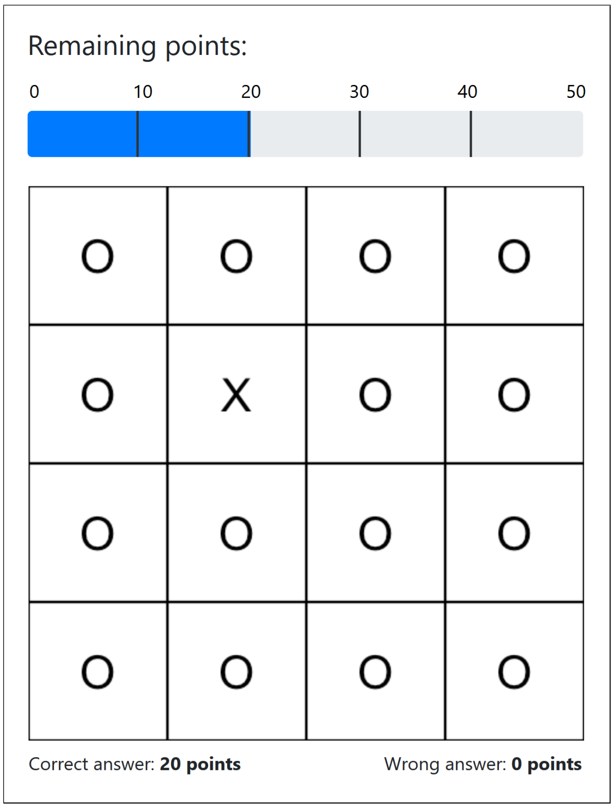


Figure A13. Screenshot: Task to Measure Reaction Time

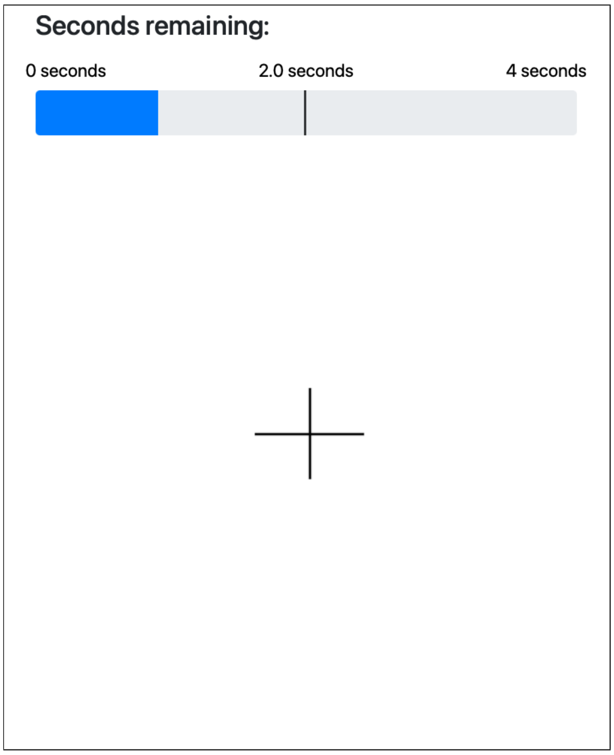


Figure A14. Screenshot: Fixation Cross at Beginning of Task

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