Behavioral Attenuation*

Benjamin Enke Thomas Graeber Ryan Oprea Jeffrey Yang

July 31, 2024

Abstract

We report a large-scale examination of *behavioral attenuation*: due to information-processing constraints, the elasticity of people's decisions with respect to economic fundamentals is generally too small. We implement more than 30 experiments, 20 of which were crowd-sourced from leading experts. These experiments cover a broad range of economic decisions, from choice and valuation to belief formation to strategic games to generic optimization problems, involving investment, savings, effort supply, product demand, taxes, environmental externalities, fairness, cooperation, beauty contests, information disclosure, search, policy evaluation, memory, forecasting and inference. In almost all experiments, the elasticity of decisions to fundamentals decreases in participants' cognitive uncertainty, our measure of the severity of information-processing constraints. Moreover, in decision problems with objective solutions, the observed elasticities are universally smaller than is optimal. Many widely-studied decision anomalies represent special cases of behavioral attenuation. We discuss both its limits and why it often gives rise to classic phenomena of diminishing sensitivity.

Keywords: Behavioral attenuation, information processing, cognitive uncertainty, experiments

*We are especially grateful to the 24 experts who volunteered an experimental design for us to test the attenuation hypothesis. We thank Raeed Kabir, Sebastian Redl and Vincent Marohl for outstanding research assistance. For comments and discussions we are grateful to Rahul Singh. This research was supported by the National Science Foundation under Grant SES-1949366 and was approved by Harvard and UC Santa Barbara IRB. Enke: Economics Department, Harvard University, enke@fas.harvard.edu. Graeber: Harvard Business School, tgraeber@hbs.edu. Oprea: Economics Department, University of California, Santa Barbara, roprea@gmail.com. Yang: Economics Department, Harvard University, jeffrey_yang@g.harvard.edu

1 Introduction

Behavioral economics has made economics significantly more realistic. However, one of the costs of this realism is a reduction in parsimony. To account for the many ways that standard models fail, behavioral economics has accumulated a library of often domain-specific exceptions to standard assumptions, giving economists a proliferating array of explanatory options. To combat this, there has been a growing movement among behavioral economists to search for shared cognitive foundations that can unify prior anomalies. This work often studies cognitive information-processing constraints, and how they shape the ways people attend to, remember, aggregate and trade off variables when making economic decisions. Ultimately, a main objective of this literature is to identify *domain-general* simplification strategies – generic responses to information-processing constraints that allow economists to explain behavior across many different, seemingly-unrelated domains.

In this paper, we experimentally study the importance of one such generic simplification strategy that we hypothesize may be particularly widespread, explaining behavior across many contexts: behavioral attenuation. The idea is that, due to information-processing constraints, people are uncertain about how exactly to map a given set of problem fundamentals into a utility-maximizing decision. This uncertainty about how parameters should impact choices induces people to treat counterfactual problems with different fundamentals alike to some degree – intuitively, if you don't know how to construct an optimum, you also don't know how the optimum changes with fundamentals. To formalize this idea, we adapt the framework of Ilut and Valchev (2023) to show how uncertainty about the mapping from fundamentals to optimal choices produces behavioral attenuation: an insensitivity of decisions to variation in parameters.

Our hypothesis is that because most decisions require intensive information processing, behavioral attenuation is widespread in economic life – that labor supply is an attenuated function of the wage, that investments are an attenuated function of expected returns, that savings vary with the interest rate in an attenuated form, that product demand is attenuated with respect to price, that cooperation is attenuated to the payoffs to cooperate, that fairness views are an attenuated function of true merit, that the evaluation of policies is an attenuated function of the outcomes they produce, and so on. To the degree this is true, behavioral attenuation may be a unifying principle of behavioral economics, jointly explaining choice anomalies that have been documented in the past, and predicting new ones in domains that have not yet been studied.

Study design. To test this hypothesis, we designed a pre-registered series of online experiments in which we (i) examine an unusually large number of distinct decision tasks from across economics (31 experiments in all) and (ii) tied our hands to a significant degree by *crowdsourcing* the selection of the majority of these tasks to experts in behavioral economics. We contacted the authors of recent top publications, explained the attenuation hypothesis, and asked them to identify a decision task that they consider economically important and in which they would like to know whether behavioral attenuation exists. Based on this procedure, we collect 20 tasks proposed by experts, and added an additional 11 tasks that we view as economically important but that were missing from the crowdsourced list. At a high level, our experiments cover eight categories from across economics: financial decisions, labor-related decisions, consumer choice, social decisions, strategic decision-making, political decisions, risk and time preference elicitations, as well as tasks related to belief formation and cognition. Examples include investment, saving, effort supply, product demand, taxes, externalities, fairness, cooperation, beauty contests, information disclosure, search, policy evaluation, memory and forecasting. In total, our experiments involve 8,200 participants and 89,000 decisions.

Our experiments include both objective and subjective problems. Objective problems are ones that have normatively correct solutions – inference or prediction problems with fully specified data-generating processes or choice experiments with induced values in which an objectively correct solutions is available to us as researchers. For example, we study forecasting as a function of the persistence of the process and signal aggregation as a function of the signal sources' relative precisions. Subjective problems, on the other hand, involve decisions in which the optimal choice potentially depends on the decision maker's own preferences or subjective beliefs. We implement experiments on savings, investment, cooperation, prosocial giving, fairness, lottery choice, effort supply, strategic beauty contests and information disclosure, policy evaluations, voting, and more. For example, we look at savings as a function of the interest rate, effort supply as a function of the wage, and giving as a function of efficiency.

In each experiment, we systematically vary the main decision-relevant parameter across usually eleven experimental rounds. Our primary object of interest is the slope of decisions to variation in these parameters (using theory-informed functional forms, when available). Importantly, our hypothesis is not only that these decisions are relatively insensitive (which can in principle occur for many reasons, including certain preferences). Rather, the hypothesis of behavioral attenuation is that decisions are insensitive due to complexity[1] and information-processing constraints, and decision makers' resulting uncertainty about their optimal decision. Thus, to help us to empirically make this distinction, we directly measure subjects' cognitive uncertainty (*CU*) about

[1]Throughout the paper, when we call a task "complex" we mean that the information processing required to make an optimal choice in the task is costly or constrained. This information processing includes the implicit or explicit computation required to aggregate or trade off economic primitives to reach a decision. In some tasks it may also include the processing required to retrieve one's own preferences, and to combine them with other problem primitives.

the optimality of their own choices: the percentage chance with which the subject believes her decision was not optimal, in the sense that either (i) it failed to maximize the decision maker's own preferences (in subjective problems); or (ii) it failed to be payoff-maximizing (in objective problems).

In objective tasks, because we know the optimal elasticity ex ante, we can measure behavioral attenuation directly by comparing observed elasticities to predicted, optimal ones. In all tasks (including subjective ones), we can also identify behavioral attenuation indirectly by examining whether subjects display a less elastic response to parameters when they exhibit higher uncertainty. A link between the elasticity of decisions and measured uncertainty about optimization (*CU*) is a direct implication of behavioral attenuation but is not implied in any obvious way by preference-based explanations for insensitivity (see Section 5 for a discussion of this point).

Evidence for behavioral attenuation. In 90% of our baseline experiments we find that higher *CU* is associated with a lower elasticity of decisions to economic fundamentals. These correlations are almost always statistically significant. On average, as *CU* – the likelihood subjects attach to the proposition that they failed to optimize – increases from 0% to 50%, the elasticity of decisions to fundamentals decreases by an average of 30% across our experiments.

What is perhaps most striking is that we find the same pattern across a wide variety of choice domains, types of preferences and even across subjective and objective tasks. The link between *CU* and lower elasticities appears in all of our eight categories of experiments; in both individual decisions and strategic games; in beliefs and cognition; in choices involving risk, intertemporal tradeoffs and social considerations; and in both naturalistic and more abstract designs. The near-universality of this pattern seems to suggest that the effect is driven precisely by what these many tasks have in common, which, given how different they are from one another, points at the fact that they all require significant information processing.

Because in objective tasks we know the 'ground truth' optimal elasticity, we also compare the estimated elasticities to their normative benchmarks. In all objective tasks, average elasticities are significantly smaller than the normative ones – direct evidence of behavioral attenuation. Moreover, the elasticities among low *CU* subjects are almost always substantially closer to the normative ones than the elasticities among high *CU* subjects. Thus, our observations of objective attenuation are anticipated and organized by subjects' *CU* – a key component of our hypothesis.

Summarizing, our results suggest that behavioral attenuation – an insensitivity deriving from information-processing constraints – arises in more than two dozen domains.

Simple points and diminishing sensitivity. Our hypothesis has a distinctive secondary prediction that we designed our experiments to test. In particular, the information-processing limits responsible for behavioral attenuation should also generate classical findings of *diminishing* sensitivity as parameters move further from the boundaries of the parameter space. As we lay out in Section 2, if behavioral attenuation is indeed driven by the cognitive difficulty of information processing (for instance, aggregating information and computing tradeoffs), then there *should* be less attenuation in the neighborhood of parameters at which information processing is easy, for instance when no tradeoffs need to be computed to infer the optimum. For example, determining optimal effort supply at wage θ may be cognitively difficult in general but it is trivial when $\theta = 0$.

We first show that, across our many experiments, the *CU* data strongly suggest that subjects find problems easier to reason about when they involve parameters at or close to (pre-registered) "simple points" at the boundaries of the parameter space, such as points at which a dominant action exists. As a result, the logic of information-processing-driven insensitivity makes the additional prediction that decisions should exhibit diminishing sensitivity away from these simple points. The data lend strong support for this prediction. We find pronounced diminishing sensitivity, including in objective decision problems in which we know that the optimal mapping between parameters and choices is linear, such that diminishing sensitivity cannot be driven by preferences.

These results suggest that *CU* and an insensitivity of decisions are linked not just across subjects but also, at the population level, across different problem configurations. Indeed, we econometrically directly link the local sensitivity of decisions (i.e., the slope of decisions to changes around any given parameter value) with local *CU* and find that they are strongly negatively correlated ($r = -0.44$). This not only explains the pervasiveness of diminishing sensitivity, it also suggests that variation in insensitivity is driven by the information-processing demands imposed by a specific problem (rather than by alternative conceivable mechanisms such as subject-level variation in preferences).

Behavioral anomalies. Because we implement such an unusually large number of experiments, we also cover many domains in which prior research has identified "anomalies". These phenomena have appeared under different labels in the literature, such as the attenuation to tax rates, insensitivity of effort supply, insensitivity of valuations to the scope or scale of a good, the attenuation puzzle in stock market investments, the central tendency effect in production decisions, hyperbolic discounting over money, probability weighting, under- and overreaction in beliefs, the bikeshedding effect in multitasking, and others. The common thread that runs through these anomalies is that they reflect (i) a low elasticity of decisions to relevant parameters and (ii) a higher elasticity at simple points. Our results suggest that these anomalies are special cases of a general attenuation pattern that is strongly linked to information-processing constraints and resulting uncertainty about how to optimize.

Limits of attenuation. We hypothesized three limits of behavioral attenuation and its direct link to *CU*. In particular, we conjectured that this phenonomenon (i) might reverse when the *rational* elasticity of decisions is near zero; (ii) is less likely to arise when decision-makers are forced to directly compare their decisions across multiple different realizations of the fundamental; and (iii) may disappear or reverse when people develop problem representations that are fundamentally incorrect but appear highly convincing (and are thus correlated with lower *CU*). We find mixed evidence for (i) and (ii), and tentative evidence for (iii). We also show that a tenfold increase in incentives does not meaningfully affect either attenuation or *CU*.

Contribution and related literature. Our main contribution is to document that behavioral attenuation (and, with it, diminishing sensitivity) occurs 'nearly everywhere' – across a large set of domains that were mostly selected by independent experts. This insight builds on recent work that suggests a link between between information-processing constraints and insensitivity effects in decision making under uncertainty and in intertemporal choice (Enke and Graeber, 2023; Enke et al., 2023a; Enke and Shubatt, 2023; Oprea, 2022; Augenblick et al., 2021; Ba et al., 2022; Yang, 2023). While with hindsight our results may provoke the reaction "of course!", we believe that, ex ante, it was equally plausible that behavioral attenuation may be fairly specific to decisions under uncertainty and over time where they have been most intensively documented. After all, much of the literature emphasizes tendencies that might counteract or dominate insensitivity, such as overreaction effects or exaggerating differences (e.g., Afrouzi et al., 2020; Bordalo et al., 2012, 2020a,b; Kőszegi and Szeidl, 2013). Indeed, to date, even theoretical work on how cognitive noise and complexity generate attenuation is largely restricted to decision-making under uncertainty and over time (Khaw et al., 2021, 2022; Frydman and Jin, 2021, 2023; Vieider, 2022, 2021; Gabaix and Laibson, 2022; Gabaix and Graeber, 2023; Gabaix, 2019).[2]

We interpret our results as suggesting that classic behavioral economics both applies more broadly than previously acknowledged and that it is more unified than we might have thought. It is more unified because we have shown that many classic and newly-documented anomalies share a similar structure and seem rooted in a similar cognitive mechanism. Yet our results also suggest that traditional models that fundamentally rest on the idea of insensitivity and diminishing sensitivity (such as prospect theory

[2]More broadly, our paper belongs to a nascent literature that studies a reasonably large number of distinct decision tasks within the same experimental framework (e.g., Falk et al., 2018; Dean and Ortoleva, 2019; Enke et al., 2023b; Chapman et al., 2023; Stango and Zinman, 2023).

and hyperbolic discounting) have a much broader scope of applicability than previously thought, because their basic logic also applies outside of their traditional domains (see Prelec and Loewenstein, 1991, for an early discussion along these lines).

Section 2 presents a formal framework that motivates the attenuation hypothesis. Sections 3 and 4 present the experimental design and results. Sections 5 and 6 study mechanisms and the limits of attenuation, and Section 7 concludes.

2 Motivating Framework

Our hypothesis is that information-processing constraints cause decision makers to be uncertain about how to formulate an optimal choice, forcing them to treat problems with different fundamentals as if they are more similar to one another than they really are. Intuitively, if a person doesn't really know how to map an hourly wage of $20 into utility-maximizing labor supply due to the complexity of the task, then compared to a counterfactual scenario in which the wage is $25, they might take decisions that are too much alike, relative to the utility-maximizing benchmark.

As noted above, we desire to distinguish between a generic *insensitivity* of decisions (which can occur for many reasons, including preferences), and *behavioral attenuation*, by which we specifically mean an insensitivity of decisions that arises due to information-processing constraints.

There are potentially many ways to formalize the broad intuition of information-processing-driven insensitivity. Here we make use of an increasingly popular modeling framework of constrained-Bayesian responses to *cognitive noise*. In particular, following prior work, we describe the problem in terms of uncertainty about the optimal policy function. Intuitively, this policy uncertainty gives rise to attenuation because it induces the DM to regress towards a common "default" decision.

Suppose a DM is tasked with making a decision a that depends on a payoff-relevant parameter θ, where the decision problem is characterized by the objective function $U(a,\theta)$. We assume that for each value of θ, the optimal action $a^*(\theta) \in \text{argmax}_a U(a,\theta)$ is unique, and that the *policy function* $a^*(\theta)$ is differentiable and monotonic. Without loss, we will assume that $a^*(\theta)$ is increasing in θ.

Example 1: Lottery Valuation. Consider a DM tasked with assessing the certainty equivalent of a lottery that pays off $18 with some probability p and nothing otherwise, who has expected utility preferences with an increasing and differentiable Bernoulli utility function u. In this setting, we have $\theta = p$, and $a^*(\theta) = u^{-1}(\theta \cdot u(18) + (1-\theta) \cdot u(0))$.

Example 2: Effort Provision. Consider a DM tasked with choosing a positive level of effort e that yields a piece-rate wage w, but who faces a convex effort cost $c(e) = 1/2\kappa e^2$;

preferences are given by $w \cdot e - c(e)$. In this setting, we have $\theta = w$, and $a^*(\theta) = \theta/\kappa$.

Suppose that because of information-processing constraints, the decision-maker is not perfectly capable of formulating her optimal policy function. For instance, the DM may struggle to trade off higher wages against the cost of effort in an effort supply decision, simply because the tradeoffs involve significant computation.

Following Ilut and Valchev (2023), we model this by assuming that the DM only has access to a noisy mental simulation of her optimal policy function $a^*(\theta)$. As formalized in Appendix C, the DM has uncertainty about the weights $\{\beta_w\}_{w \in \mathbb{R}}$ that determine the mapping of problem fundamentals (θ) into optimal decisions, $\theta \mapsto a^*(\theta)$.

When the DM reasons imperfectly about the optimum, she generates a noisy *cognitive signal* (or mental simulation) over $a^*(\theta)$, the optimal policy function at the parameter θ. This signal takes the form $s(\theta) \sim N(a^*(\theta), \sigma_a^2(\theta))$, where $\sigma_a(\theta)$ denotes the level of *cognitive noise* in the DM's efforts to compute the optimum. We can think of the level of cognitive noise – and thus the precision of the DM's cognitive signal – as being partly determined by the difficulty of the decision problem at the parameter value θ.

We assume that there is some common, parameter-independent *default policy function* that a decision maker would revert to if they were *completely* incapable of computing an optimum. This parameter-invariant default encodes the hypothesis that a completely uncertain decision maker lacks any basis for treating any one parameter systematically different from any other. Formally, we model this default as normally distributed priors over β_w (the weights that map fundamentals into the optimal decision), such that the DM's prior over the policy function evaluated at any parameter is distributed according to $N(a_d, \sigma_0^2)$, for some parameter-independent action a_d.

The DM integrates her imperfect cognitive signal with her prior over the policy function, and then takes a decision $a(\theta)$ equal to her Bayesian posterior mean over $a^*(\theta)$. In Appendix C, we show that $a(\theta)$ takes the form[3]

$$a(\theta) = \lambda s(\theta) + (1-\lambda)a_d$$
$$E[a(\theta)] = \lambda a^*(\theta) + (1-\lambda)a_d$$

where the weight placed on the cognitive signal, $\lambda = \frac{\sigma_0^2}{\sigma_a^2(\theta)+\sigma_0^2}$, is decreasing in the level of cognitive noise $\sigma_a^2(\theta)$ at the parameter θ.

Prediction 1 (Attenuation). *If $|\sigma_a'(\theta)|$ is sufficiently small:*

[3]This convexification prediction is shared with a number of cognitive noise models, many of which formalize an imperfect perception of problem components (e.g. Woodford, 2020; Khaw et al., 2021; Frydman and Jin, 2021). Perceptual noise may be one reason for why the DM has uncertainty over the optimal policy function, though we conjecture that a more significant source of noise in most applications is the difficulty of mentally mapping a given set of fundamentals into the utility-maximizing action.

(a) *Objective attenuation. If $\sigma_a(\theta) > 0$, then $\frac{\partial}{\partial\theta}E[a(\theta)] < \frac{\partial}{\partial\theta}E[a^*(\theta)]$.*

(b) *Cognitive noise and attenuation. $\frac{\partial}{\partial\theta}E[a(\theta)]$ is decreasing in $\sigma_a(\theta)$.*

In words, the first part says that the elasticity of decisions will be smaller than the elasticity of the optimal decision. The second part says that, in regions of the parameter space in which the level of cognitive noise is relatively invariant to the parameter value (i.e., in which the difficulty of accurately formulating the optimum is relatively similar across parameter values), cognitive noise should be correlated with a more strongly attenuated relationship between the decision and the parameter. This behavioral attenuation is somewhat reminiscent of attenuation bias in econometrics. The main difference is that attenuation bias typically refers to noise in the measurement of an independent variable. Here, the independent variables are economic primitives, θ, that are measured without noise. Instead, the noise arises in the cognitive mapping from independent variables into an optimal decision.

Throughout this paper, we call the behavior described by Prediction 1 "behavioral attenuation": as a result of information-processing constraints, the elasticity of people's decisions is smaller than it would be if people were able to maximize (whichever objectives they have).

This attenuation is different from underreaction – it is a shrinking of the *slope* of decisions to fundamentals, rather than a shrinking of the level.[4]

This model can be read with varying degrees of literalness. For instance, a relatively literal read could interpret this model as describing an anchoring-and-adjustment heuristic (Tversky and Kahneman, 1974). However, as the opening paragraph of this section suggests, the model is meant to be an as-if description of a more general intuition that may also apply to other imperfect heuristic behaviors.

Prediction 1 describes a setting in which the difficulty of inferring the optimum is relatively invariant to the parameter. In many settings, however, there are some points in the parameter space at which the optimal action is transparent due to the structure of the problem, reducing complexity-derived uncertainty. This occurs at what we call *simple points*, which often arise at the boundary of parameter spaces.[5] For instance, we might expect the task of assessing the certainty equivalent of a lottery that pays out \$18 with probability θ to contain the simple boundary points $\underline{\theta} = 0$ and $\overline{\theta} = 1$, since at both parameter values it is clear how to rank the lottery against certain payments due to dominance. Similarly, the task of determining optimal effort supply given a piece-rate

[4]For example, if people are attenuated to the precision of information, this produces either under- or overreaction to information depending on whether the signal is weak or strong (Augenblick et al., 2021).

[5]In principle, one could also imagine the existence of interior simple points, but in our applications – including the crowdsourced ones – they occur at the boundaries.

wage θ is trivial at the boundary point $\underline{\theta} = 0$: at a wage of 0, any positive level of effort is transparently dominated by a provision of no effort.

Formally, we consider a setting where the parameter space may contain a lower and/or upper boundary, denoted $\underline{\theta}$ and $\overline{\theta}$, respectively. Let $\underline{\delta}(\theta) = |\theta - \underline{\theta}|$ and $\overline{\delta}(\theta) = |\overline{\theta} - \theta|$ denote the distance between the parameter and the lower and upper boundary points, respectively.

Then, the following proposition states that if cognitive noise is increasing away from a boundary point, decisions will exhibit diminishing sensitivity away from that boundary. The simple intuition is that a higher noisiness further away from the simple boundary point implies greater compression to the prior, leading to a lower sensitivity of decisions. More generally, as Prediction 2(a) clarifies, the model predicts that the *local* slope of decisions at any given parameter value decreases in the *local* level of cognitive noise.

Prediction 2 (Diminishing sensitivity). *Suppose the cognitive default is somewhat intermediate: $a_d > a^*(\theta)$ for θ sufficiently low and $a_d < a^*(\theta)$ for θ sufficiently high. Then, for $|\frac{\partial^2}{\partial \theta^2} a^*(\theta)|$ sufficiently small, we have the following:*

(a) For any $\theta < \theta'$ in a neighborhood around $\underline{\theta}$ with $\frac{\partial}{\partial \underline{\delta}} \sigma_a^2(\theta') \leq \frac{\partial}{\partial \underline{\delta}} \sigma_a^2(\theta)$: if we have $\sigma_a(\theta) < \sigma_a(\theta')$, then $\frac{\partial}{\partial \theta} E[a(\theta)] > \frac{\partial}{\partial \theta} E[a(\theta')]$. An analogous logic applies to $\overline{\theta}$.

(b) If $\frac{\partial}{\partial \underline{\delta}} \sigma_a(\theta) > 0$ and $\frac{\partial^2}{\partial \underline{\delta}^2} \sigma_a^2(\theta) \leq 0$ in a neighborhood around $\underline{\theta}$, then $\frac{\partial}{\partial \theta} E[a(\theta)]$ is decreasing in $\underline{\delta}(\theta)$ in a neighborhood around $\underline{\theta}$. An analogous logic applies to $\overline{\theta}$.

To illustrate, reconsider the example of assessing certainty equivalents. Prediction 2(b) states that[6] if cognitive noise is increasing away from the simple boundary points of $\underline{\theta} = 0$ and $\overline{\theta} = 1$, valuations will exhibit diminishing sensitivity away from the boundaries. The general idea that heteroscedastic noise can generate diminishing sensitivity is well-known in the literature (e.g. Khaw et al., 2021; Frydman and Jin, 2021).

While we do not present a fully articulated theory of what a simple point is, we hypothesize *dominance* as one guiding principle: that is, if there is a dominant action at a given parameter, we hypothesize that such a parameter consistutes a simple point. As discussed in detail in Section 5.1, we pre-register simple boundary points in our experiments based on the principle of dominance in combination with other empirical considerations.

Empirical Implementation. To empirically test these predictions, we will rely on two techniques. First, in many of our tasks, the optimal policy function is *objective*, meaning that we can identify the DM's optimal action, and therefore directly observe both behavioral attenuation and diminishing sensitivity. Second, following the logic of our model,

[6]Assuming a DM's preferences are close to risk-neutral.

we directly *measure* the uncertainty associated with identifying the optimum. Following Enke and Graeber (2023), we measure the DM's *cognitive uncertainty*: the DM's posterior uncertainty over the optimal action $a^*(\theta)$. Letting $P(a^*(\theta)|S = s(\theta))$ denote the DM's posterior distribution, we define *CU* as

$$CU(\theta) = P(|a^*(\theta) - a(\theta)| > \kappa | S = s(\theta))$$

This quantity is increasing in $\sigma_a(\theta)$, and therefore serves as a measurable proxy for the level of the DM's cognitive noise at θ. Our mechanism directly predicts that people who are more uncertain/cognitively noisy, as measured by *CU*, should exhibit a lower elasticity $\frac{\partial}{\partial \theta} E[a(\theta)]$. Thus, under our model, we can identify the presence of behavioral attenuation through a correlation between *CU* and measured parameter insensitivity.

Moreover, we can also leverage *CU* to link uncertainty and diminishing sensitivity. First, *CU* should increase away from simple boundary points. Second, the local sensitivity of decisions at any given parameter value should decrease in the local *CU* that prevails at that parameter.

3 Study Design

3.1 Overall Study Setup

Our experimental design is guided by two primary objectives. First, to effectively test the generality of the attenuation hypothesis, we aim to select a broad range of tasks that cover much of economics. Second, to prevent ourselves from inadvertently selecting tasks amenable to the hypothesis, we aim to "tie our hands" to avoid "cherry-picking."

Crowdsourcing of tasks. In order to satisfy the first objective, we decided to implement 30 separate experiments, allowing us to include a very broad range of tasks. In order to satisfy the second, we largely outsourced the selection of tasks to leading experts. We identified those behavioral economists who published at least two papers in the 'top 5' journals in 2021–2023, a set that comprises 29 researchers. These experts are very heterogeneous. Some are theorists, some experimentalists, and some applied researchers. They work in macro, finance, household finance, public, labor, environmental, and basic decision science. There is also great variety in the behavioral topics that our experts work on, ranging from bounded rationality to social decision-making to motivated reasoning to other "behavioral" preferences.

We contacted these researchers, explained the attenuation hypothesis to them, and asked them to propose a setup that they consider economically relevant and in which they would like to know whether the elasticity of decisions to parameters is correlated with cognitive uncertainty. Here are the most relevant excerpts from our email:

> *... We invite you to propose an experimental task, and we commit to implement your proposal should you choose to participate. This will take very little of your time – your proposal can be as short as one sentence.*
>
> *Topic of our paper:*
> *Hypothesis ("behavioral attenuation"): Because people often rely on noisy and heuristic simplification strategies, observed decisions are usually insufficiently elastic ("attenuated") to variation in decision-relevant parameters.*
> *Concretely: Take any economic decision that depends monotonically on an objective parameter. Then, we hypothesize that the elasticity of the decision to variation in the parameter is smaller among people who report higher cognitive uncertainty (lower confidence in the optimality of their own decision)....*
>
> *What we request from you:*
> *You propose a static decision that depends on an objective parameter that we can vary in the experiment. The parameter should have a non-trivial, monotonic impact on the decision-maker's decision. For example: "Elicit certainty equivalent for binary lotteries as a function of the payout probability." ... You can select any decision task you'd like – ideally one that you consider economically relevant and where you would like to know whether behavioral attenuation is at play. Your proposal can be as short or detailed as you'd like. ...*
>
> *What would happen if you chose to participate:*
> *... We will also fill in the details for the experimental task you propose and send you a link to the software so you can verify (if you like) that our implementation complies with your proposal.*

The full email invitation is reproduced in Appendix A.1. 24 researchers replied to our invitation and volunteered a task. Because some of the proposals overlapped, we merged them into 20 tasks (after checking with the proposers). The experts generally proposed tasks that are related to their own work. This has two advantages. First, we leverage domain-specific expertise about which decisions are perceived to be important by leading experts in different sub-fields. Second, we end up with tasks that are very heterogeneous, reflecting the broad scope of research in behavioral economics that is conducted today.

The experts usually only provided broad guidance ("study effort supply as a function of a piece rate that varies across rounds in the experiment"), though some requests were very detailed. Two researchers sent us write-ups of theoretical models that they requested us to implement.

Based on these proposals, we designed and programmed 20 experiments. We piloted each of these experiments with a small number of subjects (10–30) to verify the flow of the experiment, the comprehension check questions, and that decisions indeed exhibit a monotonic relationship with the parameter that was proposed by the expert. In a small number of cases, we reached back out to the expert because the setup they proposed did not deliver a monotonic relationship (and, hence, failed one of the requirements outlined in our invitation), in which case the expert usually proposed a different task.

After we had conducted our pilots, we re-contacted the experts to give them an opportunity to verify that our experimental software complied with their requests. About 1/3 of the experts sent detailed comments on the implementation and requested that changes be made.

We had initially aimed for a total of 30 experiments, and deliberately invited fewer experts than needed to receive 30 proposals because we felt that some important economic decisions might not be covered by the requests of the experts. Our thought was that by supplementing the expert tasks with our own, we would better be able to ensure that the task list would have the feel of an overview of the decision problems that are covered in, e.g., an intermediate micro class.

One expert proposed a task that has a different structure than all other proposals, in the sense that absent information processing constraints, the elasticity of the decision to the parameter is zero. We, hence, constructed 11 tasks ourselves, leaving us with 30 baseline tasks (19 proposed by experts and 11 by us), plus one expert task designed to study the limits of attenuation.

Structure of each experiment. Each of our experiments followed the same structure. First, subjects were shown one screen of experimental instructions that followed a standardized logic: (i) outline of task; (ii) explanation of incentives; (iii) screenshot of example decision screen; and (iv) explanation of the cognitive uncertainty elicitation.

Next, subjects were shown a screen with three comprehension check questions. Prospective participants who did not answer these three questions correctly on their second attempt were immediately routed out of the experiment (19% across all experiments).

Finally, participants completed the actual experiment. Given our research hypothesis, we took care not to overburden participants with a lengthy and repetitive study. Thus almost all experiments consisted of only eleven rounds/ decisions across which a key parameter was varied (six in the REC experiment because it consisted of two separate periods). On each decision screen, participants first made a decision and, after they had locked it in, stated their cognitive uncertainty (*CU*) about that decision.

3.2 Experiments

Table 1 provides an overview of the 31 tasks. In each case we list the decision subjects make, the parameter (economic fundamental) that we vary across rounds in the experiment, the incentive scheme and the contributor of the task (EGOY refers to the authors of this paper). The last two columns summarize the empirical results, which we return to in more detail below in Section 4.

Our tasks can be placed into eight broad categories: financial decisions, labor-related decisions, consumer choice, social decision-making, strategic decisions, political decisions, risk and time preference elicitations, and tasks related to beliefs and cognition. We summarize the most important task features here, highlighting the main elasticity of interest (for which we verified monotonicity in our pilots). Appendix A.2 presents more detailed information on each task, including the precise problem configurations, how we translate experimental decisions into regression equations, and the wording of the cognitive uncertainty elicitation. Screenshots of all experimental instructions, comprehension checks and example decision screens are provided in Appendix D.

Eight of these tasks ("objective tasks") have objectively correct solutions that are known as of the writing of this paper. These are usually forecasting, inference and cognition experiments, or choice experiments in which we induce an objective function for participants. Decisions in the remaining 23 domains ("subjective tasks") depend either on subjects' preferences or on private information about the outside world.

Savings (Dmitry Taubinsky). Participants decide how much of a monetary endowment to receive today and how much to save until six months later at a known interest rate (that varies across rounds). Average savings increase in the interest rate.

Precautionary savings (Nick Netzer). In an induced values experiment, participants act as a farmer who allocates a fixed amount of water across two periods to maximize yield. The parameter that varies is the absolute size of a mean-zero shock that hits the farmer in the second period. Average water savings increase in the size of the shock. The participant's bonus is proportional to the farmer's ex post utility.

Portfolio allocation (Jonathan Zinman). Participants allocate money between a riskless savings account and a risky asset (an exchange-traded fund, ETF). The parameter of interest is the participant's subjective return expectation. To generate variation across rounds, the ETF varies and we provide an expert forecast for each ETF. The participant receives the value of their investment one year later. Average allocations to the risky asset increase in expected returns.

Table 1: Overview of experimental tasks and results

Task and label	**Decision**	**Fundamental**	**Incentive**	**Contributor**	**Attenuation to Fundamental**	
					Obj.	high vs. low *CU*
Financial decisions						
Savings – SAV	Amount saved	Interest rate	Choice	Taubinsky	n/a	61%
Precaut. savings – PRS	Savings (IV)	Size of shock	Choice	Netzer	n/a	-42%
Portfolio allocation – POA	Equity share	Return expectat.	Choice	Zinman	n/a	27%
Forecast stock return – STO	Forecast asset value	Time horizon	Hypoth.	EGOY	n/a	-21%
Estimate tax burden – TAX	Tax estimate	HH income	Accuracy	EGOY	11%	13%
Newsvendor game – NEW	Production	Marginal cost	Choice	EGOY	n/a	27%
Labor						
Effort supply – EFF	Tasks completed	Piece rate	Choice	DellaVigna	n/a	87%
Multitasking – MUL	Rel. effort allocation (IV)	Rel. importance	Optimality	EGOY	45%	24%
Search – SEA	Search effort (IV)	Search cost	Choice	Vespa	50%	35%
Consumer choice						
Product demand – PRO	WTP for food item	Quantity of item	Hypoth.	EGOY	n/a	15%
Budget allocation – CMA	Rel. product demand (IV)	Rel. prices	Optimality	Ilut	44%	7%
Avoid externalities – EXT	WTP to reduce emissions	Size of reduction	Choice	v.d. Weele / Schwardm.	n/a	42%
Invest to save energy – ENS	WTP fuel-efficient car	Miles driven	Hypoth.	Allcott	n/a	52%
Social decisions						
Fairness views – FAI	Amount redistributed	P [merit-based]	Choice	Somerville	n/a	35%
Dictator game – DIG	Giving	P [donation lost]	Choice	Kessler / Roth	n/a	29%
Contingent valuation – HEA	Societal WTP for vaccine	People saved	Hypoth.	Imas	n/a	49%
Public goods game – PGG	Contribution to group	Efficiency	Choice	EGOY	n/a	65%

Table 1: Overview of experimental tasks and results

Task and label	Decision	Fundamental	Incentive	Contributor	Attenuation to Fundamental	
					Obj.	high vs. low *CU*
Strategic decisions						
Prisoner's dilemma – PRD	Cooperate / defect	Cooper. payoff	Choice	Exley / Reuben	n/a	-5%
Beauty contest – GUE	Guess number	Multiplier	Accuracy	EGOY	n/a	31%
Disclosure game – CHT	Reveal / withhold info	True state	Choice	Serra-Garcia / Anonym.	n/a	31%
Political decisions						
Voting – VOT	Vote or not (IV)	Number of voters	Choice	Rao	n/a	24%
Policy evaluation – POL	Support for policy	Implied inflation	Hypoth.	EGOY	n/a	61%
Risk and time preference elicitations						
Risk pref. elicitation – CEE	Certainty equiv.	P [upside]	Choice	EGOY	n/a	45%
Risk pref. elicitation – PRE	Probability equiv.	Payout amount	Choice	EGOY	n/a	24%
Intertemporal RRR – TID	PV future payment	Time delay	Hypoth.	EGOY	n/a	47%
Beliefs and cognition						
Info demand – IND	WTP for info	Info accuracy	Choice	Bursztyn	n/a	34%
Belief updating – BEU	Posterior belief	Info accuracy	Prox. Bayes	Yuksel	23%	26%
Forecasting – FOR	Forecast asset value	Info accuracy	Prox. Bayes	Nielsen	48%	21%
Recall – REC	Recall company value	Company value	Accuracy	Kwon	67%	44%
Signal aggregation – SIA	Aggregate signals	Number of sources	Accuracy	Sarsons	16%	22%
Rational inattention – RIA	Lottery / safe paym.	Expected value diff.	Choice	Ambuehl	n/a	-24%

Notes. IV = induced values. Choice = payoff determined by choice. Accuracy (Prox. Bayes) = bonus iff close to truth (to Bayes). Obj. attenuation is % decrease in sensitivity b/w observed and rational decisions ($1 - \hat{\omega}^e/\omega_R^e$, see eq. (4)). Last column shows % decrease in sensitivity b/w $CU = 0\%$ and $CU = 50\%$ ($\hat{\phi}^e$, see eq. (2)).

Effort supply (Stefano DellaVigna). Participants decide how many real-effort tasks to complete, as a function of a piece rate. Participants receive their wage and work the chosen number of tasks. Average effort supply increases in the wage.

Search (Emmanuel Vespa). In a classic induced values setup, the computer randomly draws 'rewards' until a minimum reward is achieved, where each draw is costly. The participant decides which minimum reward value to set, trading off higher expected minimum rewards and higher expected costs. The cost of each draw varies across rounds. The participant receives a bonus if their decision is within a window around the decision that maximizes the expected net payout. Average minimum values set decrease in cost.

Budget allocation (Cosmin Ilut). In an induced values experiment, participants act as a hypothetical consumer and are endowed with a utility function over two goods. They allocate a fixed monetary budget across expenditure for these two goods, by deciding what fraction of the goods they buy is of either type. Across rounds, the price of one good varies, while the price of the other one is fixed. Participants receive a bonus if their decision is within a window around the decision that maximizes the hypothetical consumer's utility. Average demand for a product decreases in its relative price.

Avoid externalities (Peter Schwardmann and Joel van der Weele). Following Pace et al. (2023), in a multiple price list experiment, participants reveal their WTP for reducing CO2 emissions by a certain amount. Across rounds, the magnitude of the reduction in CO2 varies. Depending on their decisions, participants receive money or we purchase carbon offsets on their behalf. Average WTP for the carbon offsets increases in the magnitude of the CO2 reduction.

Invest to save energy (Hunt Allcott). In a series of multiple price lists, participants make hypothetical decisions between a fuel-efficient hybrid car and a less efficient conventional car, revealing their WTP for the more efficient hybrid. Across rounds, the distance that the participant is asked to imagine they would drive varies, such that average WTP for the hybrid increases in miles driven.

Fairness views (Jason Somerville). Following Cappelen et al. (2022), participants are informed that two previous participants competed in a contest, in which one of them was declared the winner. Participants make consequential decisions about how much of the prize money to redistribute from the declared winner to the declared loser. Across rounds, the probability that the winner was declared based on performance rather than luck varies, such that average redistribution decreases in the probability that the winner was declared based on performance.

Dictator game (Judd Kessler and Christopher Roth). Participants decide how much of a monetary endowment to share with another participant. Across rounds, the probability that the money sent is lost varies, such that average giving decreases in this probability. Decisions are consequential for participants' bonuses.

Contingent valuation in health (Alex Imas). Participants state a hypothetical societal WTP for a vaccine as a function of the number of sick people prevented.

Prisoner's dilemma (Christine Exley and Ernesto Reuben). Participants play a binary prisoner's dilemma matrix game. Average cooperation increases in the payoffs to cooperation (which varies across rounds). Participants' bonuses are given by the game payoffs.

Disclosure game (Marta Serra-Garcia and Anonymous). Participants act as sender in a disclosure game, deciding whether or not to reveal the true state to a receiver, being paid to make the receiver guess as high as possible. Across rounds, the realization of the true state changes, and disclosure rates increase in the true state.

Voting (Aakaash Rao). In an induced values setup, participants decide whether or not to cast a costly vote for a policy that increases their payoff. Across rounds, the number of other (computerized) voters varies. Voting probabilities decrease in the number of other voters. Participants receive their game payoff.

Information demand (Leonardo Bursztyn). Participants state their WTP for a binary signal about the outcome of a coin toss. Across rounds, the accuracy of the signal varies, and average WTP increases in accuracy. Bonuses are determined by the accuracy of subjects' guess about the coin toss as well as by whether or not they purchased information.

Belief updating (Sevgi Yuksel). In a two-states-two-signals belief updating paradigm, participants state their posterior belief after observing a signal. Across rounds, the accuracy of the signal varies, and average updating increases in accuracy. Participants receive a bonus if their posterior is in a window around the Bayesian posterior.

Forecasting (Kirby Nielsen). Participants forecast an autocorrelated process. Across rounds, the persistence of the process varies, and the persistence implied by subjects' forecasts increases in true persistence. Participants receive a bonus if their forecast is in a window around the Bayesian forecast.

Recall (Spencer Kwon). Participants recall the number of positive and negative news they observed about a hypothetical company. Across rounds, the number of positive and negative news varies. Participants receive a bonus if their estimate is within a window around the truth.

Signal aggregation (Heather Sarsons). Participants estimate a true state based on the reports of two intermediaries. Across rounds, the number of signals that each intermediary receives varies, and the average effective weight participants place on an intermediary increases in the number of signals the intermediary observed. Participants receive a bonus if their estimate is within a window around the truth.

'Special case': Rational inattention (Sandro Ambuehl). Following Ambuehl et al. (2022), participants decide whether to accept or reject a binary lottery that has positive expected value. By verifying mathematical equations, they can find out whether the lottery upside or downside will realize. Across rounds, the upside and downside of the lottery are both shifted up or down by a constant. Acceptance rates increase in this shifter. We view this experiment as a special case because in a fully rational model, the elasticity of decisions with respect to the parameter (the payoff shifter) is zero (because under a standard rational model the DM would first solve all mathematical equations and then accept the lottery if and only if the upside realizes, independently of how large it is). We defer a discussion of this experiment to Section 5, where we discuss the limits of behavioral attenuation.

Forecast stock return (EGOY). Participants forecast the future value of a $100 investment into an ETF, where the parameter that varies is the length of the time horizon. Average forecasts increase in the horizon. This task is not financially incentivized.

Estimate tax burden (EGOY). Akin to Rees-Jones and Taubinsky (2020), participants are provided with hypothetical federal and state income tax schedules and estimate a hypothetical taxpayer's tax burden. The parameter of interest is the paxpayer's income. The participant receives a bonus if their answer is within a window around the correct response. Estimated tax burdens increase in income.

Newsvendor game (EGOY). Classic game in management and operations research (Schweitzer and Cachon, 2000). Participants decide how much cola to produce, facing uncertain demand. The varying parameter is the marginal cost of producing cola. The participant's bonus is proportional to the profit of the firm. Average production levels decrease in marginal cost.

Product demand (EGOY). Participants state their hypothetical willingness-to-pay (WTP) for products such as pasta, where the parameter that varies across rounds is the quantity of the product (e.g., the number of pasta packs). This task is not incentivized. Average WTP for a product package increases in the quantity of its content.

Beauty contest (EGOY). Following Costa-Gomes and Crawford (2006), subjects participate in a two-player guessing game. Their objective is to guess their target, which is given by the other participant's guess times a multiplier. Across rounds, the multiplier varies and average guesses increase in the multiplier. Participants receive a bonus if their guess is within a window around their target.

Public goods game (EGOY). Standard 3-player PGG in which we vary the efficiency of contributions (the MPCR) varies across rounds. Average contributions increase in efficiency. Decisions are consequential for participants' bonuses.

Multitasking (EGOY). In an induced values experiment, participants allocate a budget of hours between two tasks (training two different horses), where the tasks' relative importance (the fraction of each horse's prize money that the coach gets) varies across rounds. Participant receives a bonus if their decision is within a window of the profit-maximizing decision. Average time allocation increases in a horse's relative importance.

Policy evaluation (EGOY). Participants rate their support for a hypothetical policy that increases household incomes. Across rounds, the cost of this policy (an increase in inflation) varies. Support for the policy decreases in anticipated inflation rates.

Risk preference elicitation I: Certainty equivalents (EGOY). In multiple price lists, participants reveal their certainty equivalents for a binary lottery that pays either $18 or nothing. Across rounds, the payout probability varies, and average certainty equivalents increase in this probability. Participants' bonus is determined by their chosen lottery.

Risk preference elicitation II: Probability equivalents (EGOY). In multiple price lists, participants reveal their probability equivalents for a safe payment. Across rounds, the safe payment varies, and average probability equivalents increase in the payment. Participants' bonus is determined by their chosen lottery.

Intertemporal required rate of return (EGOY). In hypothetical price lists, participants reveal their present value equivalent for a delayed payment. Across rounds, the delay varies, and average present values decrease in the delay. No incentives.

Finally, several of the experiments described above involve a second party (e.g. the receiver in the disclosure game). These secondary data points were collected to avoid deception, but we did not analyze this data.

3.3 Cognitive Uncertainty Elicitation

After each decision, we elicited cognitive uncertainty (*CU*). Loosely speaking, our general approach is to ask participants how certain they are about the optimality of their decision. Obviously, the concept of a best or optimal decision varies widely across decision domains because some are objective (such that an optimal decision is objectively defined), while others are subjective (such that optimal decisions are those that maximize the decision-maker's unobserved preferences). To the extent possible, we kept the *CU* elicitation constant across domains that belong to the same category. To illustrate, assuming that a subject took decision Y, we used the following language:

1. Continuous decisions in subjective tasks, illustrated by *Effort supply*: "*How certain are you that completing somewhere between [Y-1] and [Y+1] tasks is actually your best decision, given your preferences?*"

2. Continuous valuations in subjective tasks, illustrated by *Risk Preference (Certainty Equivalents)*: "*How certain are you that you actually value this lottery ticket somewhere between $[Y-0.5] and $[Y+0.5]?*"

3. Binary decisions in subjective tasks, illustrated by *Prisoner's Dilemma*: "*How certain are you that choosing Y is actually your best decision, given your preferences and the available information?*"

4. Decisions in objective tasks, illustrated by *Multitasking*: "*How certain are you that practicing somewhere between [Y-1] and [Y+1] hours with horse A is actually the best decision?*" Here, the instructions clarify that "best decision" refers to the decision that maximizes the bonus payment.

Subjects navigated a slider between 0% and 100% to indicate their certainty, understood as the percent chance the decision is "best" (in ways that are specific to different types of tasks).[7] Appendix A.2 contains the precise *CU* questions used for each task.

As we discuss in greater detail below, we find that this measurement of *CU* varies systematically in two ways that are relevant for this paper. First, there is large heterogeneity across subjects, potentially reflecting differences in cognitive ability or effort. Second, within a given subject, there is systematic variation across problem configurations, with *CU* increasing in the distance of the problem parameter to what we call 'simple points' (e.g., dominance points).

3.4 Logistics, Sample Size, Incentives and Pre-Registration

All experiments were conduced on *Prolific*, which Gupta et al. (2021) identify as best data-collection platform in terms of the tradeoff between response noise and cost. We tailored the fixed participation payment to each experiment to match Prolific's minimum

[7]The only exception is binary choice tasks, in which the slider only ranged from 50% to 100%. This is because in binary choice the percent chance of making the decision that is actually optimal is plausibly at least 50%, while in continuous decision problems it can easily be less. For the sake of comparability across experiments, we rescale the resulting uncertainty variable in these binary choice tasks to be in [0%,100%] by multiplying it by two.

payment rules based on median completion times in our pilots. In those tasks that involved financially incentivized decisions (the great majority of tasks), we selected one decision uniformly at random to be relevant for determining a subject's bonus. As we explained to subjects, they were eligible for a bonus payment with a probability of 1/5. Overall, average earnings across all experiments are $4.40 ($4.90 if we restrict attention to financially incentivized experiments). This includes an average participation fee of $2.80. The median time subjects took for our experiments is 9.8 minutes, for an effective hourly wage of about $27 (much larger than the typical hourly Prolific rate).

To study the role of the stake size for the results, in five of our tasks (CMA, BEU, VOT, SIA, REC) we implemented a high-stakes condition in which the de facto incentives were increased by a factor of ten: every subject was paid out and the maximal bonus (and marginal incentives) were multiplied by two relative to the baseline. Because the results in this experimental treatment are very similar to those in the baseline treatment (see Table 2 below), we pool the data in what follows.

All experiments are pre-registered in the AEA RCT Registry at AEARCTR-0013308. The pre-registration includes: (i) sample sizes; (ii) problem configurations; (iii) which parameter values constitute simple points; and (iv) regression specifications. Including the follow-up experiments described in Section 5, our experiments involved 8,199 subjects and 88,829 individual decisions. No subject participated in more than one experiment.

Our pre-registration specified sample sizes of 150, 200 or 250 subjects per experiment (in roughly equal proportions). Given the scope of this project, we were not able to run pilots that would enable informative power calculations. As a result, the pre-registered sample sizes were largely based on conjectures regarding in which experiment we might need fewer than 250 subjects to economize on research funds. Ex post, we determined that this decision caused us to be underpowered in some experiments. We thus elected to increase the sample size uniformly to 250 in all experiments, regardless of whether or not they delivered statistically significant results after the initial data-collection. For full transparency, the Appendix replicates all results using the initial, pre-registered sample. They are quantitatively very similar.

In a minor deviation from the pre-registration, we drop extreme outliers (decisions that are more than five standard deviations away from the median). This only influences 3 out of 88,829 decisions, all in the TAX experiment. The reason extreme outliers occur in this task but not in others is mostly that it is a free number-entry task and therefore liable to accidantal inclusion of extra digits.

4 Results

Figure 1 plots raw data from six of our 30 experiments, allowing us to preview the main results. Each panel shows the parameter varied in the experiment on the x-axis and mean decisions on the y-axis. Importantly, we break this data down based on subjects' decision-level cognitive uncertainty (*CU*), plotting a separate series for uncertain decisions (i.e. with *CU* greater than the median for a given parameter) in red, and relatively certain decisions (*CU* lower than the median) in blue. (Similar plots are provided for all other experiments in Online Appendix B.1.) We make four observations.

First, the left-hand column shows data from three *objective tasks* in which we know subjects' objective function and payoff-maximizing choice, plotted as dashed 45-degree lines. In all of these experiments, subjects are *behaviorally attenuated* over most of the parameter space, particularly away from the boundaries: the elasticity of their decisions is significantly *smaller* than it would be for an optimizing agent. As we show in Section 4.1, this attenuation is a universal phenomenon in our objective tasks.

Second, in all three cases attenuation is significantly *stronger* among high *CU* decisions. This difference in elasticity produces a canonical "flipping" pattern: high *CU* decisions tend to be higher when canonical economic models predict relatively low decisions, and lower when economic models predict relatively high decisions (a compression effect). As we show in Section 4.1, this linkage between *CU* and objective attenuation is nearly universal in our data.

Third, the exact same patterns occur also in the three *subjective experiments*, plotted in the right column of Figure 1. High *CU* decisions in all three tasks are markedly less sensitive to parameter variation in the interior of the parameter space, producing the same flipping pattern as observed in the objective experiments. Thus in both objective and subjective tasks, we similarly find that doubt about the optimality of one's own choices is highly predictive of a reduction in the elasticities of decisions.

Finally, in almost all experiments, the degree of insensitivity increases as parameters depart from intuitive "simple points," giving rise to *diminishing sensitivity*. Recall, these simple points are pre-registered boundary parameters at which the information processing involved in making decisions is particularly simple, for instance due to the presence of dominance relationships. For example, in effort supply (EFF, top right), there exists a single dominance point at a piece rate of zero, at which all strictly positive effort levels are transparently dominated. Indeed, the link between effort supply and piece rates exhibits pronounced diminishing sensitivity away from a piece rate of zero. In other cases like MUL or SIA we pre-registered the existence of two simple points (at the lower and upper boundaries of the parameter space) and we consistently see diminishing sensitiv-

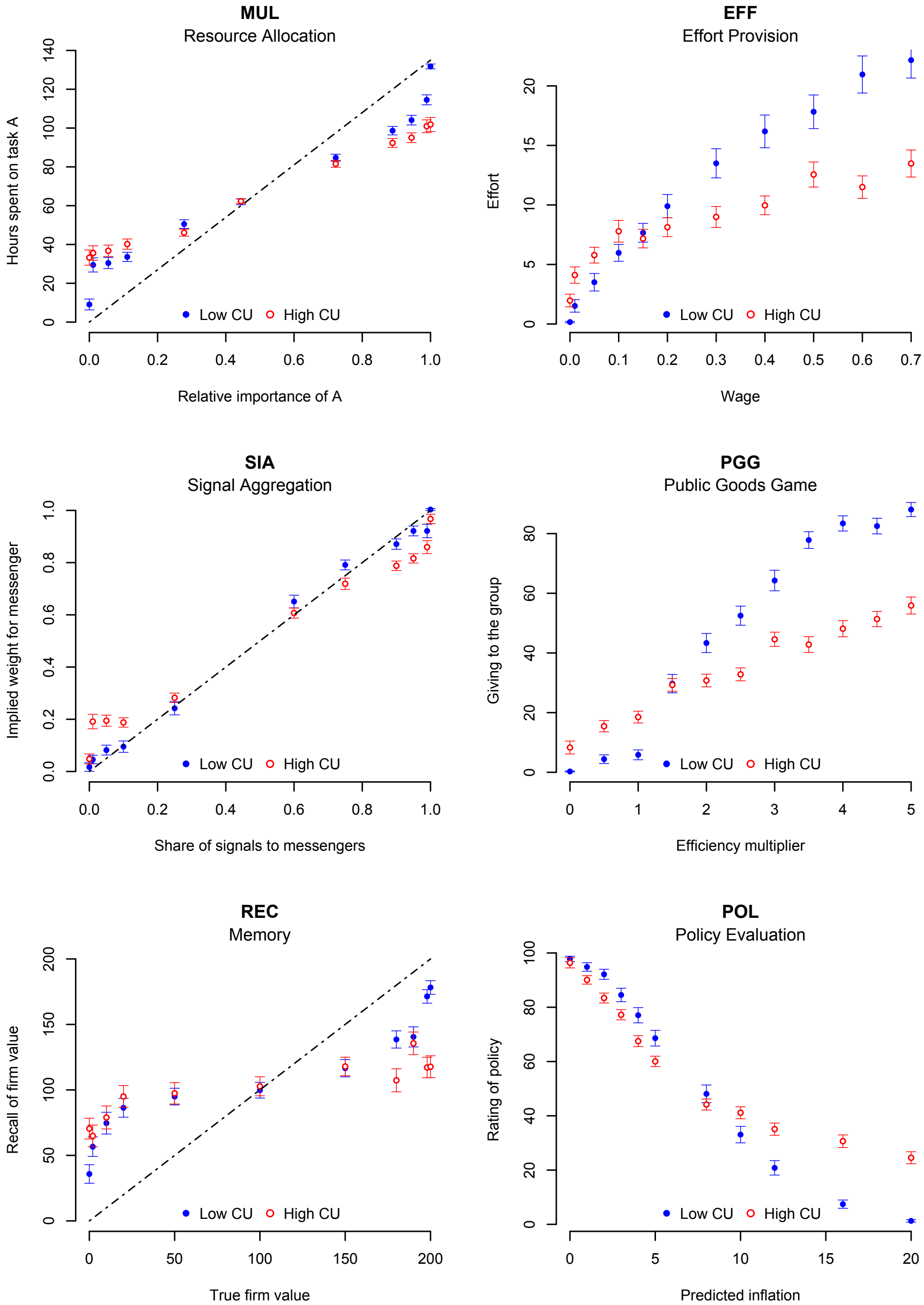


Figure 1: Decisions as a function of parameters, with sample split at median *CU* at a given parameter. Top left: Effort allocation to one of two tasks as a function of task's relative importance (MUL). Middle left: Weight placed on message as a function of number of signals observed by messenger (SIA). Bottom left: Recall of firm value as a function of true value (REC). Top right: Effort supply as a function of piece rate (EFF). Middle right: Public goods contributions as a function of efficiency (PGG). Bottom right: Evaluation of hypothetical policy as a function of implied inflation (POL). In the objective tasks, the dashed line shows the rational response.

ity away from both.[8] As we discuss in more depth in Section 5.1 below, this pattern is also near-universal in our data, and serves as a key piece of evidence for understanding the roots of insensitivity in information-processing frictions.

4.1 Insensitivity and Cognitive Uncertainty

In order to extend this analysis to all 30 of our experiments, we first follow our pre-registration by estimating the magnitude of the *interaction* between (i) the parameter varied in the task and (ii) the subject's *cognitive uncertainty*, on the subject's decision. Our hypothesis is that the sign of this interaction is negative (when the main effect of the parameter is positive), indicating that decisions that are associated with more uncertainty about how to optimize are *less sensitive* to variation in the parameter.

Econometric strategy. In each of our experiments, e, we elicit decisions $a^e_{i,j}$ from subject i at parameter values θ^e_j. We also elicit *cognitive uncertainty*, for each decision, $CU^e_{i,j}$. For ease of comparison, we recode all tasks such that decisions are increasing in the parameter. We adopt the labeling convention that the subscript j captures the ordering of parameters, i.e., $\theta_j > \theta_{j-1}$. For each experiment e, we estimate

$$a^e_{i,j} = \alpha^e + \gamma^e\ \theta^e_j + \beta^e\ \theta^e_j\ CU^e_{i,j} + \delta^e\ CU^e_{i,j} + \sum_x \chi^e d^e_x + \epsilon^e_{i,j}\ , \tag{1}$$

where $\epsilon^e_{i,j}$ is a mean-zero error term and d^e_x are controls (fixed effects) that apply in some tasks according to the pre-registration.[9] We always cluster the standard errors at the subject level. Per our pre-analysis plan, we drop from this analysis tasks involving boundary parameters that we specified as potential simple points. For instance, the analysis of attenuation does not include a wage of zero, an interest rate of zero or a payout probability of one. We analyze these potential simple points separately in Section 5.2 when we discuss diminishing sensitivity.

The attenuation hypothesis is that β^e is negative (given the normalization that γ^e is positive).

For 12 tasks, theory-inspired functional forms are available that lead us to transform either the raw decisions or the raw parameters into quantities that directly motivate

[8]For example, in the MUL experiment, subjects allocated time between two projects, as a function of the projects' relative importance. Here, two dominance points exist (a project matters exclusively or not at all), and average decisions indeed exhibit pronounced diminishing sensitivity away from 0% and 100%. Similarly, in SIA, subjects aggregate two messages as a function of the fraction of signals that either of the two messengers received, such that 0% and 100% are potential simple points (a messenger receives no signals or all of them). In both cases, we see diminishing sensitivity away from both the lower and higher simple points.

[9]For example, in STO these are fixed effects for the assets whose return the respondent forecasts.

linear regressions.[10] Appendix A.2 lists the (pre-registered) definitions of $a^e_{i,j}$ and θ^e_j in each experiment.

In principle, testing our hypothesis only requires us to report the magnitude and significance level associated with the estimated β^e, which we do in Appendix Tables 4-6. However, these magnitudes are not very instructive because they are not easily comparable across experiments, given that the decision variables and parameters have very different scales.[11]

We therefore visualize our results by plotting two quantities that are comparable across experiments. First, as an overall summary statistic, we calculate the t-statistics associated with the estimated β^e coefficients. Recall that the t-statistic is the coefficient estimate of β^e, divided by its standard error. This measure has the advantages that (i) it is scale-free and (ii) it combines information on both point estimates and associated statistical uncertainty. Our hypothesis is that these t-statistics will tend to be *negative*, indicating a *reduction* in sensitivity as people become more cognitively uncertain.

Second, to visualize the quantitative magnitude of the estimated effects, we calculate a *CU attenuation ratio* that captures by how much the sensitivity of decisions decreases as *CU* increases from 0% to 50% (the 75th percentile of the *CU* distribution across all experiments), relative to the decision slope at $CU = 0$. Formally:

$$CU \text{ attenuation ratio} = \frac{(\text{Sensitivity at } CU = 0) - (\text{Sensitivity at } CU = 0.5)}{(\text{Sensitivity at } CU = 0)} \tag{2}$$

$$= 1 - \frac{\Delta\mathbb{E}[a^e_{i,j}|CU = 0.5]/\Delta\theta^e_j}{\Delta\mathbb{E}[a^e_{i,j}|CU = 0]/\Delta\theta^e_j} = -\frac{0.5\hat{\beta}^e}{\hat{\gamma}^e} \equiv \hat{\phi}^e \tag{3}$$

This ratio equals zero if the slope of decisions is uncorrelated with *CU* (i.e., if $\hat{\beta}^e = 0$), and it equals one if the slope of decisions at $CU = 50\%$ is zero (i.e., if there is perfect *CU*-linked attenuation). Our hypothesis implies that this statistic will be positive – evidence that a reduction in *CU* is associated with an increase in responsiveness to parameters.

Results. The top panel of Figure 2 summarizes the results, by plotting t-statistics for β^e across our 30 tasks. Objective tasks are plotted in dark gray, subjective tasks in light gray. A $N(0,1)$ distribution function with confidence level thresholds is shown in the right margin as a benchmark against which to evaluate the results. A second distribution in red plots the meta-analytic posterior from the dataset as a whole, as we discuss in

[10] For example, in belief updating, following Grether (1980), the decision $a^e_{i,j}$ is a subject's log posterior odds and the parameter θ^e_j the log likelihood ratio. To take another example, in intertemporal discounting, the exponential discounting model directly motivates a regression equation in which $a^e_{i,j}$ is the natural log of the subject's present value equivalent and θ_j the time delay.

[11] Standard techniques of standardizing the data into z-scores are not helpful in our context because we are interested in an interaction coefficient.

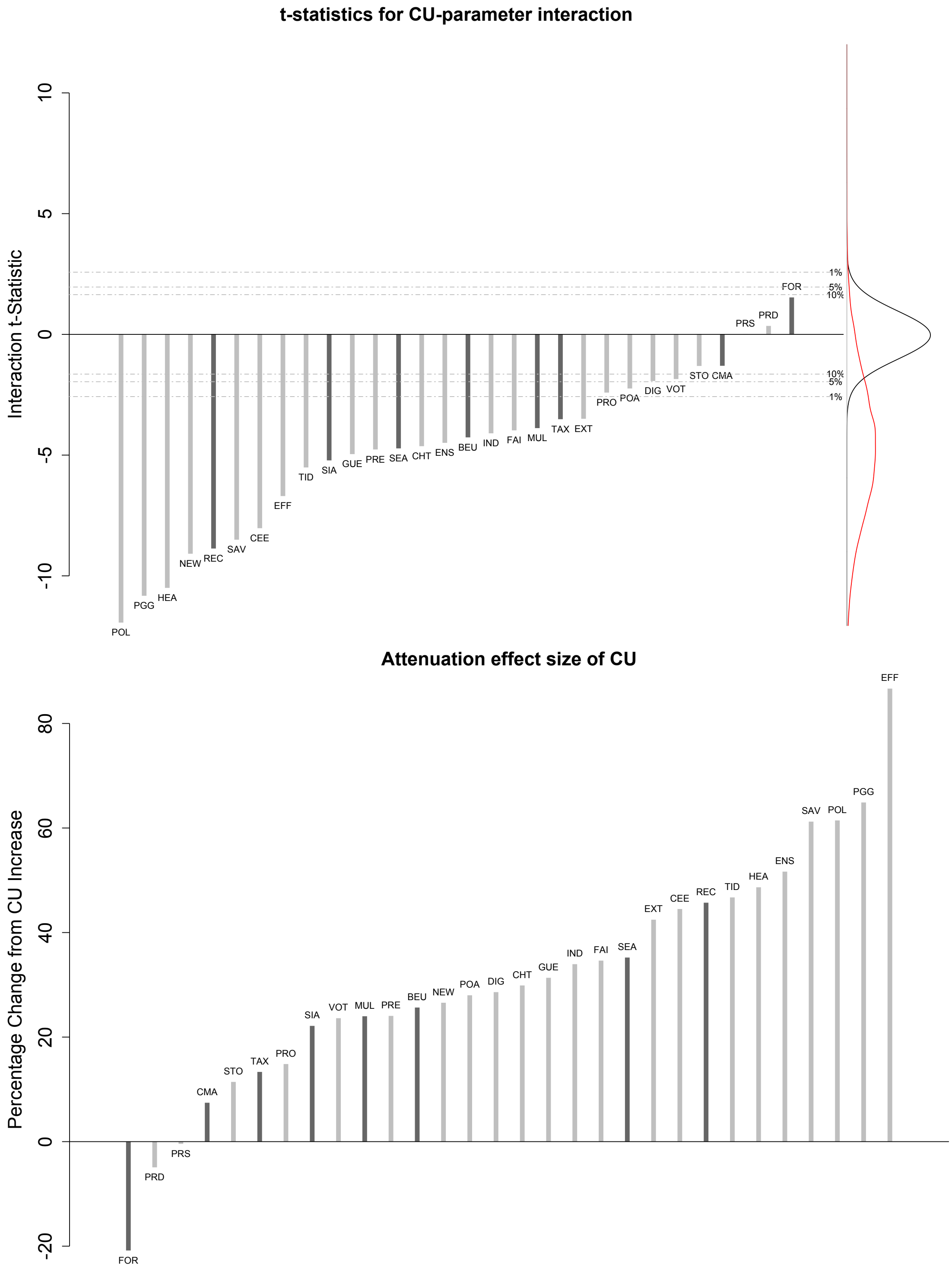


Figure 2: Behavioral attenuation and cognitive uncertainty. The top panel plots the t-statistic associated with $\hat{\beta}^e$ in (1). For comparison, we plot a standard normal distribution in black. The red distribution shows the distribution of adjusted t-statistics from a meta analysis (Bayesian hierarchical regression). The bottom panel plots $\hat{\phi}^e$. Tasks displayed in black have objectively correct solutions, while those displayed in grey are subjective decision problems that involve unknown (to us as researchers) preferences or information sets.

more detail below.

For 27 out of 30 tasks the t-statistics are negative, indicating that behavior becomes *more inelastic* as subjects become less certain in their ability to identify the optimum in almost all tasks. 21 of these are statistically significant at the 1% level, two more at the 5% level and two at the 10% level. By contrast, for only two tasks do we find the reverse relationship (PRD and FOR) and both of these exceptions are small and statistically insignificant. We thus find support for CU-linked inelasticity in the overwhelming majority of tasks.

On average, the size of these effects is large. The bottom panel of Figure 2 shows that an increase in *CU* from 0% to 50% is associated with sizable reductions in the sensitivity of decisions. On average, the reduction in sensitivity is equal to 31%, and rises to as high as 87% in effort supply (EFF).

It is worth pausing to emphasize that this link between insensitivity and *CU* arises in a very similar way in a highly diverse range of decision tasks. This pattern arises in social decisions, decisions that involve risk or intertemporal tradeoffs, elicitations of beliefs and tests of cognition, evaluations of policies, decisions related effort supply and multitasking, strategic decision making, and more. Moreover, a comparison of the light and dark lines in Figure 2 indicates that the results are very similar across the subjective and objective tasks. In both categories, most experiments show *CU*-linked insensitvity, with similar cross-experiment variation in quantitative magnitudes and statistical significance. We take this similarity in results across our tasks as a first indication that our results in the subjective tasks reflect information-processing imperfections rather than (for example) insensitivity-generating preferences that happen to be correlated with *CU*.

Meta-analysis. The main hypothesis behind our paper is that there is an overarching structure behind the many experiments we run, which is a lower sensitivity when *CU* is higher. We, hence, additionally report t-statistics adjusted using standard meta-analytic techniques, i.e., using Bayesian hierarchical regressions (see Brown et al., 2024; Nunnari and Pozzi, 2022; DellaVigna and Linos, 2022, for recent applications in behavioral economics). These adjustments effectively amount to a Bayesian shrinkage that pulls each t-statistic towards the sample mean across experiments. Appendix B.2 describes these estimations in detail.

The red distribution in the margin of the top panel of Figure 2 shows the results. We see that the adjusted distribution of t-statistics is very similar to the unadjusted one, and differs substantially from the null hypothesis. The meta-analysis estimates a mean adjusted t-statistic of -4.7.

Intensive margin of cognitive uncertainty. A potential concern is that the results simply reflect random clicking in the *CU* question, i.e., that some subjects state strictly positive *CU* simply due to carelessness, but that there is no genuine informational content in the quantitative magnitude of *CU*. To show that this is not the case, Appendix Figure 12 replicates Figure 2 by restricting attention to observations with $CU_{i,j} > 0$. The results are very similar.

Within-subject variation in cognitive uncertainty. A second potential concern is that the results reflect heterogeneous interpretations of the *CU* question across subjects. A third is that the results are purely driven by across-subject variation in 'laziness' or confusion. Both of these can be addressed by restricting attention to within-subject variation in *CU*. Averaging across all experiments, subject fixed effects explain 44% of the variation in *CU*, suggesting that much of the variation in *CU* in fact reflects variation in perceived decision difficulty across parameters, within the same person.

To study the effect of this variation, we re-estimate eq. (1) controlling for subject fixed effects. Appendix Figure 11 shows the results. Naturally these t-statistics are smaller than the ones that leverage the full variation in the data (as expected, because a significant fraction of the variation in *CU* is across subjects). Nonetheless, in a large majority of experiments, we continue to find strong evidence that lower *CU* is associated with lower elasticities of decisions.

4.2 Attenuation to Objective Benchmarks

An important diagnostic aspect of our design is our inclusion of tasks with objectively correct solutions, which allow us to *directly* measure behavioral attenuation – and to verify that objective attenuation is associated with cognitive uncertainty. In particular, as described in our pre-analysis plan, for those tasks that have an objectively correct solution, we can compute attenuation with respect to the rational benchmark. We estimate[12]

$$a^e_{i,j} = \nu^e + \omega^e\, \theta^e_j + \sum_x \chi^e d^e_x + u^e_{i,j}\,, \tag{4}$$

and then assess attenuation by dividing the observed elasticity $\hat{\omega}^e$ by the elasticity predicted in a rational model, ω^e_R. As above, we cluster standard errors at the subject level.

Figure 3 summarizes the results. For each task, we plot three quantities. First, we plot the ratio $\hat{\omega}^e/\omega^e_R$ as black dots. In *every one* of our objective tasks we find that this ratio is *significantly less than one*, indicating that subjects are insufficiently elastic to

[12]As above, this analysis is restricted to those parameter values that (according to the pre-registration) do not constitute potential simple boundary points (such as a piece rate of zero).

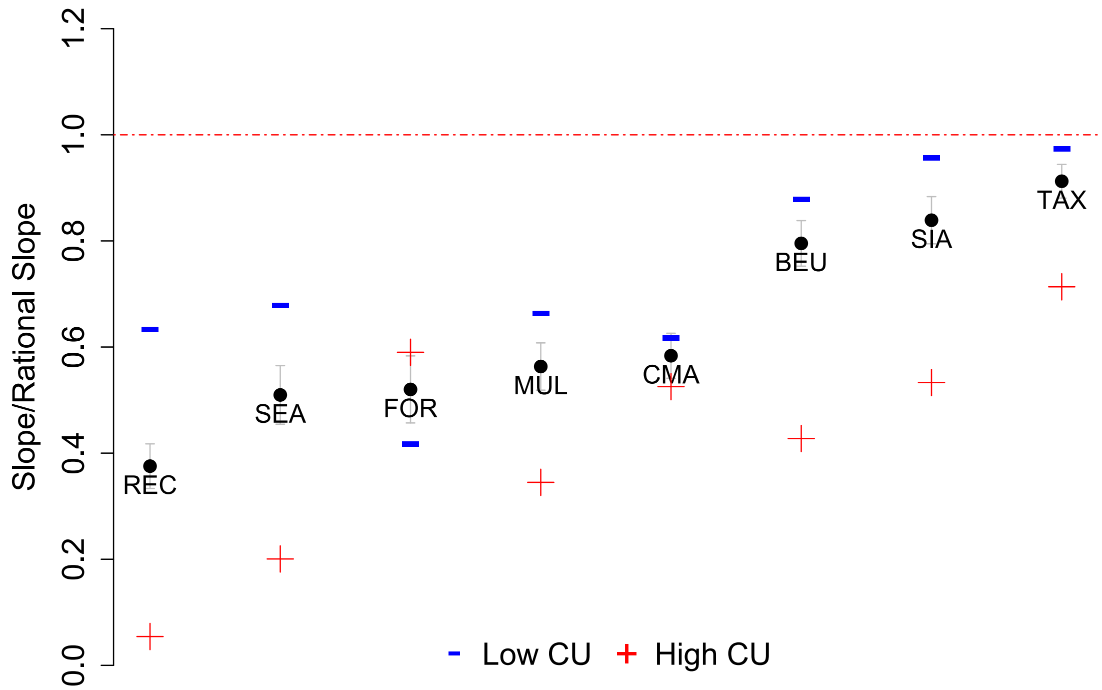


Figure 3: Behavioral attenuation relative to normative benchmarks in objective tasks. For each task, the black dot plots $\hat{\omega}^e/\omega^e_R$ and 95% CIs, see equation (4). The red and blue dots correspond to the fitted values of equation (1) for $CU = 0\%$ (blue) and $CU = 100\%$ (red).

economic fundamentals in the experiment.

Second, we estimate a variation on equation (4) in which we interact θ^e_j with $CU^e_{i,j}$, plotting fitted values for low and high CU decisions. In blue, we plot minus signs ("-") showing the fitted values for decisions with $CU = 0\%$. In red, we plot plus signs ("+") showing the fitted values for decisions with $CU = 100\%$. As already shown in Figure 2, in 7 of our 8 objective tasks we find that *CU* is strongly associated with the degree of objective attenuation. Low *CU* decisions tend to be far more responsive to parameters and in several tasks (e.g., BEU, SIA and TAX) become almost fully rationally elastic.

Overall then, we find not only direct (and universal) evidence of behavioral attenuation, we also find strong evidence that it is reliably predicted by *CU*. The one exception is FOR, in which there is strong evidence of insensitivity, but a slight reversal of the expected association with *CU*. There is an intuitive reason for this exception, which we discuss when we turn to the limits of behavioral attenuation in Section 5.

5 Mechanism: Information-Processing Constraints

Our motivating hypothesis is that the insensitivities documented in the previous section reflect constraints in the information processing required to map economic fundamentals into optimal decisions. Our evidence so far broadly supports this interpretation: in more than two dozen distinct economic contexts, we have found that it is precisely the decision-makers who doubt that their choices are optimal who make the least elastic choices. The near-universality of this pattern over many, wildly different choice contexts makes it difficult to parsimoniously account for this evidence with any account not rooted in generic information processing difficulties that seem common to all of these choice settings – a conclusion that is reinforced by the fact that we can directly associate *CU* with objective mistakes in responding optimally to variation in parameters for the subset of our tasks (i.e., our objective tasks) that have directly observable objective functions.

In this section we contrast this interpretation with a natural alternative: that *CU* predicts inelasticity because *CU* is correlated with insensitivity-inducing preferences. For example, suppose that, in the effort supply experiment (EFF), a subject's utility from effort a at piece rate θ is given by $u(a,\theta) = \theta a - \eta a^2$. Then, the utility-maximizing effort level is $a^* = \theta/\eta$, leading subjects with larger η to be less sensitive to variation in the wage. If it was true that – for whatever reason – subjects with larger η also exhibit higher *CU*, this would spuriously generate a correlation between *CU* and insensitivity.[13] To be sure, we are not aware of any ex ante reasons to expect a correlation between insensitivity-generating preferences and self-doubt, and (unlike information-processing accounts) this type of explanation cannot explain behavior in our objective tasks where subjects' own preferences play no role. Nonetheless, it stands as a conceptual possibility for our subjective tasks.

In this section, we provide additional evidence for an information-processing mechanism. To this effect, we leverage the simple insight that even within a given task, some decision problems are more difficult than others, such that we should expect to observe a link between *CU* and insensitivity also *across different problem parameters* (rather than across subjects). As suggested by our model in Section 2, this will also shed light on the linkage between behavioral attenuation and *diminishing sensitivity*.

5.1 Simple Points

Much of what makes it hard to make optimal economic decisions is the fact that decision makers typically have to intensively trade off and aggregate information to identify an optimal decision. Because of this, intuitively, we should expect the difficulty of tasks to vary across parameter configurations because at some parameters computing tradeoffs or aggregating information is not necessary for inferring the optimum. For instance, trading off money and leisure in deciding how much effort to expend as a function of

[13] Though note that even this approach cannot explain why high *CU* decisions are associated with strictly higher effort supply at low wages – the model sketched above only generates lower sensitivity, but not the canonical "flipping" pattern that we see in Figure 1.

a piece rate may be cognitively difficult in general, but it is entirely trivial when the piece rate is zero (and arguably still pretty easy when it is strictly positive but tiny). Similarly, determining one's optimal demand for noisy information may be difficult in general, but it is simple when the information is fully uninformative. Importantly, these kinds of 'simple points' typically occur at the logical boundaries of the parameter space, i.e., at an interest rate of zero, a payout probability of zero or one, a marginal cost of zero, an efficiency multiplier of zero, a time delay of zero, and so on.

In almost all experiments, we deliberately included such "potential simple points" in the design by including parameters at natural boundaries, allowing us to study how CU changes with likely task difficulty. In our pre-registration, we listed these "potential simple points" for 25 of our 30 tasks and further identified 14 of these tasks as having dominance points where we thought there was an especially strong ex ante reason to expect simplicity. Appendix A.2 contains the details for each task. Throughout Section 5.1, as we pre-registered, we restrict the sample to those 25 tasks that have a potential simple point.

Figure 5 plots median *CU* in each of these 25 experiments as a function of distance to the pre-registered potential simple points, normalizing the x-axis for comparability by showing the rank distance from the boundary. The figure reveals a strikingly uniform pattern of results. First, with very few exceptions, median *CU* is zero or close to zero at the boundary point. Second, *CU* strongly increases as parameters become more distant from the boundary, suggesting that as the information-processing requirements for optimization increase, subjects become less confident in their ability to optimize. Following our pre-registered procedure, we find that in almost all experiments the 'potential simple points' included in the design are *actually simple* in the sense that they induce significantly lower *CU* than adjacent points.[14]

These results suggest that *CU* not only predicts objective evidence of behavioral attenuation (in the objective tasks), it also strongly conforms to intuitions about what sorts of tasks should be simpler. This strong within-subject association between *CU* and apparent task difficulty, provides additional evidence for an information-processing interpretation of our results.

5.2 Diminishing Sensitivity

The secondary prediction of our model in Section 2 is that at those points at which *CU* is locally higher, the sensitivity of decisions is locally lower. Because we've just seen that *CU* is generally lowest at simple boundary points, the model predicts that information-

[14]The one exception is FOR, for which we pre-registered potential simple points of 0% (future growth is entirely random) and 100% (future growth exactly equals past growth). The *CU* data show that 100% is actually a simple point, while 0% is not.

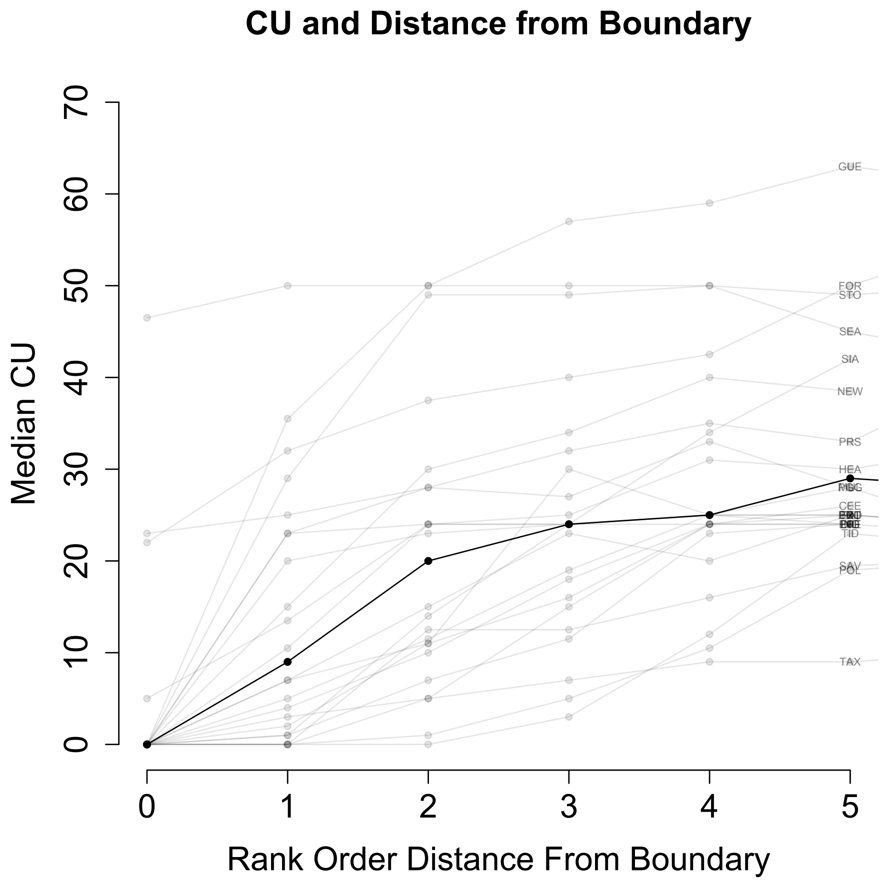


Figure 4: Median cognitive uncertainty as a function of distance to the nearest boundary point (measured in ordinal ranks), separately for each experiment. Solid line shows overall median across all experiments. Sample includes those 25 experiments for which we pre-registered at least one potential simple point at the boundary of the parameter space.

processing constraints produce *diminishing sensitivity*, a classic pattern previously documented in many decision contexts. In what follows, we provide evidence suggesting that diminishing sensitivity is indeed tightly connected to the variation in cognitive uncertainty across parameters documented in the previous subsection.[15]

Presence of diminishing sensitivity in decisions. We begin by measuring evidence of diminishing sensitivity in our data. We denote by $\Delta_j = min\{|\theta_j - \underline{\theta}|; |\overline{\theta} - \theta_j|\}$ the absolute distance between a parameter and the closest boundary point. We then test for diminishing sensitivity by estimating, for each experiment e,

[15]We exclude the binary choice tasks from this analysis. The reason is that there the idea of diminishing sensitivity cannot realistically apply because, under a standard random choice model, the slope of decisions is much larger over intermediate ranges of the parameter (close to the decision maker's indifference point). Overall, this leaves us with 22 tasks.

$$a^e_{i,j} = \alpha^e_d + \gamma^e_d\, \theta^e_j + \beta^e_d\, \theta^e_j\, \Delta^e_j + \delta^e\, \Delta^e_j + \sum_x \chi^e d^e_x + \nu^e_{i,j}\,, \tag{5}$$

where diminishing sensitivity is indicated by $\hat{\beta}^e_d < 0$.

The top panel of Figure 5 shows the t-statistics associated with $\hat{\beta}^e_d$. The Figure reveals widespread evidence of diminishing sensitivity. Almost all t-statistics are negative and sizable, and most are statistically significantly so.

Notably, this diminishing sensitivity also occurs in objective tasks in which we as researchers know that the optimal policy function is linear, such as in SEA and MUL. Moreover, as with attenuation, diminishing sensitivity is strikingly similar across objective and subjective tasks, providing a first piece of suggestive evidence that a large part of the diminishing sensitivity in the subjective tasks likely also reflects information-processing imperfections.

Link of diminishing sensitivity to CU. Next, we show that the variation in subjective task difficulty documented in Section 5.1 is connected to this pattern of diminishing sensitivity. To do this, we conduct an analysis of the sensitivity of decisions and *CU* not across subjects but, instead, across different problem parameters (averaged across all subjects). Specifically, we directly link the local sensitivity of decisions around a given parameter to local *CU* at that parameter. According to the model, at those points where *CU* is high the local slope of decisions should be low.

We estimate both local decision sensitivities and local *CU* across all subjects, in a way that is comparable across experiments. Intuitively, for each parameter in a given experiment, we compute the sensitivity of decisions around this parameter, and normalize it by the average sensitivity across all parameters in the experiment.[16] Similarly, for each parameter, we calculate *CU* at that parameter, normalized by average *CU* across all parameters in the experiment. Given that almost all of our experiments feature 11 distinct parameter values, this means that we estimate 11 local sensitivities and 11 average *CU* values for a typical experiment.

[16]More formally, for each experiment e and parameter value θ^e_j, we estimate the OLS regression

$$a^e_{i,j} = \alpha^e_j + \xi^e_j \theta^e_j + \sum_x \chi^e d^e_x + \epsilon^e_{i,j}$$

in two different samples. First, we estimate it locally around parameter θ^e_j, i.e., only including $\{\theta^e_{j-1}, \theta^e_j, \theta^e_{j+1}\}$ (for parameters that constitute the minimum or maximum parameter in our experiments, we estimate the local slope only from two points). Second, we estimate the regression in the full sample of parameters in experiment e. To arrive at a measure of the relative local sensitivity, we divide $\hat{\xi}^e_j$ as estimated in the 'local' sample by $\hat{\xi}^e$ as estimated in the full sample. These relative local sensitivities have large outliers, so we winsorize them at the 5th and 95th percentile.

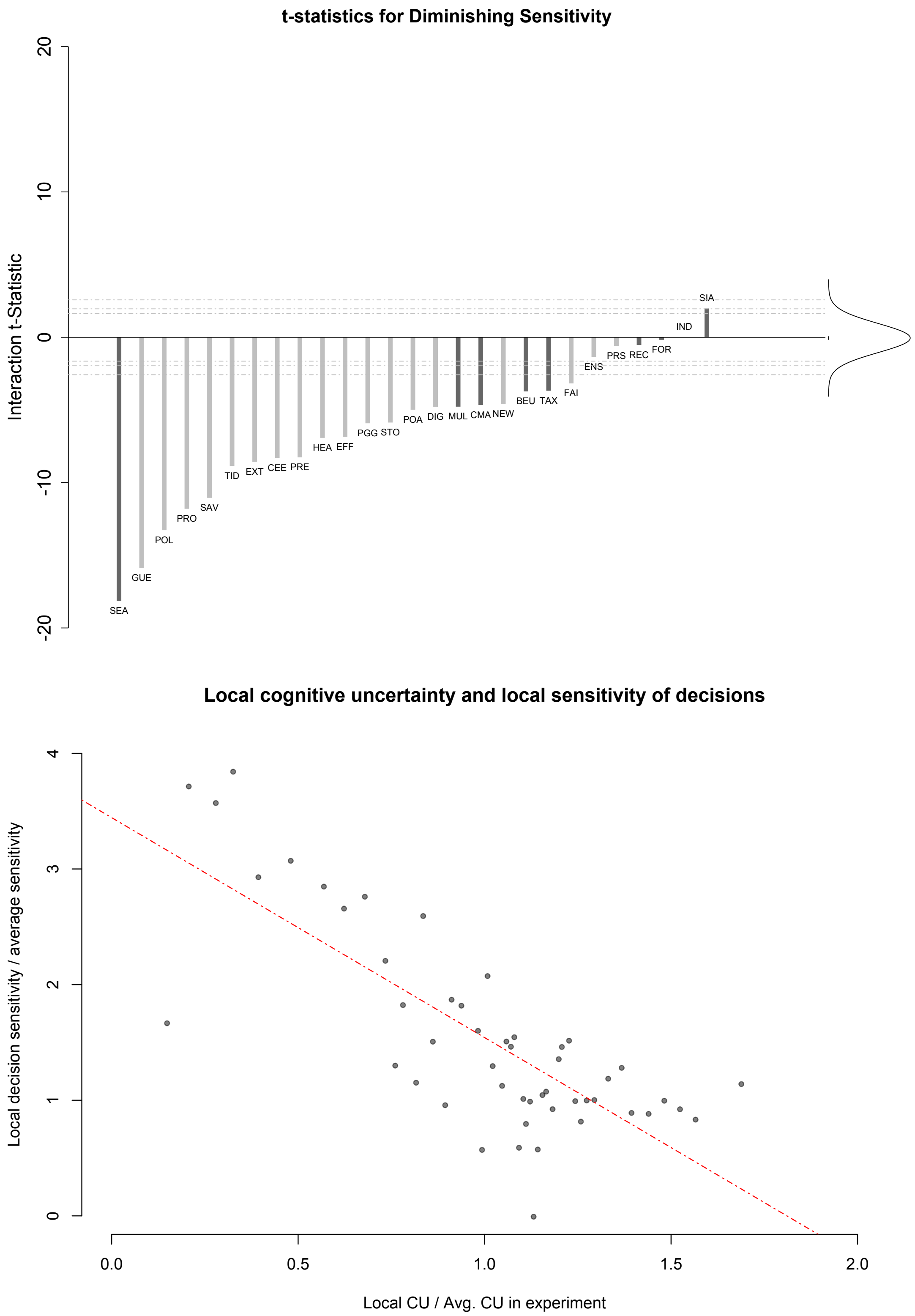


Figure 5: Top panel: Distribution of t-statistics for diminishing sensitivity ($\hat{\beta}_d^e$ in eq. (5)). Bottom panel: Binned scatter plot of the correlation between local *CU* at θ_j and local sensitivity of decisions at parameters $\{\theta_{j-1}, \theta_j, \theta_{j+1}\}$. In both panels, we restrict attention to experiments that (i) have a simple boundary point and (ii) are not binary choice tasks. In the bottom panel, an observation is a task-parameter (252 observations), binned into 50 buckets to ease readability.

The bottom panel of Figure 5 shows the results by providing a binned scatter plot of the relative local decision sensitivities against relative local *CU*. The figure pools observations from all experiments, but the figure controls for experiment fixed effects, such that the figure only reflects within-experiment across-parameter variation in local decision sensitivities and local *CU*. In total, the figure is constructed from 252 experiment-parameter combinations, but we bin those into 50 buckets to ease readability.

The Figure shows that the two quantities are strongly correlated in the direction predicted by the model (partial $r = -0.50$, $p < 0.01$). As *CU* rises, the relative sensitivity of decisions to the parameter drops. Notably, because this analysis purely leverages variation at the population level across parameters (rather than across subjects), this evidence is logically independent of the evidence presented in Section 4, which partly relied on across-subject variation. We interpret this evidence as strongly suggesting that a higher difficulty of information processing produces greater insensitivity of decisions.

Taken together, a consistent picture emerges from Figures 4 and 5. At parameter values at which *CU* is higher, the sensitivity of decisions is lower (bottom panel of Figure 5). Because *CU* increases in distance from simple boundary points (Figure 4), this pattern generates – or at least contributes to – widespread diminishing sensitivity (top panel of Figure 5).

5.3 Recap: Information-Processing Constraints or Preferences?

To summarize, multiple strands of evidence suggest that an insensitivity of economic decisions occurs in dozens of widely varying economic settings because of the difficulties involved in processing information to maximize. First, insensitivity is strongly associated with subjects' own doubt about the optimality of their choices (as measured by *CU*), and this doubt predicts variation in insensitivity both within subjects and – at the population level – across different problem parameters. Second, this pattern is nearly universal across many very different choice domains, making it difficult to parsimoniously explain on the basis of anything other than the generic complexity the tasks plausibly have in common – a conclusion reinforced by the pattern's virtually identical appearance in the eight objective tasks in which it is unambiguously a consequence of information processing constraints.

To close our main analysis, we reflect on this evidence by contrasting our hypothesis with the perennial alternative: that the insensitivities in the subjective tasks are driven not by information processing constraints, but by *preferences* that generate insensitive behavior. In order for such an account to fully explain our data, one would have to accept *all* of the following premises.

1. Looking *across* individuals, the degree to which people have preferences that gen-

erate less sensitive decisions is correlated with their own skepticism about the optimality of their choices (i.e., with the magnitude of their cognitive uncertainty).

2. Looking across different parameters of a problem (at the population level), average cognitive uncertainty is coincidentally high at exactly those points at which average preferences lead average decisions to be relatively insensitive.

3. Both of these patterns occur as *information processing mistakes* in objective tasks, but occur on a completely different basis as *preference expressions* in subjective tasks.

4. The ways in which cognitive uncertainty is correlated with preferences that generate insensitivity (both across subjects and across different problem configurations) is very similar across the many decision domains that we study: social decisions, intertemporal decisions, decisions under risk, strategic decisions, labor-related decisions, and so on.

We leave it to the reader to assess the plausibility of these premises relative to the more parsimonious possibility that information-processing imperfections (and the uncertainty they produce about how to optimize) are the common driver of attenuation and diminishing sensitivity in subjective task, just as they verifiably are in objective ones.

6 The Bounds of Attenuation

In this Section we discuss several findings and diagnostic treatments that point to the boundaries of the phenomenon.

Stake size, cognitive effort and demographics. To what degree does attenuation reflect low stakes, low cognitive effort or demographics – three perennial explanations for deviations from standard predictions? To study this, Table 2 presents OLS regressions in which the dependent variable is the subject-level slope (sensitivity) of decisions, computed in a standardized way across experiments.[17] Recall that a lower slope means more attenuation.

[17]Specifically, for each subject i, we estimate

$$a^e_{i,j} = \nu^e_i + \omega^e_i\, \theta^e_j + \sum_x \chi^e d^e_x + u^e_{i,j}\,, \tag{6}$$

and then divide the estimate $\hat{\omega}^e_i$ by $\hat{\omega}^e$ (the estimate obtained in the full sample of subjects). As always when we look at attenuation (rather than diminishing sensitivity), this analysis excludes the pre-registered potential simple points.

Table 2: Correlates and predictors of attenuation and *CU*

	Subject-level decision slope			Decision-level *CU*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1 if (incentives x 10)	0.059	0.060	0.059	−0.028	−0.018	−0.003	0.016
	(0.041)	(0.041)	(0.041)	(0.037)	(0.038)	(0.038)	(0.048)
Log [Completion time experiment] (std.)		−0.032***	−0.027***		−0.068***	−0.062***	−0.061***
		(0.008)	(0.008)		(0.009)	(0.009)	(0.010)
Age			−0.002***			−0.003***	−0.003***
			(0.001)			(0.001)	(0.001)
1 if female			−0.053***			0.127***	0.126***
			(0.016)			(0.016)	(0.017)
Log [Response time decision] (std.)					0.118***	0.117***	0.114***
					(0.006)	(0.006)	(0.006)
Distance from boundary (rank, 0-11)							0.065***
							(0.002)
Experiment fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.005	0.007	0.010	0.000	0.013	0.018	0.047
Num. obs.	7606	7606	7576	82303	80925	80611	69196

Notes. OLS estimates, robust standard errors in parentheses (columns (4)–(7) clustered at subject level). Observations include data from all experiments. In columns (1)–(3), the dependent variable is $\hat{\omega}_i$, divided by the overall (across-subject) $\hat{\omega}$ in the respective experiment, and then winsorized at the 5th and 95th percentile. In columns (4)–(7), the dependent variable is decision-level *CU*, divided by average *CU* (across all decisions and subjects) in the respective experiment. Time variables are standardized into z-scores within each experiment. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Column (1) shows that a tenfold increase in incentives – implemented in experiments BEU, CMA, REC, SIA and VOT – did not significantly affect attenuation. Column (2) documents that longer completion times in the experiment are associated with *more* attenuation – a finding that is seemingly at odds with the idea that attenuation merely reflects laziness. Rather, this correlation suggests that subjects who have greater difficulty thinking through a problem take longer to think, yet still exhibit attenuation. Column (3) controls for demographics, showing that older people and women exhibit stronger attenuation.

Given the explanatory power of *CU* for attenuation, researchers may be interested in which variables correlate with or predict it. Columns (4)–(7) of Table 2 present OLS regressions in which the dependent variable is decision-level *CU*, normalized by average *CU* in the experiment for comparability. First, again, the increase in incentives did not affect *CU*. Second, a longer response time in a given decision is associated with higher *CU*, while a longer completion time in the study as a whole is associated with lower *CU*. A potential interpretation of this is that subjects who exert higher cognitive effort overall in the study, as a whole exhibit lower uncertainty, yet whenever they find a particular decision difficult, they both take longer and exhibit higher uncertainty.

Bound #1: Rational elasticity of zero. Intuitively, behavioral attenuation arises because people often know the sign but not the magnitude of comparative statics. For example, even without intensive information processing, people know that they will want to invest more when expected returns are higher, but determining how much more exactly is difficult. This intuition suggests that there may be situations in which the opposite of behavioral attenuation will be present: when the utility-maximizing elasticity of decisions to fundamentals is tiny or even zero. In these cases, people don't know how much to respond, and because the normative change is small, they may be excessively sensitive.

Because of this, we deliberately requested proposals from our experts in which there was an expected strong monotonic relationship between parameter and response. However, the experiment proposed by one of our experts, Sandro Ambuehl, was explicitly designed to illuminate this limit of behavioral attenuation. As discussed in Section 3.2, the main feature of the RIA experiment is that – under a fully rational model without information-processing costs – the elasticity of the decision (accept or reject a positive expected-value lottery) to variation in the fundamental (the expected value of the lottery) is zero because the DM can find out whether the lottery upside or downside will realize by verifying a few mathematical equations. Because Ambuehl's proposal is interesting and illuminating, we included it in our set of tasks even though it is structurally different from all other tasks, but communicated to him that we would use his experiment as a test of the limits of the phenomenon, rather than as a baseline task.

In this experiment, we find that, if anything, decisions that are associated with higher *CU* are slightly more sensitive to variation in the problem parameter, though this is statistically not significant.[18]

Bound #2: Incorrect problem representations. The recent literature on bounded rationality has made a distinction between (i) mistakes that arise because of noisy cognition, and (ii) mistakes that arise because decision-makers have a fundamentally incorrect representation of the problem (a wrong problem-solving approach), see for example Ba et al. (2022); Enke (2020); Graeber (2023); Bordalo et al. (2023); Esponda et al. (2024); Hascher et al. (2024).

In general, these two types of mistakes are complementary. Yet this distinction is nonetheless relevant for our investigation because intuition suggests that people who hold fundamentally incorrect mental models may also lack a sufficient meta-cognitive awareness of their mistakes, especially when the incorrect representation is based on compelling intuitions (such as in the cognitive reflection test). If incorrect representations are based on strong but wrong intuitions, it may even be the case that people who are more prone to mistakes are *more certain* in the optimality of their decisions, in which case we would expect our empirical approach of associating attenuation with *CU* to fail.[19]

[18]Formally, the regression coefficient $\hat{\beta}^e$ in equation (1) is positive, with $p = 0.32$.

[19]Indeed, Enke et al. (2023b) examine the relationship between mistakes and confidence for a set of

In one of our experiments, FOR, the data suggest that mistakes are primarily driven by a specific incorrect problem representation or fundamental misunderstanding. In this task, average decisions are strongly attenuated relative to the objective benchmark (see Figure 3), yet if anything *CU* is *negatively* correlated with this insensitivity (see Figure 2). The data tentatively suggest that these patterns obtain because about 1/3 of all decisions reflect a specific incorrect problem-solving approach: subjects almost perfectly extrapolate past trends, regardless of whether the true autocorrelation of the process is high or low (even when it is zero). Notably, these fully extrapolative decisions are associated with a large decrease in *CU* of 17 percentage points ($p < 0.01$).

This explains why *CU* is uncorrelated with the elasticity of decisions in FOR even though decisions are objectively attenuated: there is an intuitively compelling (but wrong) problem representation that produces both mistakes and low *CU*.

Bound #3: Joint evaluations. Following the literature on joint vs. separate evaluations (Hsee et al., 1999), we hypothesized that people may become less attenuated to economic fundamentals when they are prodded to directly compare different circumstances, i.e., when they are asked to reason through their responses to counterfactual values of the decision-relevant parameter. For instance, people's savings decisions may become less attenuated to the interest rate when they don't just ask themselves "How much do I save when the interest rate is 3%?", but also "How much would I save if the interest rate was 1% or 5%?"

Building on this intuition, we run a pre-registered variant ("*Joint*") of two of our experiments. First, savings as a function of the interest rate (SAV, a subjective task). Second, effort allocation between two tasks in a multitasking environment with induced values (MUL, an objective task). In both experiments, subjects received the same instructions as in the corresponding baseline treatments. However, before they made their decisions, they encountered an additional screen on which they were asked to indicate which (hypothetical) decision they would take if the relevant problem parameter was either very small or very large. Then, on their actual decision screens, subjects were reminded of their answers to this hypothetical question, inducing a direct joint evaluation of the different problems. This is similar to the design in Yang (2023), who documents that people's investment decisions become substantially less attenuated to their return expectations after they are asked to indicate their hypothetical investment behavior for a large set of different potential return expectations.

15 classic cognitive tasks (ones with objectively correct solutions) from economics and psychology. While they find that for the vast majority of tasks confidence predicts mistakes, for a small subset of tasks that appear to evoke strong but misleading intuitions, people exhibit substantially lower awareness of their mistakes. Because of this, in some contexts we should expect behavioral attenuation, even if it is a mistake, to be poorly predicted by cognitive uncertainty.

We ran each of these pre-registered treatments along with a replication of our baseline experiments (randomized within experimental sessions) with 100 subjects each, for a total of 400 subjects.[20] Appendix Figure 13 shows the results. We find that the slope of decisions with respect to fundamentals is significantly higher in the *Joint* treatment in the MUL experiment ($p < 0.05$) but not in the SAV experiment. We view this as providing tentative evidence that attenuation can be corrected by external parties, at least in some circumstances. Alternative implementations of this intervention might lead to more consistent results. But it also suggests that behavioral attenuation may be more robust than we originally hypothesized.

7 Discussion

In more than two dozen seemingly unrelated economic contexts, we find consistent evidence of *behavioral attenuation*. We link this regularity to a fundamental characteristic that economic decisions have in common: they typically require the decision-maker to intensively trade off and aggregate information. Inability (or unwillingness) to comply with these severe information-processing requirements leads to *uncertainty* about how to optimize, preventing decision-makers from identifying how optima change with fundamentals, producing attenuation. We document this both by showing that people are insufficiently sensitive in a subset of tasks that have objectively correct solutions, and more generally by documenting that it is precisely those people who express the greatest doubt about the optimality of their own choices who respond least sensitively to fundamentals.

Drawing connections between anomalies. Many of the tasks we've included in our design have been studied before, and generate insensitivities that have been rationalized via domain-specific explanations, such as non-standard preferences. Table 3 presents a list of prior findings in the literature that are reproduced in our experiment and that our findings suggest are (at least in part) special cases of behavioral attenuation.

For example, prior work has puzzled over why effort supply in experiments is often very insensitive to variation in the wage (DellaVigna et al., 2022). Similarly, researchers have documented that information demand is insufficiently elastic to the accuracy of the information (Ambuehl and Li, 2018). Researchers for decades have attributed probability weighting in elicitations of certainty equivalents to exotic risk preferences, but have puzzled over the inverse probability weighting that arises in elicitations of probability

[20]The 100 subjects in the baseline condition of SAV are part of our main dataset because they were collected after the initial pre-registered data collection. The *Joint* treatments were run simultaneously with the additional data collection for the baseline experiments.

Table 3: Known anomalies as special cases

Task	Finding in literature	Example reference
CEE	Prob. weighting in certainty equivalent elicitations	Kahneman and Tversky (1979)
PRE	Inverse prob. weighting in probability equivalent elicitations	Bouchouicha et al. (2023)
BEU	Likelihood insensitivity / conservatism	Benjamin (2019)
TID	Hyperbolic discounting over money	Cohen et al. (2020)
HEA	Scope insensitivity in contingent valuation	Diamond and Hausman (1994)
EFF	Insensitivity of effort supply	DellaVigna et al. (2022)
NEW	Central tendency effect in newsvendor problem	Schweitzer and Cachon (2000)
IND	Insensitive information demand	Ambuehl and Li (2018)
POA	Attenuation puzzle in equity shares	Giglio et al. (2021)
TAX	Schmeduling of tax schedules	Rees-Jones and Taubinsky (2020)
SIA	DeGroot updating	DeGroot (1974)
EXT	Concave willingness to mitigate emissions	Pace et al. (2023)
MUL	Bikeshedding effect in multitasking	Parkinson (1957)

equivalents (Sprenger, 2015; Bouchouicha et al., 2023) – both of which are describable as forms of insensitivity of the elicited quantity to variation in the decision-relevant parameter. Likewise, widespread evidence of hyperbolic discounting of monetary rewards in the intertemporal choice literature (Cohen et al., 2020) can be described simply as insensitivity of the value of delayed payments relative to standard exponential benchmarks.

Our results suggest that the insensitivities that characterize these anomalies may be rooted in a shared cognitive mechanism, and therefore might be predicted, interpreted and explained on the same basis. Or to put it another way, the 13 examples in Table 3, which we might be tempted to model as 13 distinct phenomena, may instead be instances of one phenomenon rooted in the same implicit model. One takeaway from our paper is, hence, that there may be room to reduce the number of distinct explanations and labels that behavioral economists entertain by developing a generally-applicable model of behavioral attenuation.

Extending the reach of a classical pattern. The concepts of relative insensitivity and diminishing sensitivity away from boundary points are arguably the central ideas in some of behavioral economists's greatest success stories, such as hyperbolic discounting and prospect theory (see, for example, Prelec and Loewenstein, 1991, for an early discussion highlighting these commonalities). By rooting insensitivity in generic information-processing constraints (rather than domain-specific preferences), we show that these classic behavioral economics ideas also extend to many contexts for which they were not initially conceived, including effort supply, product demand, fairness views, strategic beauty contests and policy evaluation. To the degree this is true, highly influential ideas from behavioral economics that have been useful for understanding and predicting, e.g., risky and intertemporal behavior, may prove equally useful for predicting and explaining behavior in many other economic settings as well.

Behavioral attenution and empirical work. The apparent pervasiveness of behavioral attenuation has two implications for interpreting both estimated elasticities and the observed level of decisions. First, in settings in which the researcher observes decisions over a wide range of the decision-relevant parameter, a low estimated elasticity may partly reflect behavioral attenuation. Ignoring this possibility may lead researchers to estimate misspecified econometric models that wrongly attribute low elasticities (or diminishing sensitivity) to the decision-maker's objective function (e.g., their preferences). For instance, a low elasticity of effort to wages may lead researchers to incorrectly estimate a very steep effort cost function.

Second, in settings in which the researcher only observes behavior over a relatively narrow range of parameters (e.g., only small wages), ignoring attenuation will generally lead the researcher to also misattribute the level of decisions. For instance, we have seen that – as a side product of attenuation – people work 'too much' (relative to their true preferences) when the wage is low. Without taking into account attenuation, the researcher will thus underestimate effort costs or overestimate intrinsic motivation.

One potential lesson from our findings is that the tools we use for identifying behavioral attenuation, may also prove useful be in applied work to account for its distorting effects. Cognitive uncertainty is an easy, unincentivized measure to measure in, e.g., surveys, and our results suggest that collecting it can allow researchers to identify behavioral attenuation in the field and potentially correct for it when interpreting behavior. Indeed, a number of findings from the field suggest that behavioral attenuation may be as important in field applications as in the lab, suggesting the promise of such tests in applied contexts. For example, the link between subjective return expectations and people's equity shares is heavily attenuated relative to theoretical benchmarks such as the Merton model (Drerup et al., 2017; Ameriks et al., 2020; Giglio et al., 2021). Relatedly, the elasticity of medical testing to patient risk (Mullainathan and Obermeyer, 2022) is substantially attenuated – doctors overtest when patient risk is low but undertest when patient risk is high, the canonical "flipping" pattern that is associated with behavioral attenuation.

Expert crowd-sourcing. A methodological contribution of this paper is that we outsourced much of our experimental design to a panel of independent experts. We believe that this general strategy is particularly useful whenever researchers aim to document the generality of a phenomenon (e.g., behavioral attenuation), because it ties their hands, preventing them from cherry picking tasks. It also makes use of the expertise and interests of outside experts expanding the scope of the resulting tests – many of the tasks our experts proposed are ones we are quite sure we never whould have arrived at ourselves. This innovation is connected to and extends the growing body of work on using expert panels in research, e.g., rising interest in the use of expert forecasting to contextualize research findings (DellaVigna and Pope, 2017, 2018).

Implications for cognitive economics. Finally, although our results suggest that behavioral attenuation is wide-spread, we hardly believe it is the only cognitively-inspired regularity relevant for understanding economic behavior. To the contrary, we view our results as suggestive of the potential for researchers in the field to find other, similarly universal phenomena, rooted in information-processing limitations. The movement among behavioral economists to understand economic behavior under a cognitive lens aims to identify generic cognitive processes that can explain anomalies in a wide range of economic behavior using a limited set of cognitive principles. We view our findings as encouraging evidence for the potential of this research agenda.

References

AFROUZI, H., S. Y. KWON, A. LANDIER, Y. MA, AND D. THESMAR (2020): "Overreaction in expectations: Evidence and theory," *Available at SSRN 3709548*.

AMBUEHL, S. AND S. LI (2018): "Belief updating and the demand for information," *Games and Economic Behavior*, 109, 21–39.

AMBUEHL, S., A. OCKENFELS, AND C. STEWART (2022): "Who opts in? composition effects and disappointment from participation payments," *Review of Economics and Statistics*, 1–45.

AMERIKS, J., G. KÉZDI, M. LEE, AND M. D. SHAPIRO (2020): "Heterogeneity in expectations, risk tolerance, and household stock shares: The attenuation puzzle," *Journal of Business & Economic Statistics*, 38, 633–646.

AUGENBLICK, N., E. LAZARUS, AND M. THALER (2021): "Overinference from Weak Signals and Underinference from Strong Signals," *arXiv preprint arXiv:2109.09871*.

BA, C., J. A. BOHREN, AND A. IMAS (2022): "Over-and Underreaction to Information," *Available at SSRN*.

BENJAMIN, D. J. (2019): "Errors in Probabilistic Reasoning and Judgmental Biases," in *Handbook of Behavioral Economics*.

BORDALO, P., J. J. CONLON, N. GENNAIOLI, S. Y. KWON, AND A. SHLEIFER (2023): "How people use statistics," Tech. rep., National Bureau of Economic Research.

BORDALO, P., N. GENNAIOLI, Y. MA, AND A. SHLEIFER (2020a): "Overreaction in macroeconomic expectations," *American Economic Review*, 110, 2748–82.

BORDALO, P., N. GENNAIOLI, AND A. SHLEIFER (2012): "Salience theory of choice under risk," *Quarterly Journal of Economics*, 127, 1243–1285.

——— (2020b): "Memory, attention, and choice," *The Quarterly journal of economics*.

BOUCHOUICHA, R., J. WU, AND F. M. VIEIDER (2023): *Choice Lists and" standard Patterns" of Risk-taking*, Ghent University, Faculty of Economics and Business Administration.

BROWN, A. L., T. IMAI, F. M. VIEIDER, AND C. F. CAMERER (2024): "Meta-analysis of empirical estimates of loss aversion," *Journal of Economic Literature*, 62, 485–516.

CAPPELEN, A. W., J. MOLLERSTROM, B.-A. REME, AND B. TUNGODDEN (2022): "A meritocratic origin of egalitarian behaviour," *The Economic Journal*, 132, 2101–2117.

Chapman, J., M. Dean, P. Ortoleva, E. Snowberg, and C. Camerer (2023): "Econographics," *Journal of Political Economy Microeconomics*, 1, 115–161.

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

Costa-Gomes, M. A. and V. P. Crawford (2006): "Cognition and behavior in two-person guessing games: An experimental study," *American economic review*, 96, 1737–1768.

Dean, M. and P. Ortoleva (2019): "The empirical relationship between nonstandard economic behaviors," *Proceedings of the National Academy of Sciences*, 116, 16262–16267.

DeGroot, M. H. (1974): "Reaching a consensus," *Journal of the American Statistical Association*, 69, 118–121.

DellaVigna, S. and E. Linos (2022): "RCTs to scale: Comprehensive evidence from two nudge units," *Econometrica*, 90, 81–116.

DellaVigna, S., J. A. List, U. Malmendier, and G. Rao (2022): "Estimating social preferences and gift exchange at work," *American Economic Review*, 112, 1038–1074.

DellaVigna, S. and D. Pope (2017): "What motivates effort? Evidence and expert forecasts," *The Review of Economic Studies*, 85, 1029–1069.

——— (2018): "Predicting experimental results: who knows what?" *Journal of Political Economy*, 126, 2410–2456.

Diamond, P. A. and J. A. Hausman (1994): "Contingent valuation: is some number better than no number?" *Journal of economic perspectives*, 8, 45–64.

Drerup, T., B. Enke, and H.-M. Von Gaudecker (2017): "The precision of subjective data and the explanatory power of economic models," *Journal of Econometrics*, 200, 378–389.

Enke, B. (2020): "What you see is all there is," *The Quarterly Journal of Economics*, 135, 1363–1398.

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

Enke, B., T. Graeber, and R. Oprea (2023a): "Complexity and Hyperbolic Discounting," *Working Paper*.

——— (2023b): "Confidence, self-selection, and bias in the aggregate," *American Economic Review*, 113, 1933–1966.

Enke, B. and C. Shubatt (2023): "Quantifying Lottery Choice Complexity," *Working Paper*.

Esponda, I., E. Vespa, and S. Yuksel (2024): "Mental models and learning: The case of base-rate neglect," *American Economic Review*, 114, 752–782.

Falk, A., A. Becker, T. Dohmen, B. Enke, D. Huffman, and U. Sunde (2018): "Global evidence on economic preferences," *The Quarterly Journal of Economics*, 133, 1645–1692.

Frydman, C. and L. Jin (2021): "Efficient Coding and Risky Choice," *Quarterly Journal of Economics*.

Frydman, C. and L. J. Jin (2023): "On the Source and Instability of Probability Weighting," Tech. rep., National Bureau of Economic Research.

Gabaix, X. (2019): "Behavioral inattention," in *Handbook of Behavioral Economics-Foundations and Applications 2*, ed. by D. Bernheim, S. DellaVigna, and D. Laibson, Elsevier, 261.

Gabaix, X. and T. Graeber (2023): "The Complexity of Economic Decisions," *Available at SSRN*.

Gabaix, X. and D. Laibson (2022): "Myopia and discounting," Tech. rep., National bureau of economic research.

Giglio, S., M. Maggiori, J. Stroebel, and S. Utkus (2021): "Five facts about beliefs and portfolios," *American Economic Review*, 111, 1481–1522.

Graeber, T. (2023): "Inattentive inference," *Journal of the European Economic Association*, 21, 560–592.

Grether, D. M. (1980): "Bayes Rule as a Descriptive Model: The Representativeness Heuristic," *Quarterly Journal of Economics*, 95, 537–557.

Gupta, N., L. Rigott, and A. Wilson (2021): "The Experimenters' Dilemma: Inferential Preferences over Populations," *arXiv preprint arXiv:2107.05064*.

Hascher, J., A. Imas, M. Ungeheuer, and M. Weber (2024): "A Cognitive Foundation for Perceiving Uncertainty," *Available at SSRN*.

Hsee, C. K., G. F. Loewenstein, S. Blount, and M. H. Bazerman (1999): "Preference reversals between joint and separate evaluations of options: A review and theoretical analysis." *Psychological bulletin*, 125, 576.

Ilut, C. and R. Valchev (2023): "Economic agents as imperfect problem solvers," *The Quarterly Journal of Economics*, 138, 313–362.

Kahneman, D. and A. Tversky (1979): "Prospect Theory: An Analysis of Decision under Risk," *Econometrica*, 47, 263–292.

Khaw, M. W., Z. Li, and M. Woodford (2021): "Cognitive imprecision and small-stakes risk aversion," *The review of economic studies*, 88, 1979–2013.

——— (2022): "Cognitive Imprecision and Stake-Dependent Risk Attitudes," Tech. rep., National Bureau of Economic Research.

Kőszegi, B. and A. Szeidl (2013): "A model of focusing in economic choice," *Quarterly Journal of Economics*, 128, 53–104.

Mullainathan, S. and Z. Obermeyer (2022): "Diagnosing physician error: A machine learning approach to low-value health care," *The Quarterly Journal of Economics*, 137, 679–727.

Nunnari, S. and M. Pozzi (2022): "Meta-analysis of inequality aversion estimates," .

Oprea, R. (2022): "Simplicity Equivalents," Tech. rep., Working Paper.

Pace, D., T. Imai, P. Schwardmann, and J. van der Weele (2023): "Uncertainty about Carbon Impact and the Willingness to Avoid CO2 Emissions," Tech. rep., Discussion Paper.

Parkinson, C. N. (1957): *Parkinson's law*, Murray.

Prelec, D. and G. Loewenstein (1991): "Decision making over time and under uncertainty: A common approach," *Management science*, 37, 770–786.

Rees-Jones, A. and D. Taubinsky (2020): "Measuring "Schmeduling"," *The Review of Economic Studies*, 87, 2399–2438.

Röver, C. (2020): "Bayesian random-effects meta-analysis using the bayesmeta R package," *Journal of Statistical Software*, 93, 1–51.

Schweitzer, M. E. and G. P. Cachon (2000): "Decision bias in the newsvendor problem with a known demand distribution: Experimental evidence," *Management science*, 46, 404–420.

Sprenger, C. (2015): "An endowment effect for risk: Experimental tests of stochastic reference points," *Journal of Political Economy*, 123, 1456–1499.

Stango, V. and J. Zinman (2023): "We Are All Behavioural, More, or Less: A Taxonomy of Consumer Decision-Making," *The Review of Economic Studies*, 90, 1470–1498.

Tversky, A. and D. Kahneman (1974): "Judgment under uncertainty: Heuristics and biases," *science*, 185, 1124–1131.

Vieider, F. M. (2021): "Noisy coding of time and reward discounting," Tech. rep., Ghent University, Faculty of Economics and Business Administration.

——— (2022): "Decisions under Uncertainty as Bayesian Inference on Choice Options," .

Woodford, M. (2020): "Modeling imprecision in perception, valuation, and choice," *Annual Review of Economics*, 12, 579–601.

Yang, J. (2023): "On the Decision-Relevance of Subjective Beliefs," *Working Paper*.

ONLINE APPENDIX

A Study Details

A.1 Email to Experts

Dear X,

I hope this finds you well. I'm writing to ask for a favor. The request is below, and would take very little of your time. Thanks very much for considering to participate!

We (Ben Enke, Thomas Graeber, Ryan Oprea and Jeffrey Yang) are preparing to run a large-scale experiment, and we are emailing you to ask for your input. We plan to evaluate a hypothesis (see below) across a wide range of experimental decision-making tasks. To design the most convincing and comprehensive test of our hypothesis, we hope to leverage the profession's knowledge by "crowdsourcing" the selection of tasks. We are emailing you in particular because we identified you as one of the few behavioral economists who published more than one paper in the profession's top five journals over the last three years. We invite you to propose an experimental task, and we commit to implement your proposal should you choose to participate. This will take very little of your time – your proposal can be as short as one sentence.

Topic of our paper:
Hypothesis ("behavioral attenuation"): Because people often rely on noisy and heuristic simplification strategies, observed decisions are usually insufficiently elastic ("attenuated") to variation in decision-relevant parameters.
Concretely: Take any economic decision that depends monotonically on an objective parameter. Then, we hypothesize that the elasticity of the decision to variation in the parameter is smaller among people who report higher cognitive uncertainty (lower confidence in the optimality of their own decision). Cognitive uncertainty is our empirical proxy for how noisy or heuristic a person's decision process is. We plan to implement 30 tasks overall, 20-25 of which we crowdsource and 5-10 of which we select ourselves.

What we request from you:
You propose a static decision that depends on an objective parameter that we can vary in the experiment. The parameter should have a non-trivial, monotonic impact on the decision-maker's decision. For example: "Elicit certainty equivalent for binary lotteries as a function of the payout probability." The parameter should be varied across a wide range. The reason is that we hypothesize that behavioral attenuation will appear only away from those boundaries of the parameter space that render the decision cognitively

trivial (e.g., due to dominance relationships). In the lottery example, determining one's certainty equivalent for a p% chance of getting $25 is trivial for p=0% or p=100%. We only expect behavioral attenuation away from such trivial boundary points. Your proposal could include any of a large number of settings, ranging from preference elicitations to belief updating to generic optimization problems, covering domains involving risk, time, consumption-savings, effort supply, taxes, fairness, prediction, inference and more, in either individual decisions or strategic games.

You can select any decision task you'd like – ideally one that you consider economically relevant and where you would like to know whether behavioral attenuation is at play. Your proposal can be as short or detailed as you'd like. All we'd need from you is to fill in these bullet points:

- Decision: ...
- Parameter: ...
- Details (optional): ...

What would happen if you chose to participate:
If you agree, we will name you as the contributor of the task you propose in our paper. We will also fill in the details for the experimental task you propose and send you a link to the software so you can verify (if you like) that our implementation complies with your proposal.

We would be extremely grateful if you found the time to send us an idea by February 5, 2024, but please let us know in case you plan to submit an idea but will require more time. Please also let us know if you have any questions or comments.

We look forward to hearing from you! Thank you very much for considering our request!

Best wishes,
Ben, Jeffrey, Thomas and Ryan

A.2 Experimental Tasks, Problem Configurations and *CU* Elicitations

This Appendix summarizes the design of each of our 31 tasks using the following format:

Name of task.

1. The experimental decision subjects take.
2. The problem configurations, in particular the parameter that varies across rounds.
3. Parameters for which a dominance relationship is present (according to our pre-registration).
4. Parameters that according to our pre-registration constitute "potential simple points", and parameters that are actually simple points according to our ex-post analysis of the cognitive uncertainty data.
5. How we translate the experimental decisions and parameters into a regression equation.
6. Whether there is an objective / rational regression coefficient, and if so, what it is.
7. Wording of the cognitive uncertainty elicitation.
8. Incentives.

Savings (SAV).

1. Decide how many of 100 points (= $10) to receive today or save until six months later, at a known interest rate.
2. Interest rates (in %): 0, 1, 5, 7, 10, 15, 20, 25, 30, 40, 50.
3. Dominance points: 0
4. Potential simple points: n/a
5. Dependent variable: Points saved. Independent variable: Interest rate.
6. Rational regression coefficient: n/a
7. "*How certain are you that saving somewhere between $Y-1$ and $Y+1$ points is actually your best decision, given your preferences?*"
8. Receive money at chosen times.

Precautionary savings (PRS).

1. Act as a hypothetical farmer whose utility from his output is given by $U = \sqrt{w_1} + 0.9\sqrt{w_2}$, where w_i is water available in period i. In each round, decide how many out of 100 barrels of water to save for the second period, knowing that in the second period a weather shock hits that either depletes or adds a fixed amount of water with 50-50 chance.

2. Absolute size of shock (in gallons): 0, 1, 2, 5, 8, 10, 15, 20, 25, 30, 40.

3. Dominance points: n/a

4. Potential simple points: 0; Ex-post simple points: 0

5. Dependent variable: Amount saved. Independent variable: Absolute size of shock.

6. Rational regression coefficient: n/a

7. "*How certain are you that allocating somewhere between* $Y-1$ *and* $Y+1$ *barrels to Spring is actually your best decision, given your preferences and the available information?*"

8. Bonus = Farmer's realized utility divided by two.

Portfolio allocation (POA).

1. Decide how to allocate \$1000 between a riskless savings account (2% return) and a risky ETF (with uncertain return). Subjects receive information about the one-year return of the ETF (computed over a period of five years), then state their subjective return expectations for the ETF, and allocate their \$1000.

2. Historical returns (ETF Ticker): RSPG, RSPH, RSPS, RSPU, RSPN, RSPM, RSPD, RSPR, IBB, PPA, RSPF.

3. Dominance points: n/a

4. Potential simple points: n/a

5. Dependent variable: Amount invested in ETF. Independent variable: Subjective return expectation. Controls: ETF fixed effects.

6. Rational regression coefficient: n/a

7. "*How certain are you that investing somewhere between* $\$Y-20$ *and* $\$Y+20$ *in the Stock Account is actually your best decision, given your preferences and the available information?*"

8. Receive value of portfolio in one year, divided by 100.

Forecast stock return (STO).

1. Forecast value of \$100 investment into one of several ETFs at some point in the future.
2. Time horizon: 0 hours, 1 day, 1 week, 1 month, 6 months, 1 year, 2 years, 3 years, 4 years, 5 years, 7 years.
3. Dominance points: n/a
4. Potential simple points: 0 hours; Ex-post simple points: 0 hours
5. Dependent variable: Forecast. Independent variable: Time horizon. Controls: ETF fixed effects.
6. Rational regression coefficient: n/a
7. "*How certain are you that the best possible forecast is actually somewhere between* $\$Y - 1$ *and* $\$Y + 1$*, given the information you have?*"
8. None.

Estimate tax burden (TAX).

1. Participants are presented with hypothetical federal and state income tax schedules. A hypothetical taxpayer makes his entire income through labor income. Estimate total tax burden based on income.
2. Income (in \$): 0, 10,000, 15,000, 25,000, 35,000, 45,000, 60,000, 75,000, 90,000, 115,000, 150,000.
3. Dominance points: n/a
4. Potential simple points: 0; Ex-post simple points: 0
5. Dependent variable: Estimate. Independent variable: Income.
6. Rational regression coefficient: 0.3442633
7. "*How certain are you that the correct answer is actually somewhere between* $\$Y - 300$ *and* $\$Y + 300$*?*"
8. Receive bonus of \$10 if estimate is within +/- \$300 of correct answer.

Newsvendor game (NEW).

1. Act as hypothetical cola producer who can sell cola at a market price of \$12. Demand is unknown and uniformly distributed between 0 and 100. Cola that is produced but not sold goes to waste. Producing cola is associated with a constant marginal cost.

2. Cost (in \$): 0, 0.1, 1, 2, 4 , 6, 8, 10, 11, 11.9, 12.

3. Dominance points: 0, 12

4. Potential simple points: n/a

5. Dependent variable: Production. Independent variable: Cost.

6. Rational regression coefficient: n/a

7. "How certain are you that producing somewhere between $Y-1$ and $Y+1$ gallons is actually your best decision, given your preferences and the available information?"

8. Bonus (in \$) = 6 + 1/200 * Firm profit (or loss)

Effort supply (EFF).

1. Decide how many real-effort tasks to complete at a given piece rate. Effort task is to count number of ones in an 8x8 table.

2. Piece rate (in \$): 0, 0.01, 0.05, 0.10, 0.15, 0.20, 0.30, 0.40, 0.50, 0.60, 0.70.

3. Dominance points: 0

4. Potential simple points: n/a

5. Dependent variable: Number of tasks. Independent variable: Piece rate.

6. Rational regression coefficient: n/a

7. "*How certain are you that completing somewhere between $Y-1$ and $Y+1$ tasks is actually your best decision, given your preferences?*"

8. Receive earnings and work required amount.

Multitasking (MUL).

1. In an induced values experiment, allocate time budget of 135 hours between practicing with two horses (A and B), and receive a fraction of each horse's prize money, where the two fractions always sum up to 90%. Prize money of each horse is concave (linear-quadratic) in practice time, such that the optimal effort allocation for horse A is 135 × Absolute Profit share A/90.

2. Absolute Profit share for A (in %): 0, 1, 5, 10, 25, 40, 65, 80, 85, 89, 90.

3. Dominance points: 0, 90

4. Potential simple points: n/a

5. Dependent variable: Practice time with A. Independent variable: Relative Profit share for A.

6. Rational regression coefficient: 135

7. "*How certain are you that practicing somewhere between* $Y-1$ *and* $Y+1$ *hours with Horse A is actually the best decision?*"

8. Receive bonus of $10 if estimate is within +/- 1 hours of the optimal answer.

Search (SEA).

1. There's a bag with 100 chips labeled 1-100. The computer draws at random until it gets a number that is at least as high than the minimum value specified by the participant. Each draw is costly, with a cost that varies across rounds. Earnings are highest number drawn minus cost of drawing.

2. Cost per draw: 0, 0.1, 0.5, 1, 2.5, 5, 10, 15, 20, 30, 50.

3. Dominance points: 0

4. Potential simple points: n/a

5. Dependent variable: Minimum value set. Independent variable: Cost per draw.

6. Rational regression coefficient: -1.949051

7. "*How certain are you that setting the minimum value somewhere between* $Y-1$ *and* $Y+1$ *points is actually the best decision?*"

8. Receive bonus of $10 if estimate is within +/- 1 points of the optimal answer.

Product demand (GPT).

1. Across rounds, a participant is exposed to three different types of products: pasta, rice and coffee. Each product comes in a certain quantity (for example, three packages of pasta). Participants state their hypothetical WTP for a given product-quantity.
2. Quantity: 0, 1, 2, 3, 4, 5, 6, 7, 8, 10, 12.
3. Dominance points: 0
4. Potential simple points: n/a
5. Dependent variable: WTP. Independent variable: Quantity. Controls: Product fixed effects.
6. Rational regression coefficient: n/a
7. "*How certain are you that you actually value this product somewhere between* $\$Y-1$ *and* $\$Y+1$*?*"
8. None.

Budget allocation (CMA).

1. In an induced values setup, participants are endowed with a utility function over two goods, bottles of milk (x_1) and bottles of juice (x_1). The utility function is $U = \sqrt{x_1} + \sqrt{x_2}$. The price of good x_2 is normalized to one, and the price of x_1 varies across rounds. Participants decide what fraction of the total number of bottles they buy should be milk or juice. Once participants enter a fraction, the decision interface automatically and instantly displays the absolute number of bottles of either type and the corresponding expenditure. Subjects can revise their decisions before they get locked in.
2. Price of milk: 0.1, 0.3, 0.5, 0.7, 1.3, 1.7, 2, 2.5, 3, 5, 10.
3. Dominance points: n/a
4. Potential simple points: n/a
5. Dependent variable: Fraction of all bottles that are milk. Independent variable: Price of milk.
6. Rational regression coefficient: -9.977986

7. "*How certain are you that the best decision is actually somewhere between $Y - 1$ and $Y + 1$ percent?*"

8. Receive bonus of \$10 if estimate is within +/- 1% of optimal answer.

Avoid externalities (EXT).

1. In a multiple price list experiment, participants make binary decisions between money for themselves and reducing CO2 emissions by a certain amount, which varies across rounds. Reductions in CO2 are implemented by us purchasing carbon offsets. From each price list, we extract the participant's WTP for reducing emissions by a certain amount as the midpoint of the participant's switching interval in the list.

2. Amount of CO2 emissions (in metric tons): 0, 0.25, 0.5, 0.75, 1, 1.5, 2, 2.5, 3, 4, 5.

3. Dominance points: 0

4. Potential simple points: n/a

5. Dependent variable: WTP. Independent variable: Amount of emissions.

6. Rational regression coefficient: n/a

7. "*How certain are you that you actually value a reduction of CO2 emissions of X metric tons as much as a monetary gain somewhere between \$$Y - 1$ and \$$Y + 1$?*"

8. One randomly-selected binary choice is implemented, such that either the participant receives money or we purchase carbon offsets.

Invest to save energy (ENS).

1. Participants are exposed to a hypothetical scenario in which they need to lease one of two cars for the next two years, a Toyota Camry and a Toyota Camry Hybrid. The Hybrid is more fuel-efficient but the lease is more expensive. The scenario describes the number of miles the customer expects to drive. In a multiple price list experiment, participants make binary decisions between leasing the Camry at a certain price and the Camry Hybrid at a certain price. From each list, we extract the participant's WTP for the Camry Hybrid (i.e., the additional money the participant is willing to pay to get the Camry Hybrid rather than the Camry), as the midpoint of the switching interval. Across rounds (lists), the scenario about how many miles the customer expects to drive varies.

2. Expected miles driven: 2,000, 3,000, 4,000, 5,000, 6,000, 8,000, 10,000, 11,000, 12,000, 13,000, 14,000.
3. Dominance points: n/a
4. Potential simple points: n/a
5. Dependent variable: WTP. Independent variable: Expected miles driven.
6. Rational regression coefficient: n/a
7. "*How certain are you that you are actually willing to pay somewhere between* $\$Y-50$ *and* $\$Y+50$ *more annually to lease the Camry Hybrid as opposed to the Camry?*"
8. None.

Fairness views (FAI).

1. In a spectator design, participants are informed that two previous participants competed in a contest (a letter transcription task). The winner of the contest is declared either based on performance or based on a 50-50 coin toss. The declared winner receives $10. The participant decides how much of this amount to redistribute to the declared loser. The participant does not know whether the winner was declared based on performance or luck, but knows the probability that the winner was declared based on performance. This probability varies across rounds.
2. Probability winner declared based on performance (in %): 0, 1, 5, 10, 25, 40, 75, 90, 95, 99, 100.
3. Dominance points: n/a
4. Potential simple points: 0, 100; Ex-post simple points: 0, 100
5. Dependent variable: Amount redistributed. Independent variable: Probability winner declared based on performance.
6. Rational regression coefficient: n/a
7. "*How certain are you that transferring somewhere between* $Y-1$ *and* $Y+1$ *points is actually your best decision, given your preferences and the available information?*"
8. Participant's own payoff is unaffected by their decision, but the payoffs of the other participants are implemented accordingly.

Dictator game (DIG).

1. Participants decide how much out of an endowment of $10 to send to a receiver. The amount sent gets doubled. However, there's a known percent chance that the receiver never gets the money but it gets burned instead.

2. Probability amount sent is lost (in %): 0, 1, 5, 10, 25, 50, 75, 90, 95, 99, 100.

3. Dominance points: n/a

4. Potential simple points: 0, 100; Ex-post simple points: 0, 100

5. Dependent variable: Amount sent. Independent variable: Probability amount sent is lost.

6. Rational regression coefficient: n/a

7. "*How certain are you that sending somewhere between* $Y - 1$ *and* $Y + 1$ *points is actually your best decision, given your preferences and the available information?*"

8. Participants and receivers are paid according to the dictator's decisions.

Contingent valuation (HEA).

1. Participants are presented with a hypothetical scenario about a disease that get a number of people very sick. The participants states a Dollar value to indicate how much they think the government should at most be willing to pay to cure the disease.

2. Number of people affected: 0, 1, 10, 100, 500, 1,000, 5,000, 10,000, 25,000, 75,000, 100,000.

3. Dominance points: 0

4. Potential simple points: n/a

5. Dependent variable: WTP. Independent variable: People affected.

6. Rational regression coefficient: n/a

7. "*How certain are you that spending somewhere between* $\$Y - 2500$ *and* $\$Y + 2500$ *is actually your best decision, given your preferences and the available information?*"

8. None.

Prisoner's dilemma (PRD).

1. Standard two-player matrix game with a prisoner's dilemma structure. Participants decide to cooperate or defect. Payoffs are given by $\pi(C,C) = (X,X)$, $\pi(C,D) = (1,7)$ and $\pi(D,D) = (2,2)$ Across rounds, the payoff to cooperation X varies.

2. Payoff to cooperation X (in \$): 2.2, 2.5, 2.7, 3, 3.5, 3.7, 4, 4.5, 4.7, 5, 5.2.

3. Dominance points: n/a

4. Potential simple points: n/a

5. Dependent variable: 1 if cooperate. Independent variable: Cooperation payoff X.

6. Rational regression coefficient: n/a

7. "*How certain are you that choosing Top/Bottom is actually your best decision, given your preferences and the available information?*"

8. Game payoff.

Beauty contest (GUE).

1. In a two-player guessing game, participants guess a number between 0 and 100. Their target is the other player's guess times a multiplier. The other participant's target is the participant's guess.

2. Multiplier: 0, 0.01, 0.1, 0.2, 0.5, 0.7, 1.3, 2, 3, 4, 5.

3. Dominance points: n/a

4. Potential simple points: 0; Ex-post simple points: 0

5. Dependent variable: Guess. Independent variable: Multiplier.

6. Rational regression coefficient: n/a

7. "*How certain are you that the best possible guess is actually somewhere between $Y-1$ and $Y+1$, given the information you have?*"

8. Bonus (in \$) = 10 - 1/50 * |Guess-target|

Disclosure game (CHT).

1. Participants act as sender in a disclosure game. They observe the true state (which ranges from 0 to 20) and are incentivized to make the receiver make a guess about the true state that is as high as possible. Participants decide whether or not to reveal the true state before the receiver makes their guess.

2. True state: 0, 1, 3, 5, 7, 10, 13, 15, 17, 19, 20.

3. Dominance points: n/a

4. Potential simple points: 0, 20; Ex-post simple points: 0, 20

5. Dependent variable: 1 if revealed. Independent variable: True state.

6. Rational regression coefficient: n/a

7. "*How certain are you that choosing Revealing/Hiding is actually your best decision, given your personal preferences and the available information?*"

8. Bonus (in \$) $= 10 - 0.0025 * (20 - \text{receiver's guess})^2$

Voting (VOT).

1. Decide whether or not to vote for policy A when both A and B are on the ballot. When B receives a weak majority of the votes, the participant loses \$8 of their \$10 endowment, while if A receives a strict majority, the participant can keep their endowment. Voting costs \$1. The other voters in the election are a certain number of computers who vote uniformly randomly.

2. Number of other voters: 0, 2, 6, 10, 20, 30, 40, 50, 60, 80, 100.

3. Dominance points: 0

4. Potential simple points: n/a

5. Dependent variable: 1 if voted. Independent variable: Number of other voters.

6. Rational regression coefficient: n/a

7. "*How certain are you that choosing to vote/not vote is actually your best decision, given your preferences and the available information?*"

8. Game payoff.

Policy evaluation (POL).

1. Decide on a Likert scale (from 0 to 100) how strongly to support a policy. The policy would increase each household's next year by \$10,000 but it would also produce an increase in inflation.

2. Inflation (in %): 0, 1, 2, 3, 4, 5, 8, 10, 12, 16, 20.

3. Dominance points: 0

4. Potential simple points: n/a

5. Dependent variable: Support for policy. Independent variable: Inflation.

6. Rational regression coefficient: n/a

7. "*How certain are you that rating the policy somewhere between* $Y-1$ *and* $Y+1$ *is actually your best decision, given my personal preferences and the available information?*"

8. None.

Rational inattention (RIA).

1. Decide whether to accept or reject a binary 50-50 lottery that results in a gain of \$X or a loss of \$(X-10). The participant has a budget of \$10. The participant can acquire information about whether the upside or downside will realize – the decision screen contains 60 mathematical equations, of which 35 are correct when the upside realizes and 25 when the downside realizes.

2. Payoff shifter X (in points): 40, 45, 50, 55, 60, 70, 75, 80, 85, 90, 95.

3. Dominance points: n/a

4. Potential simple points: n/a

5. Dependent variable: 1 if accept lottery. Independent variable: Payoff shifter X.

6. Rational regression coefficient: n/a

7. "*How certain are you that Accepting/Rejecting the lottery is actually your best decision, given your preferences and the available information?*"

8. Endowment plus / minus outcome of choice.

Risk preference elicitation – certainty equivalents (CEE).

1. In a multiple price list experiment, participants make binary decisions between varying safe payments and a binary lottery that pays \$18 with probability p. The payout probability varies across rounds. From each price list, we extract the participant's normalized certainty equivalent of the lottery as the midpoint of the participant's switching interval in the list, divided by 18.

2. Payout probability (in %): 0, 1, 5, 10, 25, 50, 75, 90, 95, 99, 100.

3. Dominance points: 0, 100

4. Potential simple points: n/a

5. Dependent variable: Normalized certainty equivalent. Independent variable: Payout probability.

6. Rational regression coefficient: n/a

7. "*How certain are you that you actually value this lottery ticket somewhere between* $\$Y-1$ *and* $\$Y+1$*?*"

8. One randomly selected binary choice.

Risk preference elicitation – probability equivalents (PRE).

1. In a multiple price list experiment, participants make binary decisions between a safe payment and a varying binary lottery that pays \$18 with probability p. The safe payment varies across rounds. From each price list, we extract the participant's probability equivalent of the safe payment as the midpoint of the participant's switching interval in the list.

2. Safe payment (in \$): 0, 0.2, 1, 2, 4.5, 9, 13.5, 16, 17, 17.8, 18.

3. Dominance points: 0, 18

4. Potential simple points: n/a

5. Dependent variable: Probability equivalent. Independent variable: Safe payment.

6. Rational regression coefficient: n/a

7. "*How certain are you that you actually value the safe payment of* X *as much as \$18 received with a percentage chance somewhere between* $Y-5\%$ *and* $Y+5\%$*?*"

8. One randomly selected binary choice.

Intertemporal RRR (TID).

1. In a hypothetical multiple price list experiment, participants make binary decisions between varying payments today and a fixed delayed payment of \$18. The delayed payment varies across rounds. From each price list, we extract the participant's normalized present value of the delayed payment as the midpoint of the participant's switching interval in the list, divided by 100.

2. Delay: 0 days, 1 day, 1 week, 1 month, 6 months, 1 year, 2 years, 3 years, 4 years, 5 years, 7 years.

3. Dominance points: 0 days

4. Potential simple points: n/a

5. Dependent variable: Ln (Normalized present value). Independent variable: delay in days. This log specification is directly motivated by the exponential discounting model.

6. Rational regression coefficient: n/a

7. "*How certain are you that you actually value \$100 somewhere between* $\$Y-5$ *and* $\$Y+5$ *received now?*"

8. None.

Information demand (IND).

1. Participants are incentivized to accurately guess the outcome of a fair coin toss. Prior to making their binary guess, they can purchase an informative binary signal that has accuracy (in %) of $P(report = H|truth = H) = q \geq 50$. Participants have a budget of \$5 and state their WTP for the signal using a BDM mechanism.

2. Accuracy q (in %): 50, 51, 55, 60, 65, 75, 85, 90, 95, 99, 100.

3. Dominance points: 50, 100

4. Potential simple points: n/a

5. Dependent variable: Willingness to pay. Independent variable: Value of hint [(Accuracy-0.5)*5].

6. Rational regression coefficient: n/a

7. "*How certain are you that you actually value this hint somewhere between \$$Y-1$ and \$$Y+1$?*"

8. Bonus (in \$) = Budget of \$5 + \$5 if guessed correctly - price paid for signal (if any).

Belief updating (BEU).

1. In a standard binary balls-and-urns belief updating experiment, participants know the prior is 50% and receive a binary signal with accuracy $P(report = H|truth = H) = q \geq 50$. They state a posterior probability.

2. Accuracy q (in %): 50, 51, 55, 60, 65, 75, 85, 90, 95, 99, 100.

3. Dominance points: n/a

4. Potential simple points: 50, 100; Ex-post simple points: 0, 100

5. Dependent variable: Log posterior odds. Independent variable: Log accuracy odds. This transformation is directly motivated by the Grether (1980) decomposition. Control: signal FE.

6. Rational regression coefficient: 1

7. "*How certain are you that the statistically correct likelihood that Bag R was selected is actually somewhere between $Y-1$ and $Y+1$ percent?*"

8. Get \$10 if posterior is within +/-1 percentage points of Bayesian posterior.

Forecasting (FOR).

1. Forecast the 2024 earnings of a fictional firm based on the firm's earnings in 2022 and 2023. Participants are told that the change in earnings between 2023 and 2024 is given by a linear combination of (1) the change in earnings between 2022 and 2022; and (2) and unpredictable mean-zero component. Participants observe past earnings and the persistence parameter (the weight of (1)) and the forecast 2024 earnings. The persistence of the AR(1) process varies across rounds.

2. Persistence parameter: 0, 0.01, 0.05, 0.10, 0.25, 0.50, 0.75, 0.90, 0.95, 0.99, 1.

3. Dominance points: n/a

4. Potential simple points: 0,1; Ex-post simple points: 1

5. Dependent variable: Implied predictability = (response - earnings 2023) / (earnings 2023 - earnings 2022). Independent variable: predictability.

6. Rational regression coefficient: 1

7. "*How certain are you that the statistically correct forecast of the firm's 2024 earnings is actually somewhere* $\$Y - 1$ *and* $\$Y + 1$*?*"

8. Receive $10 if answer is within +/-1$ of Bayesian answer.

Recall (REC).

1. Participants estimate the value of a hypothetical firm, which is given by 100 plus the net number of positive (vs. negative) news. In a first period, participants observe 100 news through memorable images and estimate the company value based on counting or estimating the number of positive and negative news. In a second period a few minutes later (the period of interest in the experiment), subjects are surprised with a recall task and are asked to estimate the value of the company again, without having access to the news again. The total number of news is always 100, but the composition (positive / negative) varies across rounds.

2. Number of positive news: 0, 1, 5, 10, 25, 50, 75, 90, 95, 99, 100.

3. Dominance points: n/a

4. Potential simple points: n/a

5. Dependent variable: Estimate of company value. Independent variable: True value.

6. Rational regression coefficient: 1

7. "*How certain are you that the stock price is actually somewhere between* $\$Y - 1$ *and* $\$Y + 1$*?*"

8. Receive $10 if answer is within +/-1$ of correct answer.

Signal aggregation (SIA).

1. Participants estimate the weight of a hypothetical bucket based on other people's estimates. There are two so-called Communicators (A and B) and 100 so-called Estimator. Each Estimator gives an independent unbiased estimate of the bucket's weight and transmits it to one of the Communicators. The Communicators compute the average of the estimates they observe and communicate those averages to

the participant. The true weight is given by the average estimate of the Estimators. Across rounds, the number of Estimators that transmits to either Communicator varies.

2. Number of Estimators who report to Communicator A: 0, 1, 5, 10, 25, 60, 75, 90, 95, 99, 100.

3. Dominance points: n/a

4. Potential simple points: 0, 100; Ex-post simple points: 0, 100

5. Dependent variable: Implied weight on A = (response - weight reported from B)/(weight reported from A - weight reported from B). Independent variable: Correct weight on A (number of Estimators who report to A).

6. Rational regression coefficient: 1

7. "*How certain are you that the weight of the bucket is actually somewhere between* $Y - 1$ *and* $Y + 1$ *pounds?*"

8. Receive $10 if answer is within +/-1 pounds of Bayesian answer.

B Additional Analyses

B.1 Taskwise Raw Data

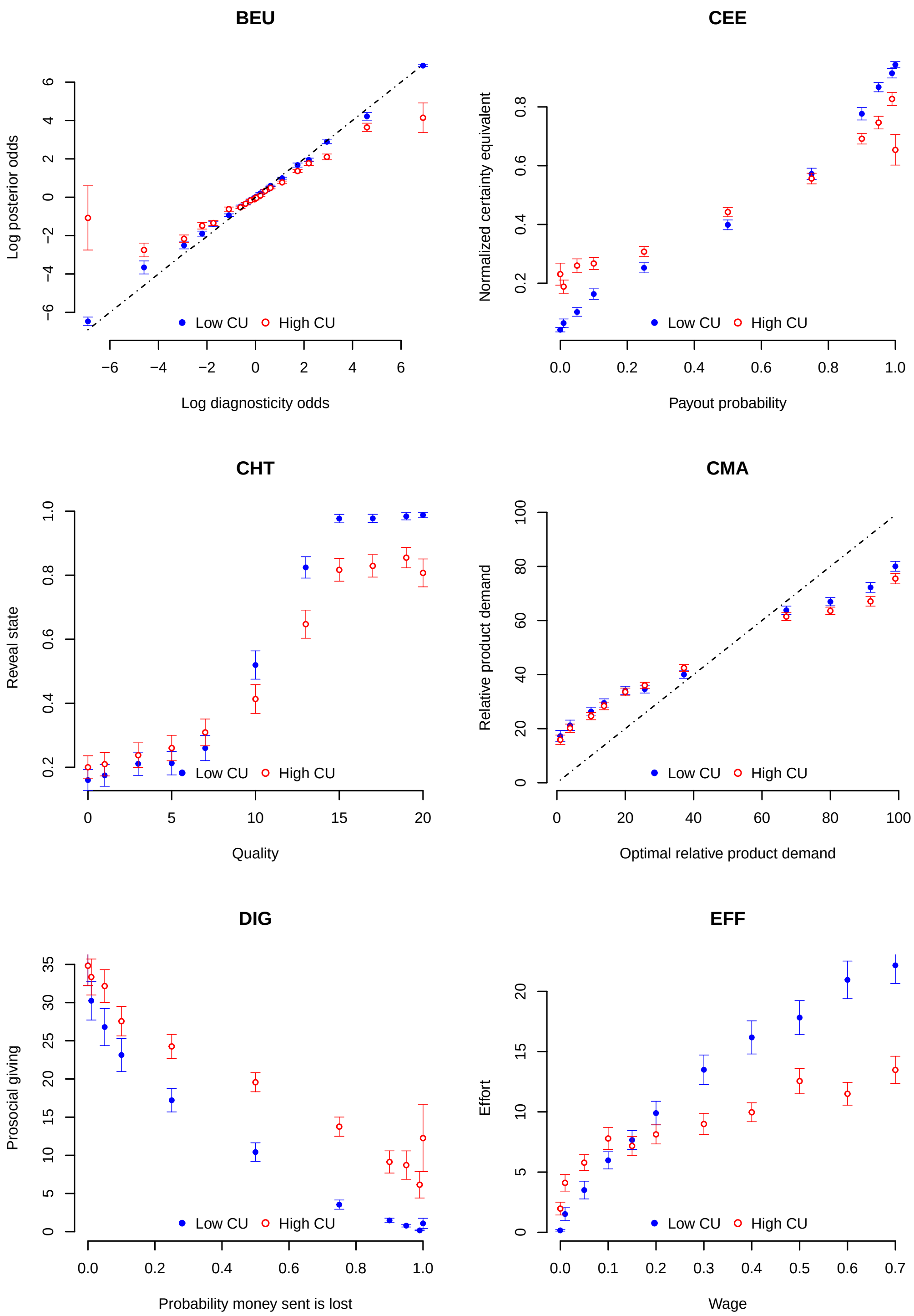


Figure 6: Decisions as a function of parameters.

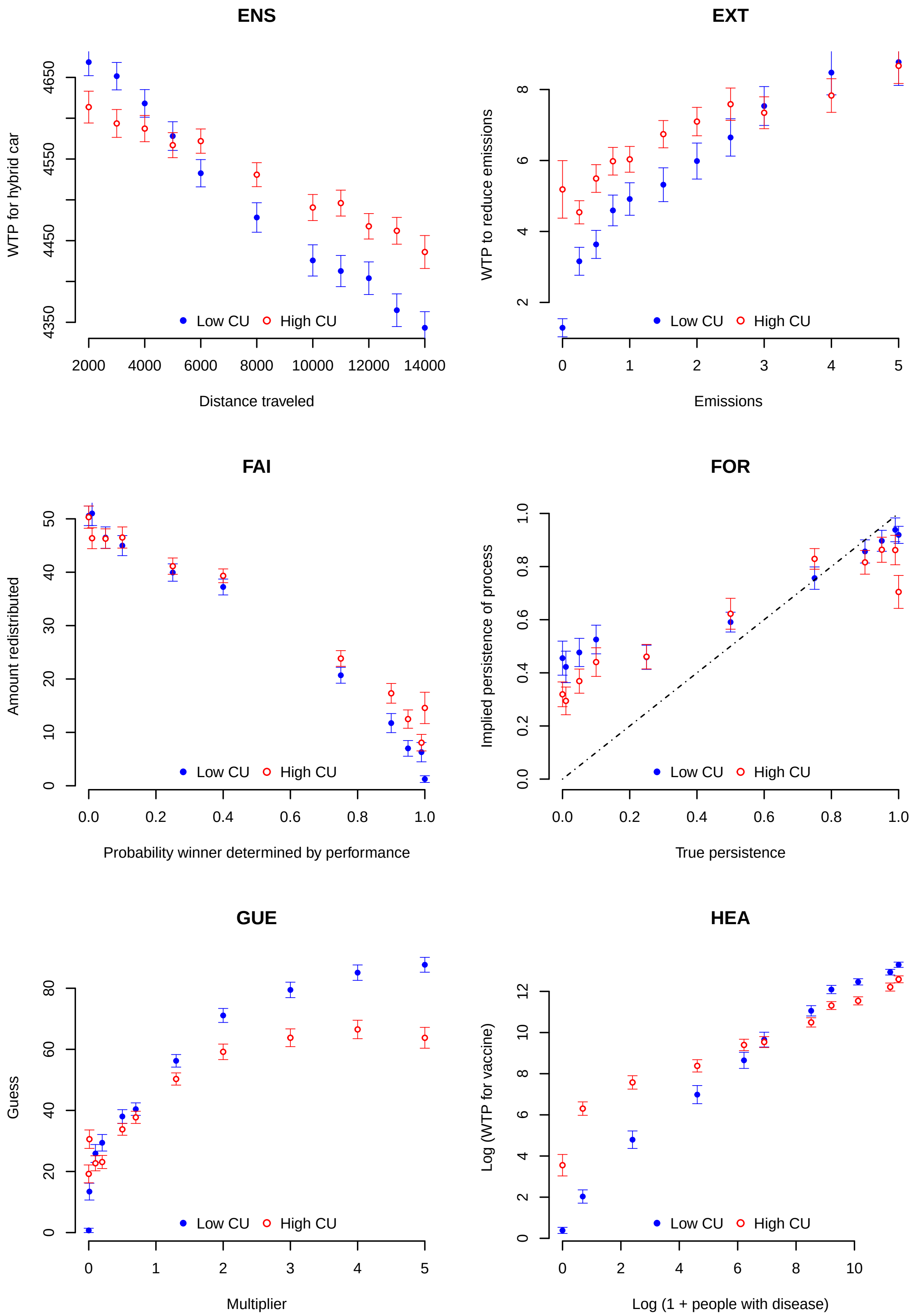


Figure 7: Decisions as a function of parameters.

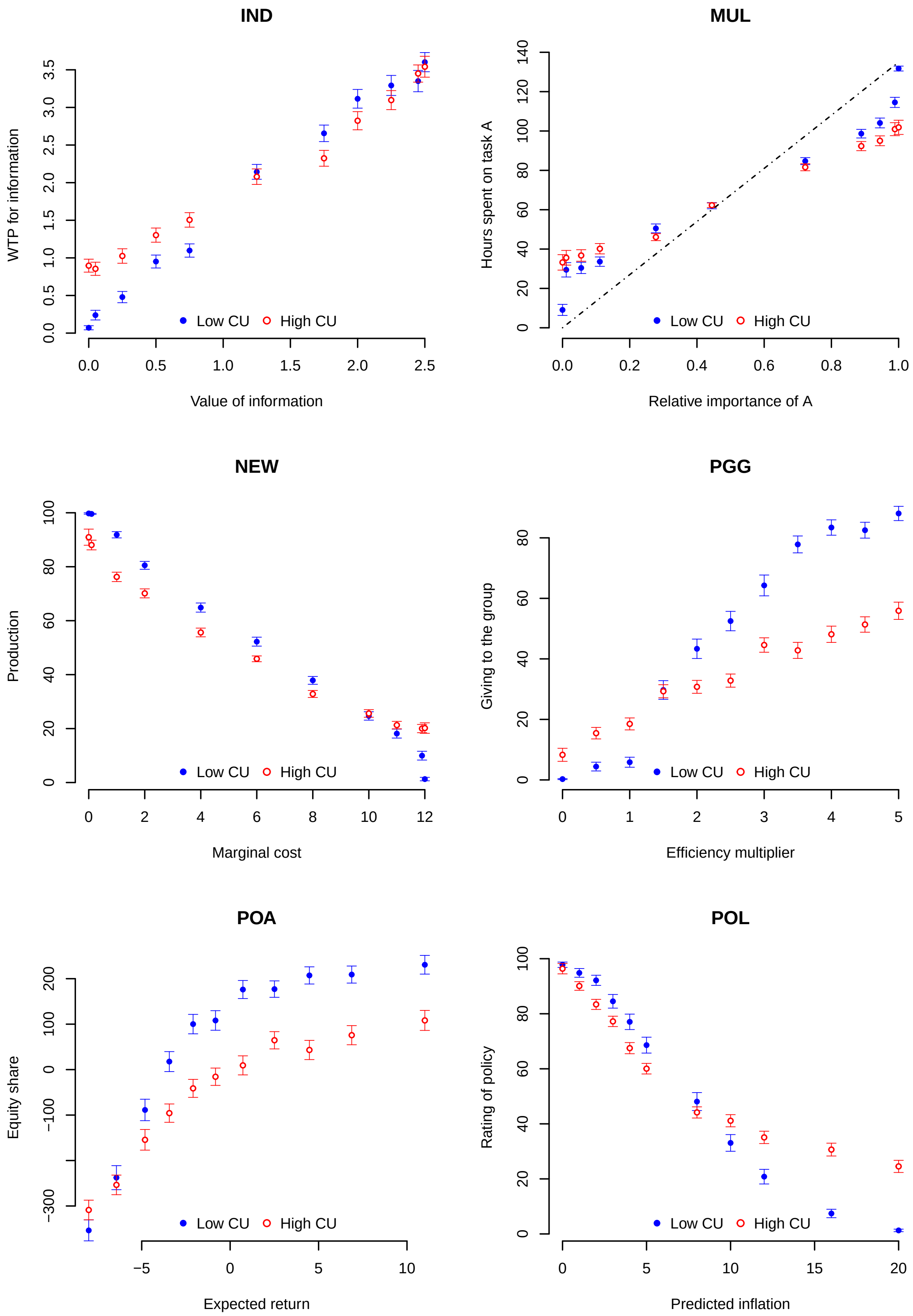


Figure 8: Decisions as a function of parameters.

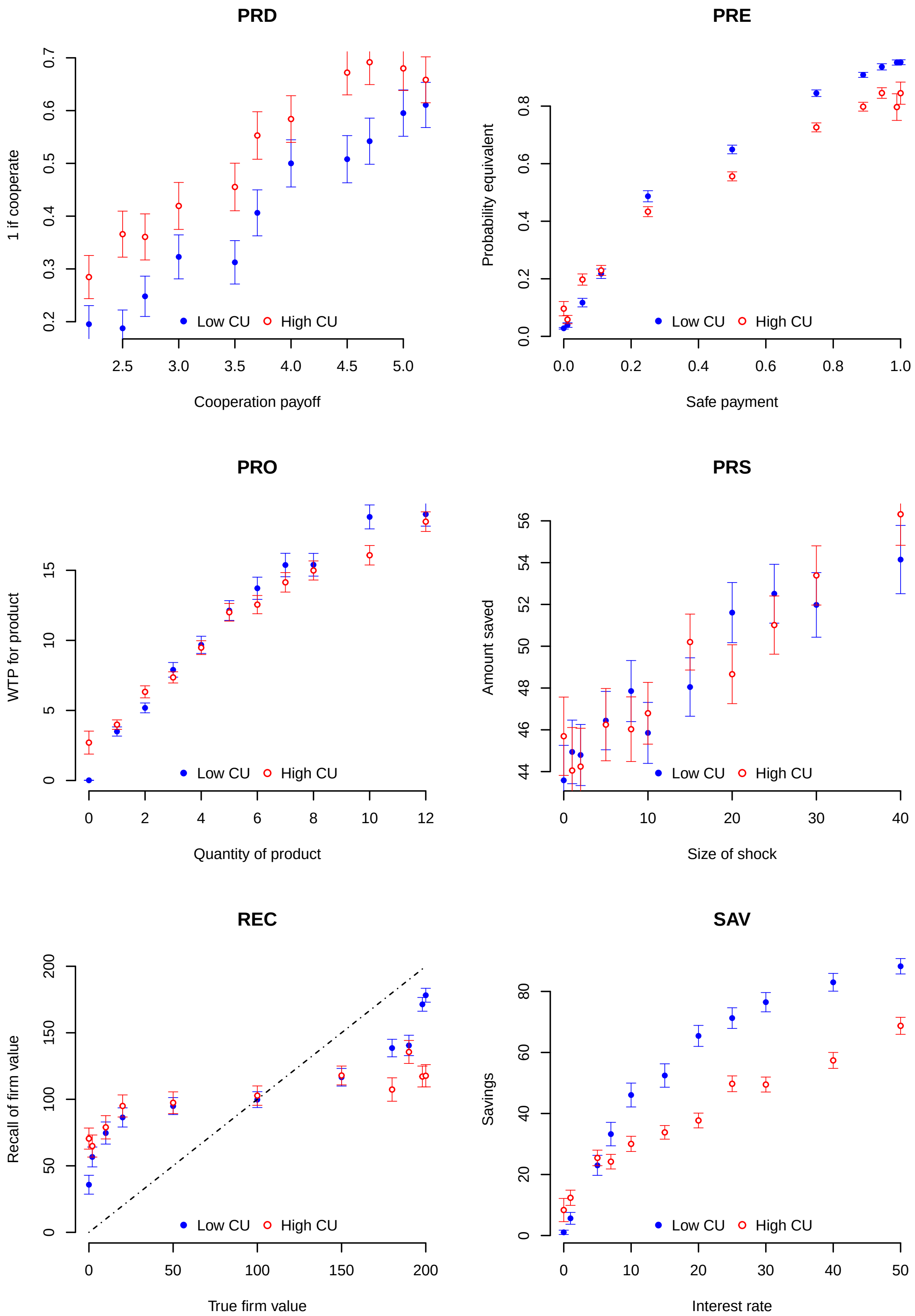


Figure 9: Decisions as a function of parameters.

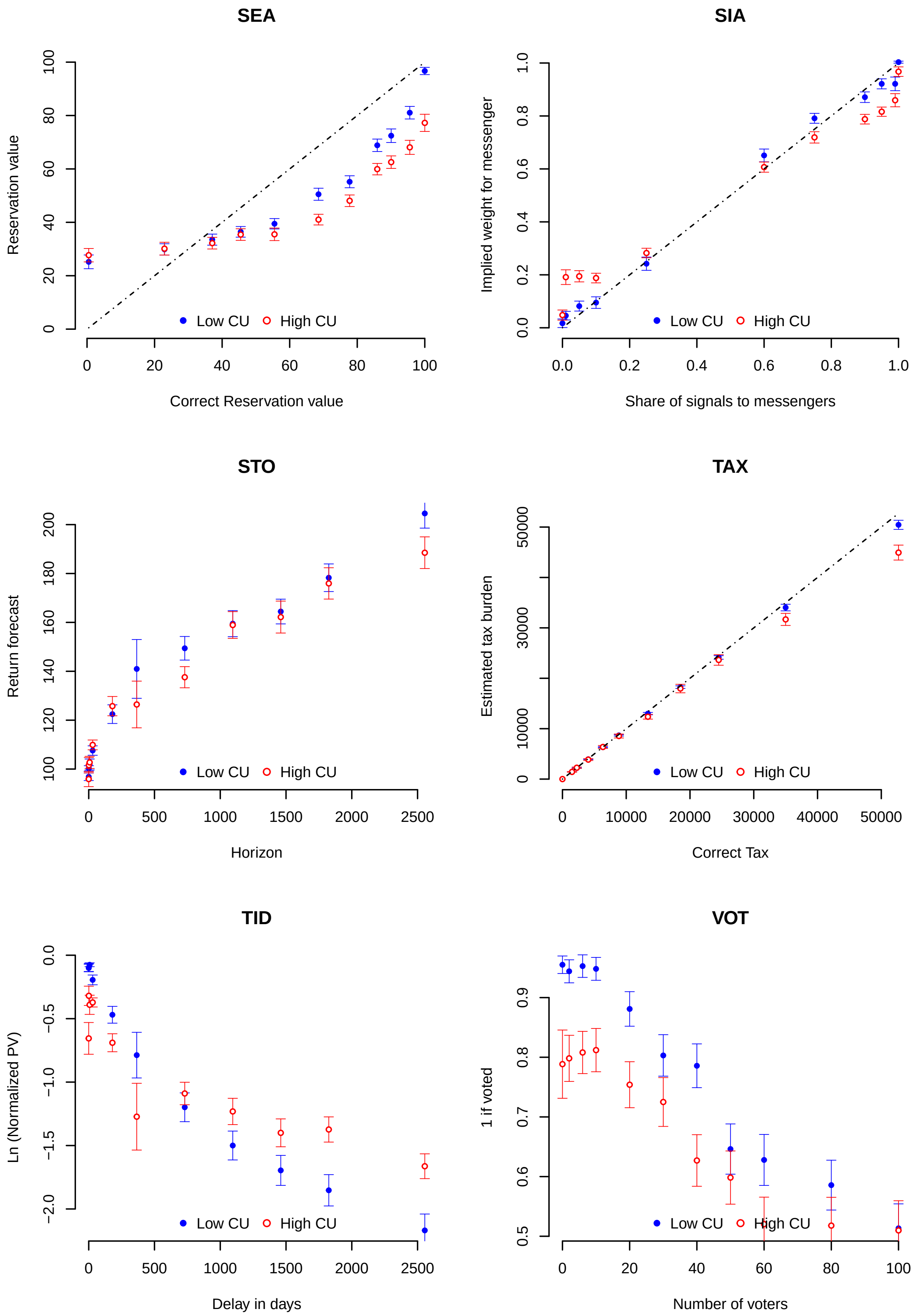


Figure 10: Decisions as a function of parameters.

B.2 Bayesian Meta-Analysis

These meta-analyses are implemented as follows. Recall that applying standard meta-analytic formulas requires a vector of point estimates and associated standard errors. First, to adjust the t-statistics, we treat the t-statistics as 'point estimates' and assign them the same standard error of one. Second, to adjust the attenuation magnitude, we collect the estimated ϕ^e and their estimated standard errors, which are calculated using the delta method.

All meta-analyses are done using a normal-normal hierarchical model (NNHM). This model features two levels. The first level links the point estimate $\hat{x}_e$ of task e to its "true" effect x_e. The second level links the "true" effects $x_1, x_2, \ldots$ across tasks $e = 1, 2, \ldots$ to a common effect x_0. In our case, $\hat{x}_e$ is a t-statistic or a ϕ^e estimate, x_e is the true value of those variables net of sampling error, and x_0 is the underlying attenuation behavior shared across tasks. For a given task, our certainty about how close $\hat{x}_e$ is to the task's "true" effect x_e is measured by the associated standard error σ_e. We assume $\hat{x}_e$ is normally distributed around the true value x_e:

$$\hat{x}_e | x_e, \sigma_e \sim \mathcal{N}(x_e, \sigma_e^2) \tag{7}$$

where the variability of the $\hat{x}_e$ point-estimate is due to the sampling error, whose magnitude is given by the standard error σ_e. All tasks e measure the same attenuation effect x_0, but there is some "true" between-study heterogeneity that introduces variance to task-specific effects x_e. The second level of the NNHM assumes that task-specific effects x_e are distributed normally around common effect x_0:

$$x_e | x_0, \tau \sim \mathcal{N}(x_0, \tau^2) \tag{8}$$

where the "true" heterogeneity between tasks is captured by parameter τ. The NNHM can be rewritten as a single draw from a Normal distribution centered at common effect x_0 via the law of total variance:

$$\hat{x}_e \mid x_0, \sigma_e, \tau \sim \mathcal{N}(x_0, \sigma_e^2 + \tau^2) \tag{9}$$

Estimating this model requires empiric estimates of $\hat{x}_e$ with associated standard errors σ_e and assumptions on the prior distribution of x_0 and τ. For all meta-analyses, we assume x_0 is distributed uniformly over the real line and that τ is drawn from a half-normal distribution with scale 1. These choices are commonly used as non-informative priors. We estimate the NNHM model using the bayesmeta R package (Röver, 2020).

B.3 Additional Tables

	BEU	CEE	CHT	CMA	DIG	EFF	ENS	EXT	FAI	FOR
Intercept	−0.00	0.06***	0.04	18.79***	−27.51***	2.96***	−4724.98***	3.72***	−51.85***	0.48***
	(0.08)	(0.01)	(0.04)	(2.11)	(2.04)	(0.70)	(23.63)	(0.43)	(1.92)	(0.07)
Par.	0.88***	0.83***	0.06***	0.62***	28.52***	29.97***	0.03***	1.26***	46.73***	0.42***
	(0.03)	(0.02)	(0.00)	(0.04)	(2.24)	(2.28)	(0.00)	(0.12)	(2.42)	(0.07)
CU	−0.24*	0.27***	0.30	2.05	−7.23	7.24***	150.86**	2.21**	8.46*	−0.17*
	(0.14)	(0.05)	(0.20)	(3.61)	(5.96)	(1.96)	(64.46)	(1.08)	(5.03)	(0.10)
Par. × CU	−0.45***	−0.74***	−0.07***	−0.09	−16.32*	−51.95***	−0.03***	−1.07***	−32.37***	0.17
	(0.11)	(0.09)	(0.01)	(0.07)	(8.44)	(7.76)	(0.01)	(0.31)	(8.14)	(0.11)
FE	YES	NO	NO	NO	NO	NO	NO	NO	NO	NO
R^2	0.72	0.65	0.37	0.56	0.27	0.19	0.18	0.08	0.41	0.13
Num. obs.	2340	2259	2250	2871	2268	2530	2783	2500	2277	2520

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.
Robust standard errors, clustered on subject-level.

Table 4: Separate estimates of equation (1) from the body of the paper for each of ten experiments.

	GUE	HEA	IND	MUL	NEW	PGG	POA	POL	PRD	PRE
Intercept	26.23^{***}	1.89^{***}	0.17^{**}	24.27^{***}	-99.98^{***}	0.54	419.05^{***}	-98.44^{***}	-0.16^{***}	0.13^{***}
	(3.03)	(0.44)	(0.07)	(2.95)	(1.03)	(2.30)	(34.08)	(2.02)	(0.06)	(0.01)
Par.	15.85^{***}	1.05^{***}	1.39^{***}	89.52^{***}	7.58^{***}	19.03^{***}	27.77^{***}	5.32^{***}	0.14^{***}	0.88^{***}
	(1.12)	(0.04)	(0.05)	(4.70)	(0.17)	(0.69)	(2.55)	(0.11)	(0.02)	(0.01)
CU	7.68^{*}	8.32^{***}	1.27^{***}	15.22^{**}	37.64^{***}	31.66^{***}	-111.48	67.83^{***}	0.44	0.07^{**}
	(4.29)	(0.98)	(0.22)	(6.61)	(4.23)	(6.59)	(77.88)	(8.40)	(0.29)	(0.03)
Par. × CU	-9.94^{***}	-1.02^{***}	-0.95^{***}	-42.95^{***}	-4.03^{***}	-24.70^{***}	-15.55^{**}	-6.54^{***}	0.03	-0.42^{***}
	(2.00)	(0.10)	(0.23)	(11.06)	(0.44)	(2.28)	(6.94)	(0.55)	(0.08)	(0.09)
FE	NO	NO	NO	NO	NO	NO	YES	NO	NO	NO
R^2	0.32	0.46	0.44	0.52	0.74	0.40	0.28	0.54	0.10	0.76
Num. obs.	2500	2520	2277	2250	2268	2530	2750	2520	2761	2268

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.
Robust standard errors, clustered on subject-level.

Table 5: Separate estimates of equation (1) from the body of the paper for each of ten experiments.

	PRO	PRS	REC	SAV	SEA	SIA	STO	TAX	TID	VOT
Intercept	0.45	43.19***	46.27***	22.29***	14.06***	0.02	96.93***	85.42	0.23***	−1.01***
	(0.48)	(1.81)	(5.42)	(2.67)	(3.67)	(0.02)	(3.26)	(124.29)	(0.03)	(0.02)
Par.	1.55***	0.26***	0.63***	1.54***	0.68***	0.96***	0.04***	0.97***	0.00***	0.00***
	(0.07)	(0.06)	(0.04)	(0.06)	(0.05)	(0.03)	(0.00)	(0.02)	(0.00)	(0.00)
CU	1.60	3.67	45.68***	−3.05	10.74*	0.23***	−1.04	2117.90**	1.02***	0.66***
	(1.26)	(5.05)	(9.42)	(6.59)	(6.44)	(0.04)	(5.93)	(934.56)	(0.17)	(0.11)
Par. × CU	−0.46**	0.00	−0.58***	−1.89***	−0.48***	−0.42***	−0.01	−0.26***	−0.00***	−0.00*
	(0.19)	(0.14)	(0.07)	(0.22)	(0.10)	(0.08)	(0.01)	(0.07)	(0.00)	(0.00)
FE	YES	NO	NO	NO	NO	NO	YES	NO	NO	NO
R^2	0.39	0.04	0.22	0.31	0.28	0.64	0.30	0.82	0.29	0.12
Num. obs.	2570	2510	1632	2520	2500	2421	2510	2517	2500	2520

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.
Robust standard errors, clustered on subject-level.

Table 6: Separate estimates of equation (1) from the body of the paper for each of ten experiments.

B.4 Additional Figures

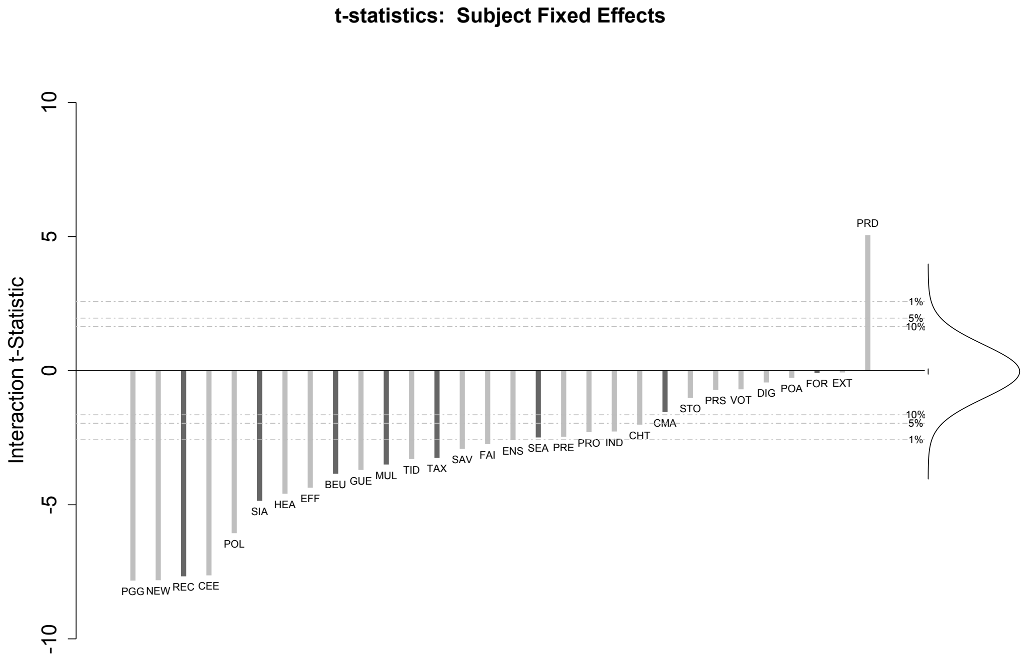


Figure 11: Sensitivity to parameters and cognitive uncertainty within subjects. The figure plots the t-statistic associated with $\hat{\beta}^e$, when estimating (1) controlling for subject fixed effects.

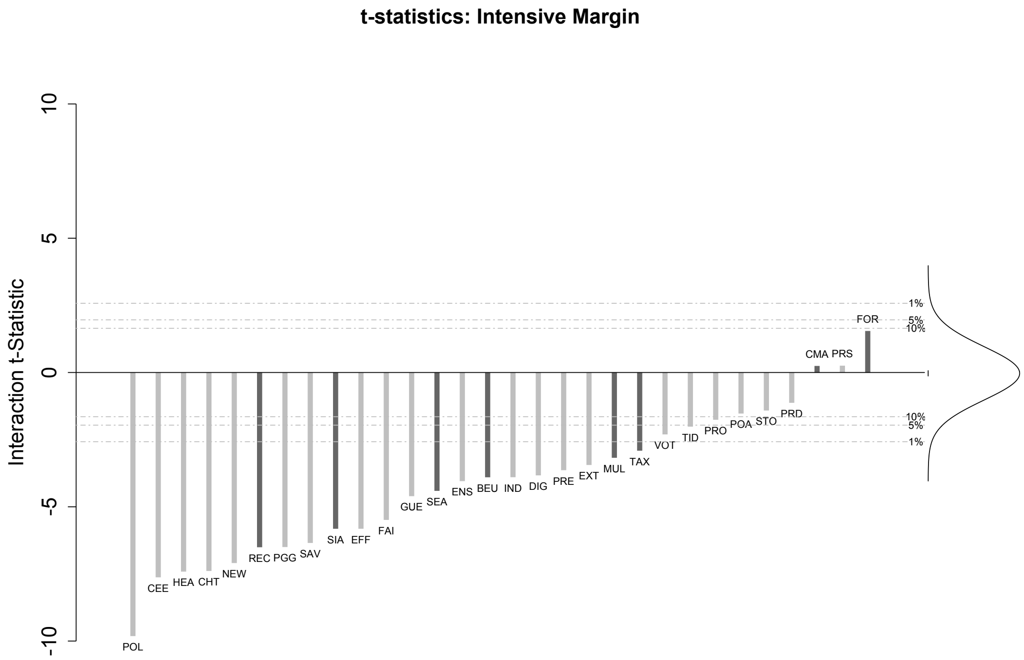


Figure 12: Sensitivity to parameters and cognitive uncertainty within subjects. The figure plots the t-statistic associated with $\hat{\beta}^e$, when estimating (1), restricting only to subjects with $CU > 0$.

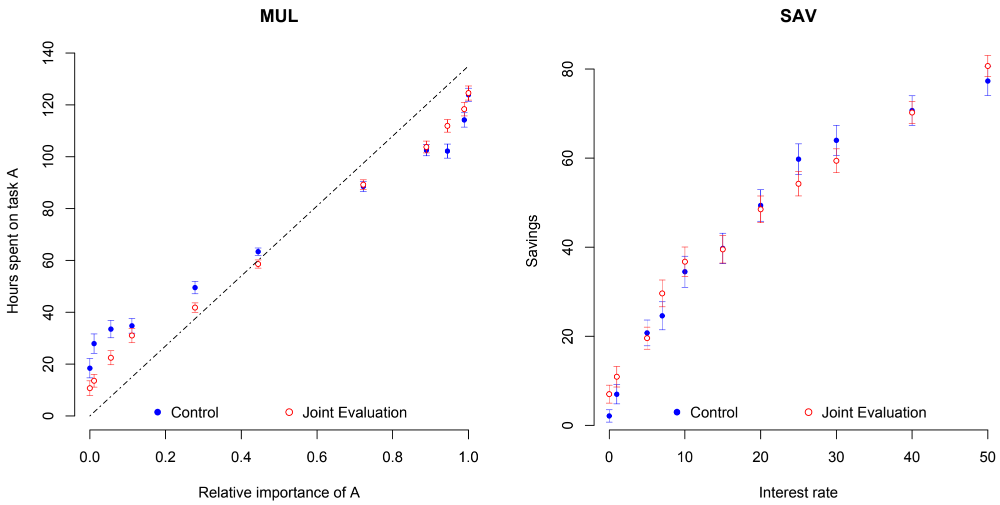


Figure 13: Raw data for the *Joint* treatment in tasks MUL and SAV.

C Derivations for Theoretical Framework

In our formal framework, we follow Ilut and Valchev (2023) who model policy function uncertainty using Gaussian processes. Given a known parameter value θ, the DM faces a decision problem $\max_a U(a, \theta)$, where the optimal action $a^*(\theta) \in \text{argmax}_a U(a, \theta)$ is unique, and the *policy function* $a^*(\theta)$ is differentiable and monotonically increasing.

Note that $a^*(\theta)$ can be expressed as a projection of a complete set of Gaussian basis functions:

$$a^*(\theta) = \int \beta_w \phi_w(\theta)\, dw$$
$$\phi_w(\theta) = \exp(-\psi(\theta - w))$$

The weights of this projection $\{\beta_w\}_{w\in\mathbb{R}}$ are unknown to the DM, reflecting uncertainty over the policy function. In particular, the DM's priors over β_w are independent and Gaussian-distributed with mean $\overline{\beta}_w$ and constant variance. Letting

$$a_d(\theta) \equiv \int \overline{\beta}_w \exp(-\psi(\theta - w))\, dw$$

denote the DM's *default policy function*, we make the restriction that the prior means of the basis weights $\overline{\beta}_w$ are such that $a_d(\theta)$ is weakly increasing in θ — again, the idea is that the DM correctly understands that her action should be increasing in the parameter. Given this structure, Lemma 1 of Illut and Valchev (2023) implies that for any parameter θ, the DM's prior distribution over $a^*(\theta)$ is given by

$$a^*(\theta) \sim N(a_d(\theta), \sigma_0^2)$$

for some $\sigma_0^2 > 0$. Given this fact, the rest of the analysis is routine. The DM has access to a cognitive signal over the her optimal action at the parameter value θ:

$$s(\theta) \sim N(a^*(\theta), \sigma_a^2(\theta))$$

where $\sigma_a^*(\theta)$ denotes the level of *cognitive noise* in the DM's deliberation process. The DM then takes the decision $a(\theta)$ equal to her Bayesian posterior mean over $a^*(\theta)$, given her prior and the signal realization $s(\theta)$.

Given the Gaussian prior and signal, a routine derivation shows that the DM's posterior distribution over $a^*(\theta)$ given the signal realization $s(\theta)$ is given by

$$
\begin{aligned}
a^*(\theta)|s(\theta) &\sim N(a(\theta), \tilde{\sigma}_a^2(\theta)), \text{ where} \\
a(\theta) &= \lambda s(\theta) + (1-\lambda)a_d(\theta) \\
\tilde{\sigma}_a^2(\theta) &= \lambda \sigma_a^2(\theta) \\
\lambda &= \frac{\sigma_0^2}{\sigma_a^2(\theta) + \sigma_0^2}
\end{aligned}
$$

We now state and prove two generalizations of the predictions in the main text, which allow for the default policy function $a_d(\theta)$ to be non-constant. The following proposition corresponds to Prediction 1 in the main text.

Proposition 1. *(Cognitive Noise and Attenuation). Suppose $\frac{\partial}{\partial\theta}a^*(\theta) > \frac{\partial}{\partial\theta}a_d(\theta)$. If $|\sigma_a'(\theta)|$ is sufficiently small, then $\frac{\partial}{\partial\theta}E[a(\theta)]$ is decreasing in $\sigma_a(\theta)$.*

Proof. Consider the case where $\sigma_a'(\theta) = 0$. We have

$$\frac{\partial}{\partial\theta}E[a(\theta)] = \lambda\frac{\partial}{\partial\theta}a^*(\theta) + (1-\lambda)\frac{\partial}{\partial\theta}a_d(\theta)$$

which in turn implies

$$
\begin{aligned}
\frac{\partial}{\partial\sigma_a(\theta)}\frac{\partial}{\partial\theta}E[a(\theta)] &= -\frac{\sigma_0^2}{(\sigma_a^2(\theta)+\sigma_0^2)^2}\left[\frac{\partial}{\partial\theta}a^*(\theta) - \frac{\partial}{\partial\theta}a_d(\theta)\right] \\
&< 0
\end{aligned}
$$

since $\frac{\partial}{\partial\theta}a^*(\theta) > \frac{\partial}{\partial\theta}a_d(\theta)$. By continuity, there exists $\epsilon > 0$ such that for $|\sigma_a'(\theta)| < \epsilon$, we maintain $\frac{\partial}{\partial\sigma_a(\theta)}\frac{\partial}{\partial\theta}E[a(\theta)] < 0$. □

We now turn to Prediction 2 in the main text. Say that $a_d(\theta)$ is *interior* if for θ large enough, we have $a_d(\theta) < a^*(\theta)$ and for θ small enough, we have $a_d(\theta) > a^*(\theta)$.

Proposition 2. *(Cognitive Noise and Diminishing Sensitivity). Suppose $\frac{\partial}{\partial\theta}a^*(\theta) > \frac{\partial}{\partial\theta}a_d(\theta)$, and that $a_d(\theta)$ is interior. For $|\frac{\partial^2}{\partial\theta^2}a^*(\theta)|$ and $|\frac{\partial^2}{\partial\theta^2}a_d(\theta)|$ sufficiently small, we have the following:*

(a) Suppose $\underline{\theta}$ exists. There exists a neighborhood around $\underline{\theta}$ such that for any $\theta < \theta'$ in that neighborhood with $0 < \frac{\partial}{\partial\underline{\delta}}\sigma_a^2(\theta') \leq \frac{\partial}{\partial\underline{\delta}}\sigma_a^2(\theta)$: if $\sigma_a(\theta) < \sigma_a(\theta')$ then $\frac{\partial}{\partial\theta}E[a(\theta)] > \frac{\partial}{\partial\theta}E[a(\theta')]$.

Suppose $\overline{\theta}$ exists. There exists a neighborhood around $\overline{\theta}$ such that for any $\theta > \theta'$ in that neighborhood with $0 < \frac{\partial}{\partial\overline{\delta}}\sigma_a^2(\theta') \leq \frac{\partial}{\partial\overline{\delta}}\sigma_a^2(\theta)$: if $\sigma_a(\theta) < \sigma_a(\theta')$ then $\frac{\partial}{\partial\theta}E[a(\theta)] > \frac{\partial}{\partial\theta}E[a(\theta')]$.

(b) *Suppose $\underline{\theta}$ exists. If $\frac{\partial}{\partial \underline{\delta}}\sigma_a(\theta) > 0$ and $\frac{\partial^2}{\partial \underline{\delta}^2}\sigma_a^2(\theta) \leq 0$ in a neighborhood around $\underline{\theta}$, then $\frac{\partial}{\partial \theta}E[a(\theta)]$ is decreasing in $\underline{\delta}(\theta)$ in a neighborhood around $\underline{\theta}$.*

Suppose $\overline{\theta}$ exists. If $\frac{\partial}{\partial \overline{\delta}}\sigma_a(\theta) > 0$ and $\frac{\partial^2}{\partial \overline{\delta}^2}\sigma_a^2(\theta) \leq 0$ in a neighborhood around $\overline{\theta}$, then $\frac{\partial}{\partial \theta}E[a(\theta)]$ is decreasing in $\overline{\delta}(\theta)$ in a neighborhood around $\overline{\theta}$.

Proof. Begin by proving the first statement of part a) of the proposition. Consider the case where $\frac{\partial^2}{\partial \theta^2}a^*(\theta) = \frac{\partial^2}{\partial \theta^2}a_d(\theta) = 0$, and let $\gamma = \frac{\partial}{\partial \theta}a^*(\theta)$. Let $N(\underline{\theta})$ denote the neighborhood around $\underline{\theta}$ such that for any $\theta \in N(\underline{\theta})$, $a^*(\theta) < a_d(\theta)$; this neighborhood is guaranteed to be non-empty since $a_d(\theta)$ is intermediate.

Now take any $\theta, \theta' \in N(\underline{\theta})$ with $\theta < \theta'$, $\frac{\partial}{\partial \underline{\delta}}\sigma_a^2(\theta') \leq \frac{\partial}{\partial \underline{\delta}}\sigma_a^2(\theta)$, and $\sigma_a(\theta) < \sigma_a(\theta')$. Note that

$$\begin{aligned}
\frac{\partial}{\partial \theta}E[a(\theta)] &= \frac{\partial}{\partial \theta}\lambda(\theta)(a^*(\theta) - a_d(\theta)) + \lambda(\theta)\gamma \\
\frac{\partial}{\partial \theta}E[a(\theta')] &= \frac{\partial}{\partial \theta}\lambda(\theta')(a^*(\theta') - a_d(\theta')) + \lambda(\theta')\gamma
\end{aligned}$$

We want to show that $\frac{\partial}{\partial \theta}E[a(\theta')] < \frac{\partial}{\partial \theta}E[a(\theta)]$. Since $\sigma_a(\theta) < \sigma_a(\theta') \implies \lambda(\theta') < \lambda(\theta)$, it suffices to show that $\frac{\partial}{\partial \theta}\lambda(\theta')(a^*(\theta') - a_d(\theta')) < \frac{\partial}{\partial \theta}\lambda(\theta)(a^*(\theta) - a_d(\theta))$. To see this, note that $a^*(\theta) - a_d(\theta) < a^*(\theta') - a_d(\theta') < 0$ since $\theta, \theta' \in N(\underline{\theta})$ and $\frac{\partial}{\partial \theta}a^*(\theta) > \frac{\partial}{\partial \theta}a_d(\theta)$. In addition, we have

$$\begin{aligned}
\frac{\partial}{\partial \theta}\lambda(\theta) &= -\frac{\sigma_0^2}{(\sigma_0^2 + \sigma_a^2(\theta))^2}\frac{\partial}{\partial \theta}\sigma_a^2(\theta) \\
&\leq -\frac{\sigma_0^2}{(\sigma_0^2 + \sigma_a^2(\theta'))^2}\frac{\partial}{\partial \theta}\sigma_a^2(\theta') \\
&= \frac{\partial}{\partial \theta}\lambda(\theta')
\end{aligned}$$

since by assumption we have $\sigma_a(\theta) < \sigma_a^2(\theta')$ and $\frac{\partial}{\partial \underline{\delta}}\sigma_a^2(\theta') < \frac{\partial}{\partial \underline{\delta}}\sigma_a^2(\theta) \implies \frac{\partial}{\partial \theta}\sigma_a^2(\theta') < \frac{\partial}{\partial \theta}\sigma_a^2(\theta)$, and so the desired inequality obtains; for any $\theta, \theta' \in N(\underline{\theta})$ with $\theta < \theta'$, $\frac{\partial}{\partial \underline{\delta}}\sigma_a^2(\theta') \leq \frac{\partial}{\partial \underline{\delta}}\sigma_a^2(\theta)$, and $\sigma_a(\theta) < \sigma_a(\theta')$, we have $\frac{\partial}{\partial \theta}E[a(\theta')] < \frac{\partial}{\partial \theta}E[a(\theta)]$. By continuity, we can conclude that there exists some $\epsilon > 0$ such that when $|\frac{\partial^2}{\partial \theta^2}a^*(\theta)| < \epsilon$ and $|\frac{\partial^2}{\partial \theta^2}a_d(\theta)| < \epsilon$ such that the above statement continues to hold. The proof of the second statement of part a) follows from an analogous argument.

We now prove the first statement of part b) of the proposition. Consider the case where $\frac{\partial^2}{\partial \theta^2}a^*(\theta) = \frac{\partial^2}{\partial \theta^2}a_d(\theta) = 0$. Suppose $\frac{\partial}{\partial \underline{\delta}}\sigma_a(\theta) > 0$ and $\frac{\partial^2}{\partial \underline{\delta}^2}\sigma_a^2(\theta) \leq 0$ in a neighborhood around $\underline{\theta}$. Since $a_d(\theta)$ is interior, there exists a neighborhood around $\underline{\theta}$ for which $\frac{\partial}{\partial \underline{\delta}}\sigma_a(\theta) > 0$, $\frac{\partial^2}{\partial \underline{\delta}^2}\sigma_a^2(\theta) \leq 0$, and $a_d(\theta) > a^*(\theta)$. Note that for θ in this neighborhood, we have

$$
\begin{aligned}
\frac{\partial}{\partial \underline{\delta}}\frac{\partial}{\partial \theta}E[a(\theta)] &= \frac{\partial^2}{\partial \theta^2}E[a(\theta)] \\
&= \left(\frac{\partial^2}{\partial \theta^2}\lambda\right)[a^*(\theta)-a_d(\theta)] + 2\left(\frac{\partial}{\partial \theta}\lambda\right)\left[\frac{\partial}{\partial \theta}a^*(\theta) - \frac{\partial}{\partial \theta}a_d(\theta)\right]
\end{aligned}
$$

To see that the second term is strictly negative, note that by assumption $\frac{\partial}{\partial \theta}a^*(\theta) - \frac{\partial}{\partial \theta}a_d(\theta) > 0$ and

$$
\frac{\partial}{\partial \theta}\lambda = -\frac{\sigma_0^2}{(\sigma_a^2(\theta)+\sigma_0^2)^2}\frac{\partial}{\partial \theta}\sigma_a^2(\theta) < 0
$$

since by assumption $\frac{\partial}{\partial \theta}\sigma_a^2(\theta) = \frac{\partial}{\partial \underline{\delta}}\sigma_a^2(\theta) > 0$. To see that the first term is strictly negative, note that by assumption $a^*(\theta) - a_d(\theta) < 0$ and

$$
\begin{aligned}
\frac{\partial^2}{\partial \theta^2}\lambda &= -\frac{\sigma_0^2}{(\sigma_a^2(\theta)-\sigma_0^2)^2}\cdot\frac{\partial}{\partial \theta^2}\sigma_a^2(\theta) + 2\frac{\sigma_0^2}{(\sigma_a^2(\theta)-\sigma_0^2)^3}\cdot\left(\frac{\partial}{\partial \theta}\sigma_a^2(\theta)\right)^2 \\
&= -\frac{\sigma_0^2}{(\sigma_a^2(\theta)-\sigma_0^2)^2}\cdot\frac{\partial}{\partial \underline{\delta}^2}\sigma_a^2(\theta) + 2\frac{\sigma_0^2}{(\sigma_a^2(\theta)-\sigma_0^2)^3}\cdot\left(\frac{\partial}{\partial \theta}\sigma_a^2(\theta)\right)^2 \\
&> 0
\end{aligned}
$$

since by assumption $\frac{\partial^2}{\partial \underline{\delta}^2}\sigma_a^2(\theta) \leq 0$. We therefore have $\frac{\partial}{\partial \underline{\delta}}\frac{\partial}{\partial \theta}E[a(\theta)] < 0$. By continuity, we can conclude that there exists some $\epsilon > 0$ such that when $|\frac{\partial^2}{\partial \theta^2}a^*(\theta)| < \epsilon$ and $|\frac{\partial^2}{\partial \theta^2}a_d(\theta)| < \epsilon$, we have $\frac{\partial}{\partial \underline{\delta}}\frac{\partial}{\partial \theta}E[a(\theta)] < 0$ in a neighborhood around $\underline{\theta}$.

We now prove the second statement of part b). Consider the case where $\frac{\partial^2}{\partial \theta^2}a^*(\theta) = \frac{\partial^2}{\partial \theta^2}a_d(\theta) = 0$. Suppose $\frac{\partial}{\partial \overline{\delta}}\sigma_a(\theta) > 0$ and $\frac{\partial^2}{\partial \overline{\delta}^2}\sigma_a^2(\theta) \leq 0$ in a neighborhood around $\overline{\theta}$. Since $a_d(\theta)$ is interior, there exists a neighborhood around $\overline{\theta}$ for which $\frac{\partial}{\partial \overline{\delta}}\sigma_a(\theta) > 0$, $\frac{\partial^2}{\partial \overline{\delta}^2}\sigma_a^2(\theta) \leq 0$, and $a_d(\theta) < a^*(\theta)$. Note that for θ in this neighborhood, we have

$$
\begin{aligned}
\frac{\partial}{\partial \underline{\delta}}\frac{\partial}{\partial \theta}E[a(\theta)] &= -\frac{\partial^2}{\partial \theta^2}E[a(\theta)] \\
&= -\left(\frac{\partial^2}{\partial \theta^2}\lambda\right)[a^*(\theta)-a_d(\theta)] - 2\left(\frac{\partial}{\partial \theta}\lambda\right)\left[\frac{\partial}{\partial \theta}a^*(\theta) - \frac{\partial}{\partial \theta}a_d(\theta)\right]
\end{aligned}
$$

To see that the second term is negative, note that by assumption $\frac{\partial}{\partial \theta}a^*(\theta) - \frac{\partial}{\partial \theta}a_d(\theta) > 0$

and that

$$\frac{\partial}{\partial\theta}\lambda = -\frac{\sigma_0^2}{(\sigma_a^2(\theta)+\sigma_0^2)^2}\frac{\partial}{\partial\theta}\sigma_a^2(\theta)$$
$$= \frac{\sigma_0^2}{(\sigma_a^2(\theta)+\sigma_0^2)^2}\frac{\partial}{\partial\overline{\theta}}\sigma_a^2(\theta) > 0$$

since $\frac{\partial}{\partial\overline{\theta}}\sigma_a^2(\theta) > 0$ by assumption. To see that the first term is negative, note that $a^*(\theta)$–$a_d(\theta) > 0$ by assumption and that

$$\frac{\partial^2}{\partial\theta^2}\lambda = -\frac{\sigma_0^2}{(\sigma_a^2(\theta)-\sigma_0^2)^2}\cdot\frac{\partial}{\partial\theta^2}\sigma_a^2(\theta) + 2\frac{\sigma_0^2}{(\sigma_a^2(\theta)-\sigma_0^2)^3}\cdot\left(\frac{\partial}{\partial\theta}\sigma_a^2(\theta)\right)^2$$
$$= -\frac{\sigma_0^2}{(\sigma_a^2(\theta)-\sigma_0^2)^2}\cdot\frac{\partial}{\partial\overline{\delta}^2}\sigma_a^2(\theta) + 2\frac{\sigma_0^2}{(\sigma_a^2(\theta)-\sigma_0^2)^3}\cdot\left(\frac{\partial}{\partial\theta}\sigma_a^2(\theta)\right)^2$$
$$> 0$$

since by assumption $\frac{\partial^2}{\partial\overline{\delta}^2}\sigma_a^2(\theta) \leq 0$. We therefore have $\frac{\partial}{\partial\underline{\delta}}\frac{\partial}{\partial\theta}E[a(\theta)] < 0$. By continuity, we can conclude that there exists some $\epsilon > 0$ such that when $|\frac{\partial^2}{\partial\theta^2}a^*(\theta)| < \epsilon$ and $|\frac{\partial^2}{\partial\theta^2}a_d(\theta)| < \epsilon$, we have $\frac{\partial}{\partial\underline{\delta}}\frac{\partial}{\partial\theta}E[a(\theta)] < 0$ in a neighborhood around $\underline{\theta}$ □

As in the main text, let $P(a^*(\theta)|S = s(\theta))$ denote the DM's posterior distribution over the optimal action given the signal realization $s(\theta)$, and define cognitive uncertainty as $p_{CU}(\theta) = P(|a^*(\theta) - a(\theta)| > \kappa)$

Proposition 3. *(Measurement of Cognitive Noise) $p_{CU}(\theta)$ is increasing in $\sigma_a(\theta)$*

Proof. Given the signal $s(\theta)$, the DM's posterior over $a^*(\theta)$–$a(\theta)$ is distributed $N(0, \tilde{\sigma}_a(\theta))$. This implies that

$$p_{CU}(\theta) = 2\left[1 - \Phi\left(\kappa\sqrt{1/\sigma_a^2(\theta) + 1/\sigma_0^2}\right)\right]$$

which is increasing in $\sigma_a(\theta)$. □

D Experimental Instructions and Decision Screens

D.1 CHT

Instructions

Please read these instructions carefully. There will be comprehension questions. If you fail these questions twice in a row, you will be excluded from the study and you will not receive the completion payment.
You have a chance to win an additional bonus if you complete this study in its entirety. One out of five participants will be eligible for a bonus. If you are eligible for a bonus, we will randomly select one of your decisions (with equal probability) to determine your bonus.

Your task:

In this study, you act as a financial advisor **who can give advice to a customer on the quality of a hypothetical financial investment product. You are paid more the higher the customer evaluates the investment product's quality.**

- The investment product's quality is determined by the computer. Specifically, the computer **selects a number between 0 and 20.** You will see which quality was selected.
- Your customer is another participant who was randomly matched to you. Your customer **does not see the investment quality.** Instead, they need to estimate it. Both yours and your customer's earnings depend on your customer's estimate. However, you are paid in different ways:
  - **Your customer receives more money the more accurate their estimate,** i.e. the closer their estimate is to the actual investment quality.
  - **You (the advisor) receive more money the higher your customer's estimate,** independent of what the true investment quality is.
- This means: you get a higher bonus if the other participant's estimate is higher.
- In case you're interested in how your as well as your customer's bonuses are calculated, please hover here.
- After you see the investment product's quality and before your customer makes their estimate, you can decide **to Reveal the true investment quality to them or to Hide it.**
  - If you decide to **Reveal**, your customer will learn the investment product's quality. You cannot lie about the quality.
  - If you decide to **Hide**, they will not learn the investment product's quality.
- Whatever you decide, your customer knows that you had the choice between revealing and hiding the product's investment quality.
- In total, you will complete 11 rounds of this task. Across these rounds, the investment product's quality will vary. If one of the rounds of this task is selected to determine your bonus, only your decision in this one round will determine your bonus.

Your bonus payment:

Your decisions may affect your bonus payment. If a decision in this study is selected for payment, you will earn a larger bonus the higher your customer's estimate, up to a maximum of \$10. Specifically, your bonus will be equal to

$$\text{Bonus (in \$)} = \$10 - 0.025 \times (20 - \text{your customer's estimate})^2$$

Example:

Reminder:
- The computer selects the investment quality as a number between 0 and 20.
- You are a financial advisor who observes the investment quality and then decides to Reveal it to or Hide it from your customer.
- You receive more money **the higher your customer estimates the investment quality.**
- Your customer receives more money **the closer their estimate is to the investment quality.**

In this round: Investment product's quality: **11**.

Do you want to reveal or hide the product's quality?

○ Reveal ○ Hide

- In this example, the investment product's quality is 11.
- You then then decide to reveal or hide the investment product's quality from your customer.

Your certainty:

In each round, we will ask you two questions:

- You will decide to reveal or hide the investment product's quality.
- We will ask you **how certain** you are about your decision. Specifically, we are interested in how likely you think it is (in percentage terms) that yours is actually the best possible decision given your personal preferences and the available information.

Next

Figure 14: The instruction screen for the CHT task.

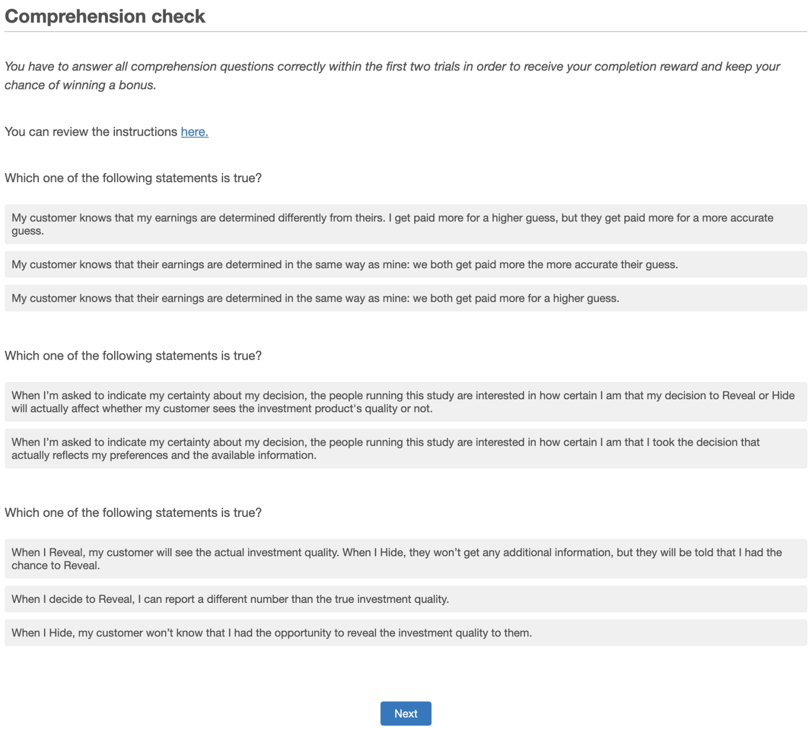


Figure 15: The comprehension screen for the CHT task.

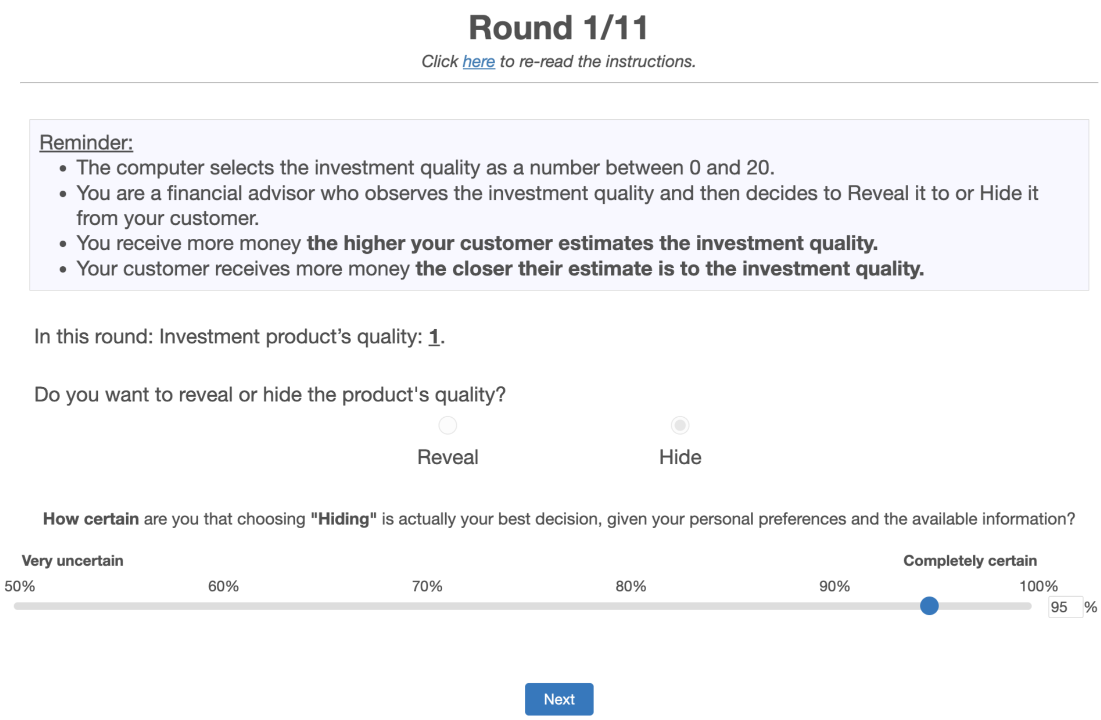


Figure 16: The decision screen for the CHT task.

D.2 CMA

Instructions

Please read these instructions carefully. There will be comprehension questions. If you fail these questions twice in a row, you will be excluded from the study and you will not receive the completion payment.

You have a chance to win an additional bonus if you complete this study in its entirety. Every participants will be eligible for a bonus. If you are eligible for a bonus, we will randomly select one of your decisions (with equal probability) to determine your bonus.

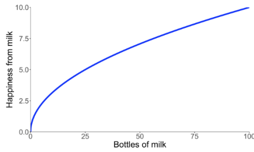
Your task:

In this study, you will act as a consumer who only consumes milk and juice. Your task is **to maximize the consumer's overall happiness by deciding how much juice and milk to consume**.

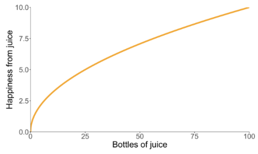
- The consumer's overall happiness is given by the square root of the amount of milk consumed plus the square root of the amount of juice consumed, where amounts are measured in bottles:

$$\text{Overall happiness} = \sqrt{\text{Bottles of milk}} + \sqrt{\text{Bottles of juice}}$$

Here's how the number of milk and juice bottles consumed translate into happiness:



$\text{Happiness from milk} = \sqrt{\text{Bottles of milk}}$



$\text{Happiness from juice} = \sqrt{\text{Bottles of juice}}$

- As you can see in the figures, the **consumer's happiness increases in how much milk and juice s/he drinks.** However, **each additional bottle of milk or juice produces less and less additional happiness.** For example, while the happiness derived from 100 bottles of milk is higher than the happiness derived from 99 bottles, the happiness **increase** resulting from the additional bottle is much smaller than the happiness **increase** that results from consuming one bottle instead of zero bottles.
- The consumer has a total budget of $100 to spend on milk and juice. You need to spend your entire budget in each round.
- Juice always costs $1 a bottle, **but the price of milk varies.**
- To keep things simple, we will ask you **what fraction (between 0 and 100%) of the bottles you consume should be milk bottles or juice bottles,** and then the computer will automatically and instantly display for you how many bottles of milk/juice you would get with the given prices. The computer will also instantly display for you how much you would spend on milk/juice.
- For instance, you may decide that 60% of the bottles you consume should be milk bottles and 40% juice bottles.
- In total, you will complete 11 rounds of this task. Across these rounds, the cost of milk varies. These rounds are completely independent from one another. If one of the rounds of this task is selected to determine your bonus, only your decision in this one round will determine your bonus.

Your bonus payment:

Your decisions may affect your bonus payment. If a decision in this study is selected for payment, you will receive $20 if your answer is within +/-1 percentage point of the answer that maximizes the consumer's overall happiness at the prevailing prices, and nothing otherwise.

Example:

Reminder: The consumer's budget is $100. The consumer's overall happiness is given by:

$$\text{Overall happiness} = \sqrt{\text{bottles of milk}} + \sqrt{\text{bottles of juice}}$$

In this round: Each bottle of milk costs **$2.10** and each bottle of juice costs **$1.00**.

What fraction of the bottles you consume (between 0 and 100%) are milk or juice?

Milk: ____ %
Juice: ____ %

	Price per bottle	Quantity bought	Total expenditure
Milk	**$2.10**	____ bottles	$____
Juice	**$1.00**	____ bottles	$____

- In this example, the price of milk is $2.10 per bottle.
- You then need to decide what fraction of the bottles you consume are milk. Based on your decision, the computer will instantly calculate how much milk and juice you would get, given the prices and your total budget.

Your certainty:

In each round, we will ask you two questions:

- What fraction of the bottles you consume are milk.
- We will ask you **how certain** you are about your decision. Specifically, we are interested in how likely you think it is (in percentage terms) that the decision you made is actually the best decision, by which we mean the decision that maximizes your bonus.

Next

Figure 17: The instruction screen for the CMA task.

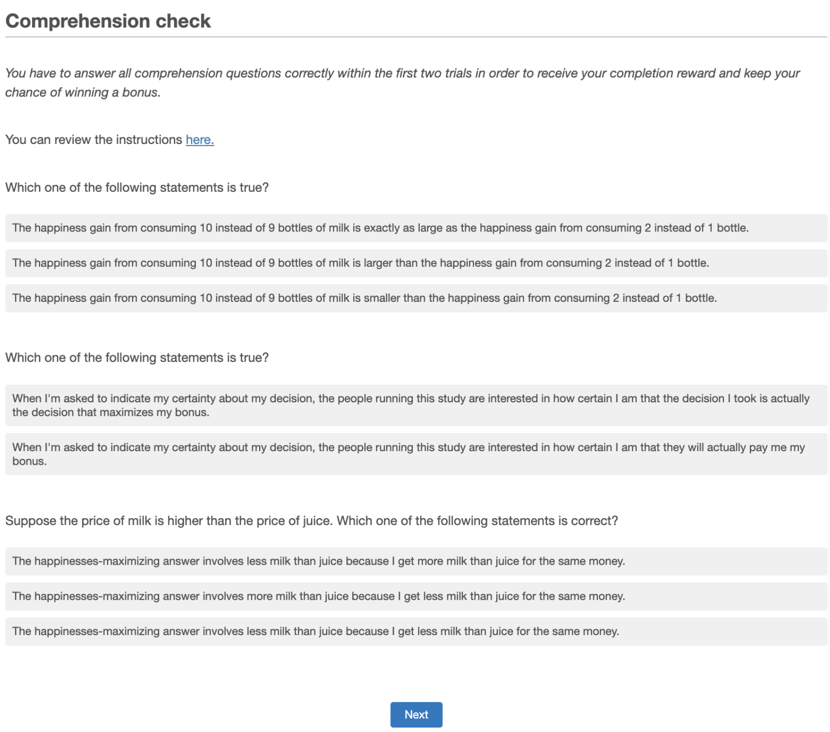


Figure 18: The comprehension screen for the CMA task.

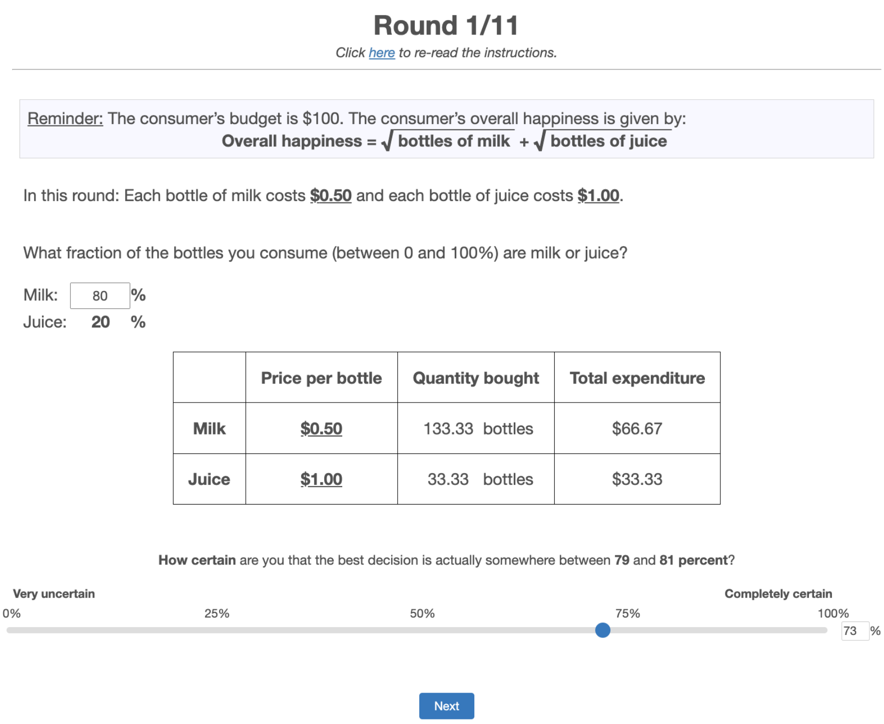
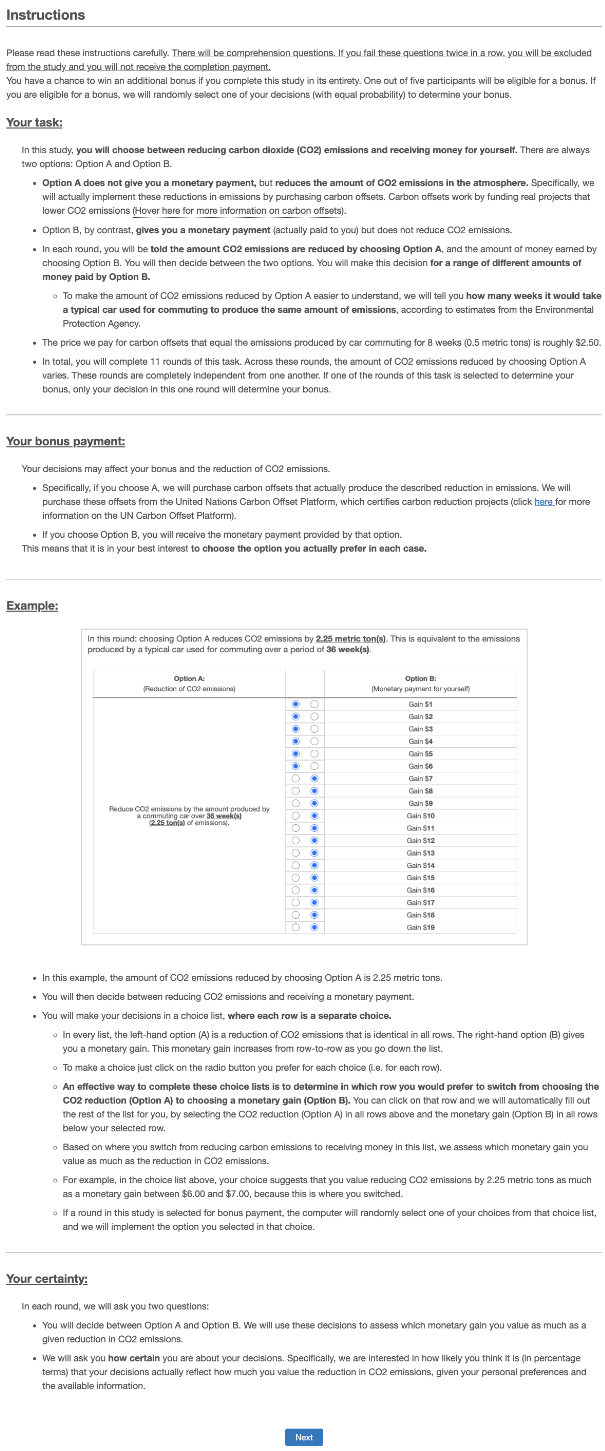


Figure 19: The decision screen for the CMA task.

D.3 EXT



Instructions

Please read these instructions carefully. There will be comprehension questions. If you fail these questions twice in a row, you will be excluded from the study and you will not receive the completion payment.
You have a chance to win an additional bonus if you complete this study in its entirety. One out of five participants will be eligible for a bonus. If you are eligible for a bonus, we will randomly select one of your decisions (with equal probability) to determine your bonus.

Your task:

In this study, **you will choose between reducing carbon dioxide (CO2) emissions and receiving money for yourself.** There are always two options: Option A and Option B.

- **Option A does not give you a monetary payment,** but **reduces the amount of CO2 emissions in the atmosphere.** Specifically, we will actually implement these reductions in emissions by purchasing carbon offsets. Carbon offsets work by funding real projects that lower CO2 emissions (Hover here for more information on carbon offsets).
- Option B, by contrast, **gives you a monetary payment** (actually paid to you) but does not reduce CO2 emissions.
- In each round, you will be **told the amount CO2 emissions are reduced by choosing Option A**, and the amount of money earned by choosing Option B. You will then decide between the two options. You will make this decision **for a range of different amounts of money paid by Option B.**
  - To make the amount of CO2 emissions reduced by Option A easier to understand, we will tell you **how many weeks it would take a typical car used for commuting to produce the same amount of emissions**, according to estimates from the Environmental Protection Agency.
- The price we pay for carbon offsets that equal the emissions produced by car commuting for 8 weeks (0.5 metric tons) is roughly $2.50.
- In total, you will complete 11 rounds of this task. Across these rounds, the amount of CO2 emissions reduced by choosing Option A varies. These rounds are completely independent from one another. If one of the rounds of this task is selected to determine your bonus, only your decision in this one round will determine your bonus.

Your bonus payment:

Your decisions may affect your bonus and the reduction of CO2 emissions.

- Specifically, if you choose A, we will purchase carbon offsets that actually produce the described reduction in emissions. We will purchase these offsets from the United Nations Carbon Offset Platform, which certifies carbon reduction projects (click here for more information on the UN Carbon Offset Platform).
- If you choose Option B, you will receive the monetary payment provided by that option.

This means that it is in your best interest **to choose the option you actually prefer in each case.**

Example:

In this round: choosing Option A reduces CO2 emissions by **2.25 metric ton(s)**. This is equivalent to the emissions produced by a typical car used for commuting over a period of **36 week(s)**.

Option A: (Reduction of CO2 emissions)		**Option B:** (Monetary payment for yourself)
Reduce CO2 emissions by the amount produced by a commuting car over **36 week(s)** (**2.25 ton(s)** of emissions).	◉ ○	Gain **$1**
	◉ ○	Gain **$2**
	◉ ○	Gain **$3**
	◉ ○	Gain **$4**
	◉ ○	Gain **$5**
	◉ ○	Gain **$6**
	○ ◉	Gain **$7**
	○ ◉	Gain **$8**
	○ ◉	Gain **$9**
	○ ◉	Gain **$10**
	○ ◉	Gain **$11**
	○ ◉	Gain **$12**
	○ ◉	Gain **$13**
	○ ◉	Gain **$14**
	○ ◉	Gain **$15**
	○ ◉	Gain **$16**
	○ ◉	Gain **$17**
	○ ◉	Gain **$18**
	○ ◉	Gain **$19**

- In this example, the amount of CO2 emissions reduced by choosing Option A is 2.25 metric tons.
- You will then decide between reducing CO2 emissions and receiving a monetary payment.
- You will make your decisions in a choice list, **where each row is a separate choice.**
  - In every list, the left-hand option (A) is a reduction of CO2 emissions that is identical in all rows. The right-hand option (B) gives you a monetary gain. This monetary gain increases from row-to-row as you go down the list.
  - To make a choice just click on the radio button you prefer for each choice (i.e. for each row).
  - **An effective way to complete these choice lists is to determine in which row you would prefer to switch from choosing the CO2 reduction (Option A) to choosing a monetary gain (Option B).** You can click on that row and we will automatically fill out the rest of the list for you, by selecting the CO2 reduction (Option A) in all rows above and the monetary gain (Option B) in all rows below your selected row.
  - Based on where you switch from reducing carbon emissions to receiving money in this list, we assess which monetary gain you value as much as the reduction in CO2 emissions.
  - For example, in the choice list above, your choice suggests that you value reducing CO2 emissions by 2.25 metric tons as much as a monetary gain between $6.00 and $7.00, because this is where you switched.
  - If a round in this study is selected for bonus payment, the computer will randomly select one of your choices from that choice list, and we will implement the option you selected in that choice.

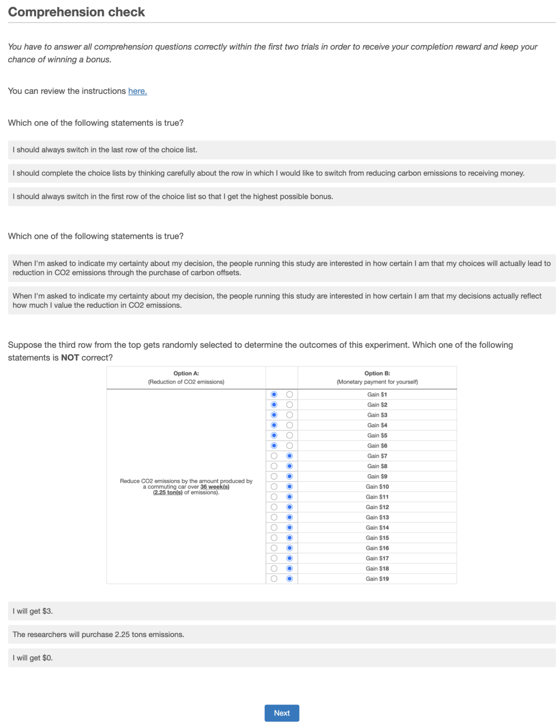
Your certainty:

In each round, we will ask you two questions:

- You will decide between Option A and Option B. We will use these decisions to assess which monetary gain you value as much as a given reduction in CO2 emissions.
- We will ask you **how certain** you are about your decisions. Specifically, we are interested in how likely you think it is (in percentage terms) that your decisions actually reflect how much you value the reduction in CO2 emissions, given your personal preferences and the available information.

Next

Figure 20: The instruction screen for the EXT task.



Comprehension check

You have to answer all comprehension questions correctly within the first two trials in order to receive your completion reward and keep your chance of winning a bonus.

You can review the instructions here.

Which one of the following statements is true?

I should always switch in the last row of the choice list.

I should complete the choice lists by thinking carefully about the row in which I would like to switch from reducing carbon emissions to receiving money.

I should always switch in the first row of the choice list so that I get the highest possible bonus.

Which one of the following statements is true?

When I'm asked to indicate my certainty about my decision, the people running this study are interested in how certain I am that my choices will actually lead to reduction in CO2 emissions through the purchase of carbon offsets.

When I'm asked to indicate my certainty about my decision, the people running this study are interested in how certain I am that my decisions actually reflect how much I value the reduction in CO2 emissions.

Suppose the third row from the top gets randomly selected to determine the outcomes of this experiment. Which one of the following statements is **NOT** correct?

Option A: (Reduction of CO2 emissions)		**Option B:** (Monetary payment for yourself)
Reduce CO2 emissions by the amount produced by a commuting car over **36 week(s)** (**2.25 ton(s)** of emissions).		Gain **$1**
		Gain **$2**
		Gain **$3**
		Gain **$4**
		Gain **$5**
		Gain **$6**
		Gain **$7**
		Gain **$8**
		Gain **$9**
		Gain **$10**
		Gain **$11**
		Gain **$12**
		Gain **$13**
		Gain **$14**
		Gain **$15**
		Gain **$16**
		Gain **$17**
		Gain **$18**
		Gain **$19**

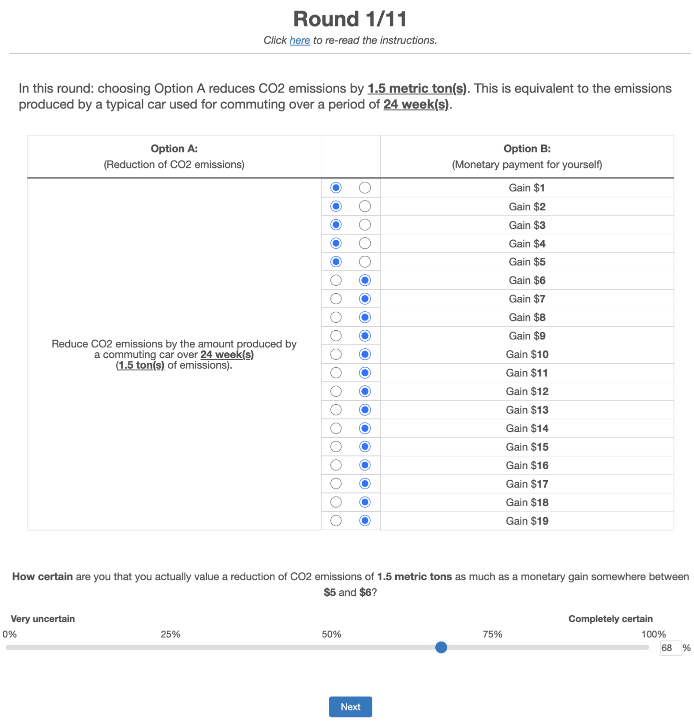
I will get $3.

The researchers will purchase 2.25 tons emissions.

I will get $0.

Next

Figure 21: The comprehension screen for the EXT task.



Round 1/11

Click here to re-read the instructions.

In this round: choosing Option A reduces CO2 emissions by **1.5 metric ton(s)**. This is equivalent to the emissions produced by a typical car used for commuting over a period of **24 week(s)**.

Option A: (Reduction of CO2 emissions)		**Option B:** (Monetary payment for yourself)
Reduce CO2 emissions by the amount produced by a commuting car over **24 week(s)** (**1.5 ton(s)** of emissions).		Gain **$1**
		Gain **$2**
		Gain **$3**
		Gain **$4**
		Gain **$5**
		Gain **$6**
		Gain **$7**
		Gain **$8**
		Gain **$9**
		Gain **$10**
		Gain **$11**
		Gain **$12**
		Gain **$13**
		Gain **$14**
		Gain **$15**
		Gain **$16**
		Gain **$17**
		Gain **$18**
		Gain **$19**

How certain are you that you actually value a reduction of CO2 emissions of **1.5 metric tons** as much as a monetary gain somewhere between **$5** and **$6**?

Very uncertain **Completely certain**

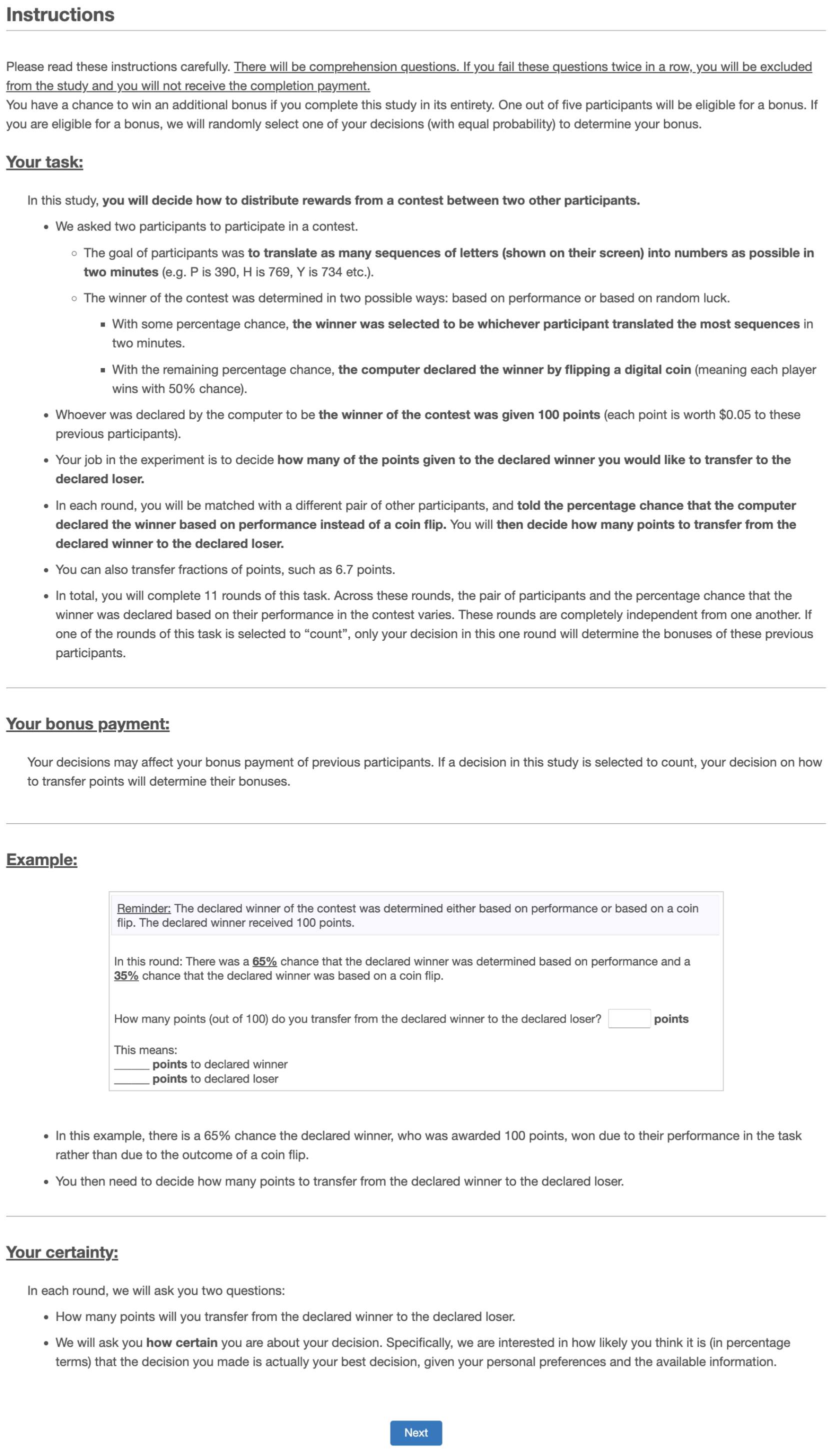
0% 25% 50% 75% 100%

68 %

Next

Figure 22: The decision screen for the EXT task.

D.4 FAI



Instructions

Please read these instructions carefully. There will be comprehension questions. If you fail these questions twice in a row, you will be excluded from the study and you will not receive the completion payment.
You have a chance to win an additional bonus if you complete this study in its entirety. One out of five participants will be eligible for a bonus. If you are eligible for a bonus, we will randomly select one of your decisions (with equal probability) to determine your bonus.

Your task:

In this study, **you will decide how to distribute rewards from a contest between two other participants.**

- We asked two participants to participate in a contest.
  - The goal of participants was **to translate as many sequences of letters (shown on their screen) into numbers as possible in two minutes** (e.g. P is 390, H is 769, Y is 734 etc.).
  - The winner of the contest was determined in two possible ways: based on performance or based on random luck.
    - With some percentage chance, **the winner was selected to be whichever participant translated the most sequences** in two minutes.
    - With the remaining percentage chance, **the computer declared the winner by flipping a digital coin** (meaning each player wins with 50% chance).
- Whoever was declared by the computer to be **the winner of the contest was given 100 points** (each point is worth $0.05 to these previous participants).
- Your job in the experiment is to decide **how many of the points given to the declared winner you would like to transfer to the declared loser.**
- In each round, you will be matched with a different pair of other participants, and **told the percentage chance that the computer declared the winner based on performance instead of a coin flip.** You will **then decide how many points to transfer from the declared winner to the declared loser.**
- You can also transfer fractions of points, such as 6.7 points.
- In total, you will complete 11 rounds of this task. Across these rounds, the pair of participants and the percentage chance that the winner was declared based on their performance in the contest varies. These rounds are completely independent from one another. If one of the rounds of this task is selected to “count”, only your decision in this one round will determine the bonuses of these previous participants.

Your bonus payment:

Your decisions may affect your bonus payment of previous participants. If a decision in this study is selected to count, your decision on how to transfer points will determine their bonuses.

Example:

Reminder: The declared winner of the contest was determined either based on performance or based on a coin flip. The declared winner received 100 points.

In this round: There was a **65%** chance that the declared winner was determined based on performance and a **35%** chance that the declared winner was based on a coin flip.

How many points (out of 100) do you transfer from the declared winner to the declared loser? ______ **points**

This means:
______ **points** to declared winner
______ **points** to declared loser

- In this example, there is a 65% chance the declared winner, who was awarded 100 points, won due to their performance in the task rather than due to the outcome of a coin flip.
- You then need to decide how many points to transfer from the declared winner to the declared loser.

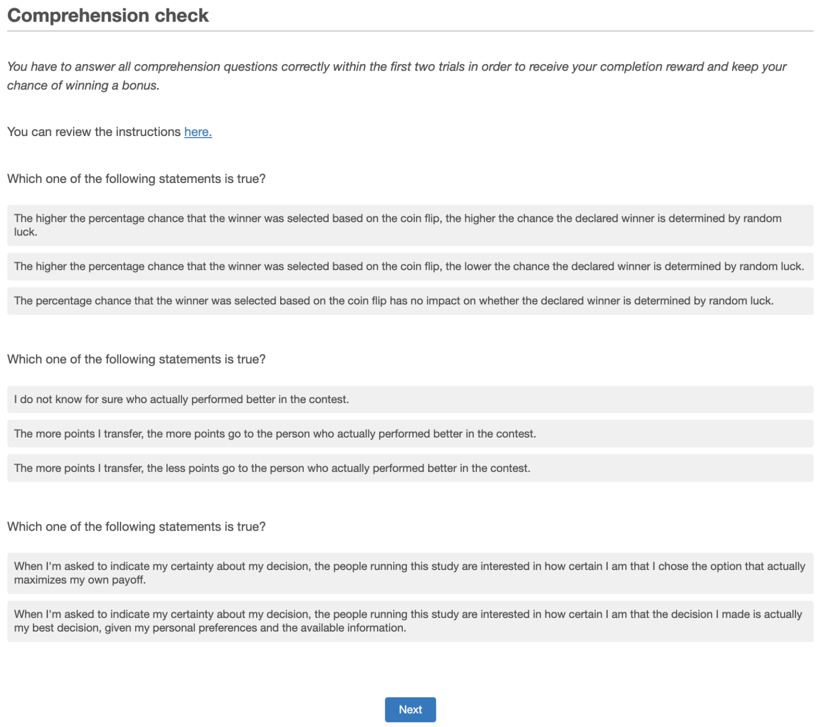
Your certainty:

In each round, we will ask you two questions:

- How many points will you transfer from the declared winner to the declared loser.
- We will ask you **how certain** you are about your decision. Specifically, we are interested in how likely you think it is (in percentage terms) that the decision you made is actually your best decision, given your personal preferences and the available information.

Next

Figure 23: The instruction screen for the FAI task.



Comprehension check

You have to answer all comprehension questions correctly within the first two trials in order to receive your completion reward and keep your chance of winning a bonus.

You can review the instructions here.

Which one of the following statements is true?

The higher the percentage chance that the winner was selected based on the coin flip, the higher the chance the declared winner is determined by random luck.

The higher the percentage chance that the winner was selected based on the coin flip, the lower the chance the declared winner is determined by random luck.

The percentage chance that the winner was selected based on the coin flip has no impact on whether the declared winner is determined by random luck.

Which one of the following statements is true?

I do not know for sure who actually performed better in the contest.

The more points I transfer, the more points go to the person who actually performed better in the contest.

The more points I transfer, the less points go to the person who actually performed better in the contest.

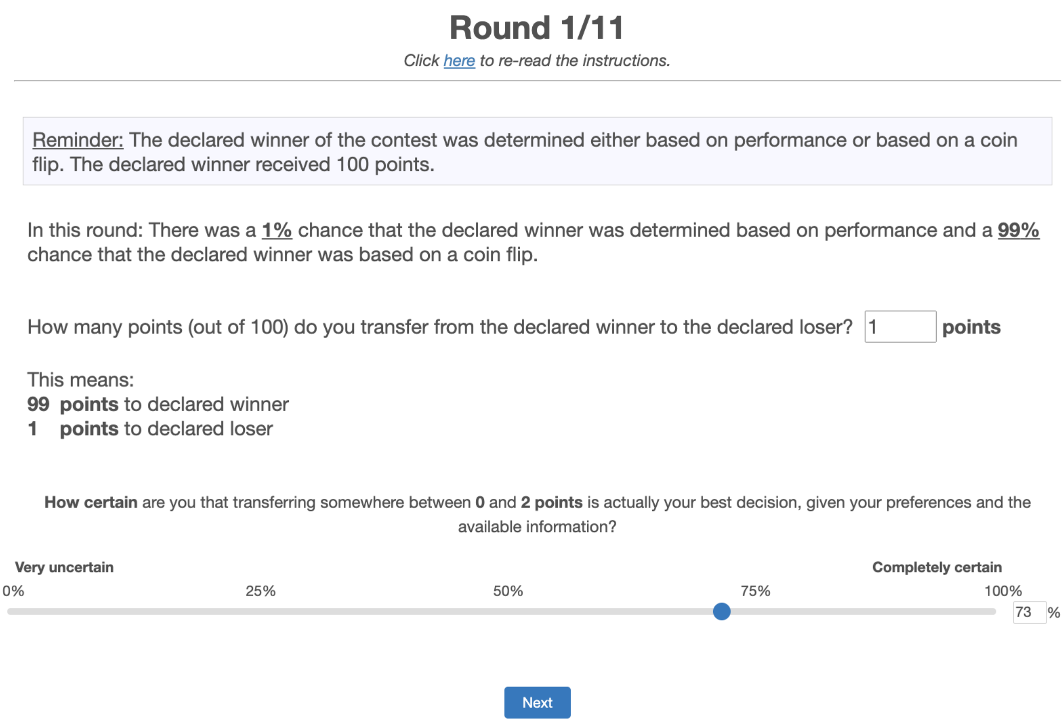
Which one of the following statements is true?

When I'm asked to indicate my certainty about my decision, the people running this study are interested in how certain I am that I chose the option that actually maximizes my own payoff.

When I'm asked to indicate my certainty about my decision, the people running this study are interested in how certain I am that the decision I made is actually my best decision, given my personal preferences and the available information.

Next

Figure 24: The comprehension screen for the FAI task.



Round 1/11

Click here to re-read the instructions.

Reminder: The declared winner of the contest was determined either based on performance or based on a coin flip. The declared winner received 100 points.

In this round: There was a **1%** chance that the declared winner was determined based on performance and a **99%** chance that the declared winner was based on a coin flip.

How many points (out of 100) do you transfer from the declared winner to the declared loser? 1 **points**

This means:
99 **points** to declared winner
1 **points** to declared loser

How certain are you that transferring somewhere between **0** and **2 points** is actually your best decision, given your preferences and the available information?

Very uncertain **Completely certain**

0% 25% 50% 75% 100%

73 %

Next

Figure 25: The decision screen for the FAI task.

D.5 IND

Instructions

Please read these instructions carefully. <u>There will be comprehension questions. If you fail these questions twice in a row, you will be excluded from the study and you will not receive the completion payment.</u>
You have a chance to win an additional bonus if you complete this study in its entirety. One out of five participants will be eligible for a bonus. If you are eligible for a bonus, we will randomly select one of your decisions (with equal probability) to determine your bonus.

<u>Your task:</u>

In this study, **the computer will flip a digital coin which may land on Heads or Tails.**

With **50%** chance: **Heads**
With **50%** chance: **Tails**

- If this study is selected for bonus payment, you will guess whether the coin landed Heads or Tails. If your guess is correct, you will be paid a **$5 bonus.**
- You will have the chance **to obtain information that may help you make an informed guess about the coin flip.**
  - The information comes in the form of a **hint**, such as "The coin came up Heads."
  - The hint is not always correct but instead has an **accuracy rate**: the percent chance that the hint correctly states the outcome of the coin flip.
  - This accuracy rate is always between 50% and 100%.
    - If it is **50%:** The hint is **equally likely to be right or wrong.** This means that if you follow the hint, your guess will be **no more accurate than if you had guessed randomly.**
    - If it is **100%:** The hint is **always correct.** This means that if you follow the hint, your guess **is guaranteed to be correct**.
    - If it is greater than 50% but less than 100%, the hint is **more likely to be right than wrong.**
- In each round, we will **tell you what the accuracy rate of the hint is.** You will then indicate how much you would at most be willing to pay, out of a budget of $5, to actually receive the hint. As explained in greater detail below, the more you are willing to pay, the more likely it is that you actually receive the hint in the event that this round is selected for payment.
- In total, you will complete 11 rounds of this task. Across these rounds, the accuracy rate of the hint varies. These rounds are completely independent from one another. If one of the rounds of this task is selected to determine your bonus, only your decision in this one round will determine your bonus.

<u>Your bonus payment:</u>

Your decisions may affect your bonus payment. If a round in this study is selected for payment, you will be asked to guess the coin flip for a $5 bonus. Prior to making your guess, you may receive a hint, depending on how much you indicate you are willing to pay for it. This works as follows:

- You will be given a budget of $5, and the computer will randomly select a price between $0 and $5.
- If the price selected by the computer is lower than your stated willingness to pay for the hint, you will receive the hint, and the price selected by the computer will be subtracted from your budget. Then, your bonus payment will be your remaining budget plus $5 or $0, depending on whether you are able to correctly guess the side the coin landed on.
- If the price selected by the computer is higher than your stated willingness to pay for the hint, you will not receive the hint. Then, your bonus payment will be your budget plus $5 or $0, depending on whether you are able to correctly guess the side the coin landed on.
- This procedure may seem complicated, but all it means is that **it is in your best interest to truthfully indicate how much you would at most pay for the hint, and to make you best guess whether the coin came up Heads or Tails.**

<u>Example:</u>

<u>Reminder:</u> The computer flipped a coin, and if this round is selected for payment, you will receive $5 for correctly guessing whether the coin landed Heads or Tails. You can purchase a hint about which side the coin landed on.
- The hint has an accuracy rate between 50% and 100%.
- 100% means the hint is always correct.
- 50% means the hint is equally likely to be correct or incorrect (contains no new information).

In this round: The hint has an accuracy rate of **<u>70%</u>**.
→ This means that if you follow the hint, your guess will have a **<u>70%</u>** chance of being correct, and a **<u>30%</u>** chance of being incorrect.

How much (out of a budget of $5) are you at most willing to pay for the hint? **$**

- In this example, the hint has an accuracy rate of 70%. This means that if the coin flip landed on Heads, there is a 70% chance the hint will correctly say Heads, and if the coin flip landed Tails, there is a 70% chance the hint will correctly say Tails.
- You would then indicate how much you would at most be willing to pay for the hint.
- If this task is selected for payment, the computer will determine whether you receive the hint, following the procedure described above. You would then state your guess whether the coin came up Heads or Tails.

<u>Your certainty:</u>

In each round, we will ask you two questions:

- You will decide how much you are willing to pay for the hint.
- We will ask you **how certain** you are about your decision. Specifically, we are interested in how likely you think it is (in percentage terms) that your decision actually reflects how much you value the hint, given your personal preferences and the available information.

Next

Figure 26: The instruction screen for the IND task.

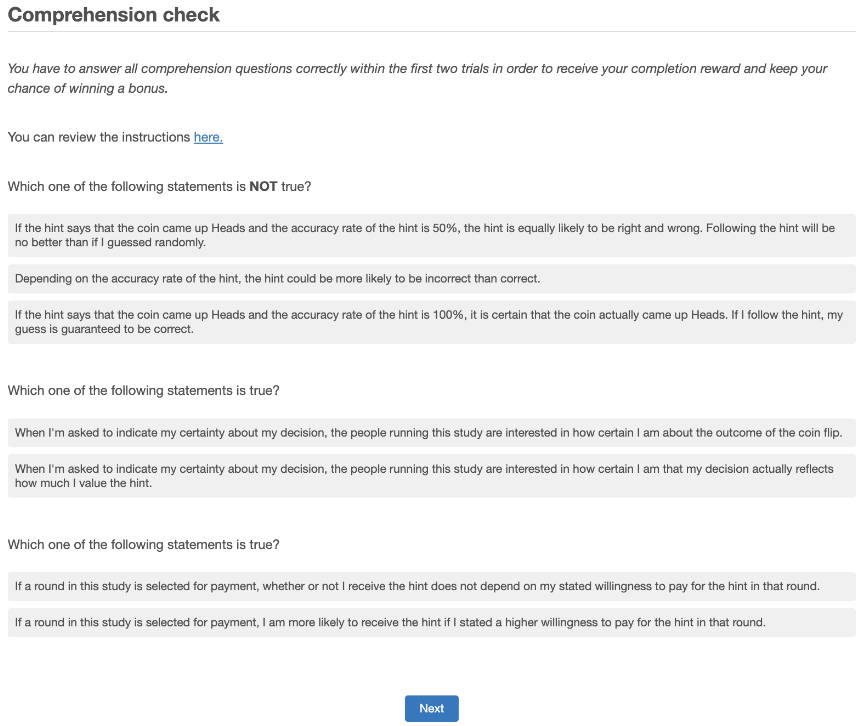


Figure 27: The comprehension screen for the IND task.

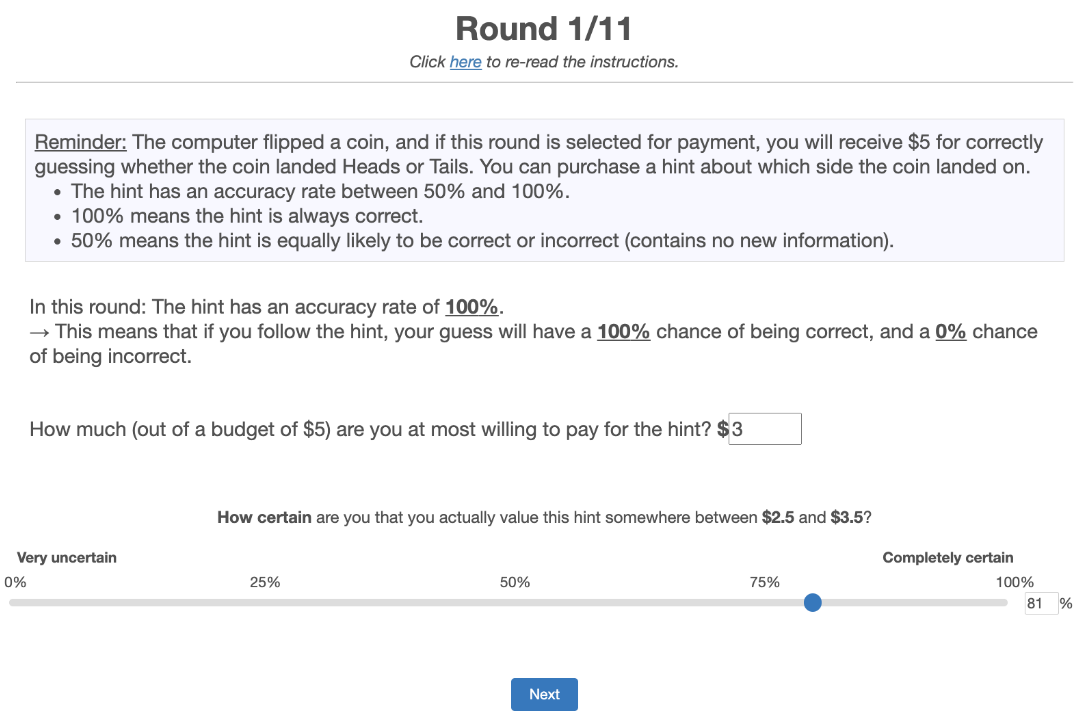
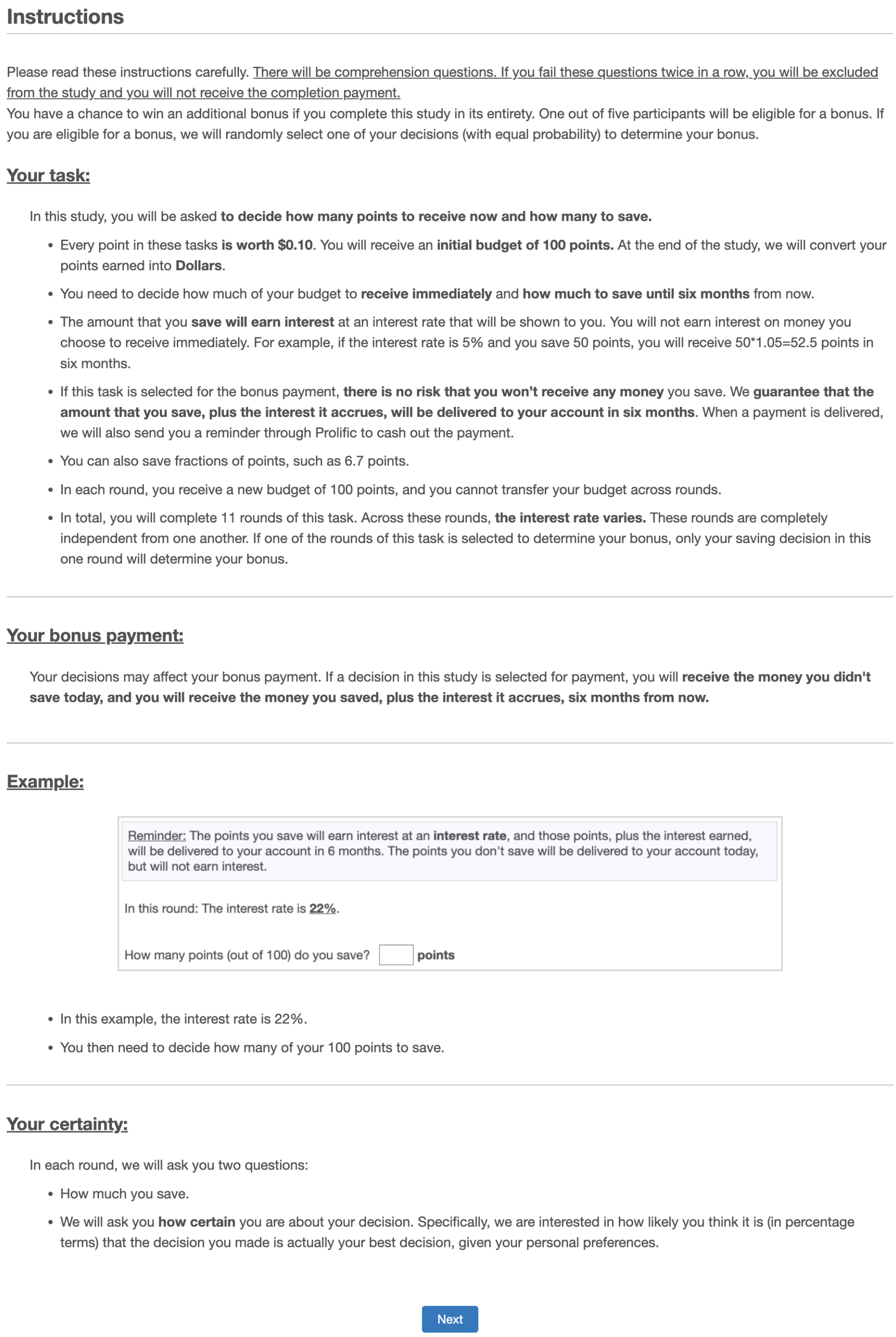


Figure 28: The decision screen for the IND task.

D.6 SAV



Instructions

Please read these instructions carefully. <u>There will be comprehension questions. If you fail these questions twice in a row, you will be excluded from the study and you will not receive the completion payment.</u>
You have a chance to win an additional bonus if you complete this study in its entirety. One out of five participants will be eligible for a bonus. If you are eligible for a bonus, we will randomly select one of your decisions (with equal probability) to determine your bonus.

<u>Your task:</u>

In this study, you will be asked **to decide how many points to receive now and how many to save.**

- Every point in these tasks **is worth $0.10**. You will receive an **initial budget of 100 points.** At the end of the study, we will convert your points earned into **Dollars**.
- You need to decide how much of your budget to **receive immediately** and **how much to save until six months** from now.
- The amount that you **save will earn interest** at an interest rate that will be shown to you. You will not earn interest on money you choose to receive immediately. For example, if the interest rate is 5% and you save 50 points, you will receive 50*1.05=52.5 points in six months.
- If this task is selected for the bonus payment, **there is no risk that you won't receive any money** you save. We **guarantee that the amount that you save, plus the interest it accrues, will be delivered to your account in six months**. When a payment is delivered, we will also send you a reminder through Prolific to cash out the payment.
- You can also save fractions of points, such as 6.7 points.
- In each round, you receive a new budget of 100 points, and you cannot transfer your budget across rounds.
- In total, you will complete 11 rounds of this task. Across these rounds, **the interest rate varies.** These rounds are completely independent from one another. If one of the rounds of this task is selected to determine your bonus, only your saving decision in this one round will determine your bonus.

<u>Your bonus payment:</u>

Your decisions may affect your bonus payment. If a decision in this study is selected for payment, you will **receive the money you didn't save today, and you will receive the money you saved, plus the interest it accrues, six months from now.**

<u>Example:</u>

<u>Reminder:</u> The points you save will earn interest at an **interest rate**, and those points, plus the interest earned, will be delivered to your account in 6 months. The points you don't save will be delivered to your account today, but will not earn interest.

In this round: The interest rate is **<u>22%</u>**.

How many points (out of 100) do you save? **points**

- In this example, the interest rate is 22%.
- You then need to decide how many of your 100 points to save.

<u>Your certainty:</u>

In each round, we will ask you two questions:

- How much you save.
- We will ask you **how certain** you are about your decision. Specifically, we are interested in how likely you think it is (in percentage terms) that the decision you made is actually your best decision, given your personal preferences.

Next

Figure 29: The instruction screen for the SAV task.

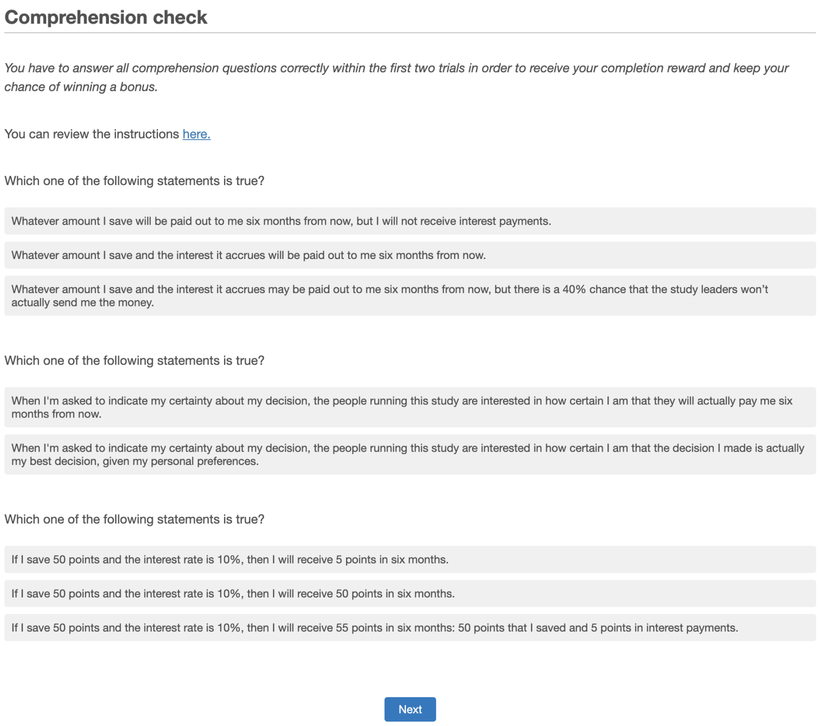


Figure 30: The comprehension screen for the SAV task.

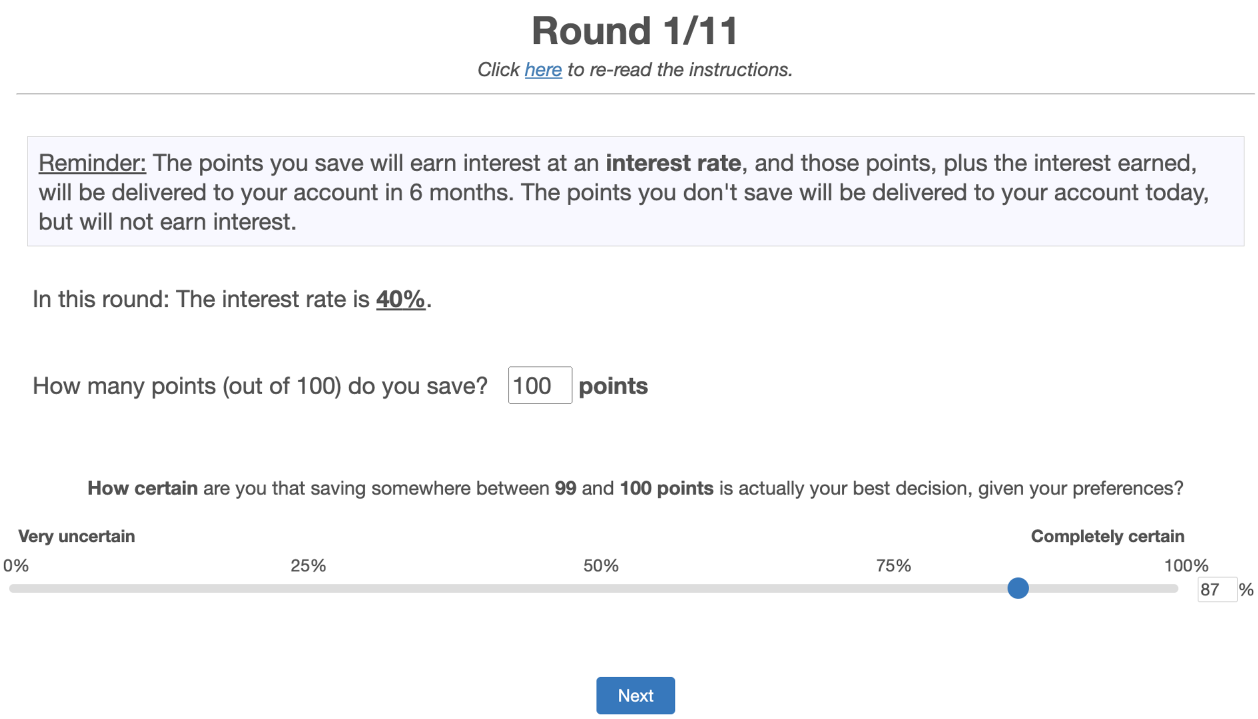


Figure 31: The decision screen for the SAV task.

D.7 SEA

Instructions

Please read these instructions carefully. <u>There will be comprehension questions. If you fail these questions twice in a row, you will be excluded from the study and you will not receive the completion payment.</u>
You have a chance to win an additional bonus if you complete this study in its entirety. One out of five participants will be eligible for a bonus. If you are eligible for a bonus, we will randomly select one of your decisions (with equal probability) to determine your bonus.

<u>Your task:</u>

In this study, the computer **will repeatedly draw poker chips from a digital bag** to determine your score (which will determine your bonus). You need to decide for how long you want the computer to keep drawing.

- The bag contains 100 poker chips, each worth a different number of points.
  - The least valuable chip in the bag is worth 1 point and the most valuable is worth 100 points. There is a chip in the bag worth each point value in-between.
- Your score (which determines your bonus) is given by

  Score = Highest chip value drawn - Total cost of drawing chips.
- The computer will **repeatedly draw a poker chip from the bag (replacing the chip in the bag after each draw) until it gets one that is higher than some minimum threshold.** Your job is to tell the computer **what you would like this threshold to be: the first chip that the computer draws that is at least as large as the threshold will determine your base score.**
- However, **each time** the computer draws a chip from the bag, it will **charge you some cost that will be subtracted** from your base score to determine your overall score.
- Your task is to set the threshold. Setting this threshold has two effects:
  - First, **the higher the threshold you set, the more valuable the chip that will determine your base score, on average.**
  - Second, **the higher your threshold, the larger the number of times (on average)** the computer will have to draw from the bag before getting a chip that is large enough, **meaning a higher cost.**
- In each round, **you will be told the cost** the computer will charge each time it draws a chip from the bag. You will then decide on the threshold value (between 1 and 100) the computer uses to stop drawing chips from the bag.
- In total, you will complete 11 rounds of this task. Across these rounds, the cost charged per draw from the bag varies. These rounds are completely independent from one another. If one of the rounds of this task is selected to determine your bonus, only your decision in this one round will determine your bonus.

<u>Your bonus payment:</u>

Your decisions in this study may affect your bonus payment. If a decision in this study is selected for payment, you will receive $10 if your decision is within +/- 1 points of the **best decision** which is the **threshold that leads to the highest score, on average.** Specifically, we will have the computer make the full set of draws 1 million times and calculate the average score for every possible threshold you could have chose. If the threshold you chose was within +/- 1 points of the choice that maximized the score in these computer simulations, you will earn a $10 bonus. This procedure may seem complicated, but it simply means that you should choose the threshold that you think will earn you the highest score, on average.

<u>Example:</u>

<u>Reminder:</u> A bag contains 100 poker chips, which include each value between 1 and 100 points once. The computer will draw chips (replacing each time) until it draws one worth at least as much as your threshold, and pay you the value of this final chip. A higher threshold means:
- The final chip will tend to have a higher value.
- You will tend to pay a higher cost because the computer draws more times.

In this round: The computer charges you **<u>3 points</u>** each time it draws a chip.

What threshold (between 1 and 100) should the computer use to decide when to stop drawing chips?
points

- In this example, the computer will charge you 3 points every time it draws a poker chip from the bag.
- You then need to decide on the threshold, between 1 and 100, that the computer should use to stop drawing chips from the bag.

<u>Your certainty:</u>

In each round, we will ask you two questions:

- You will decide on the threshold the computer can use to stop drawing chips from the bag.
- We will ask you **how certain** you are about your decision. Specifically, we are interested in how likely you think it is (in percentage terms) that the decision you made is actually the best decision, by which we mean the decision that maximizes your bonus.

Next

Figure 32: The instruction screen for the SEA task.

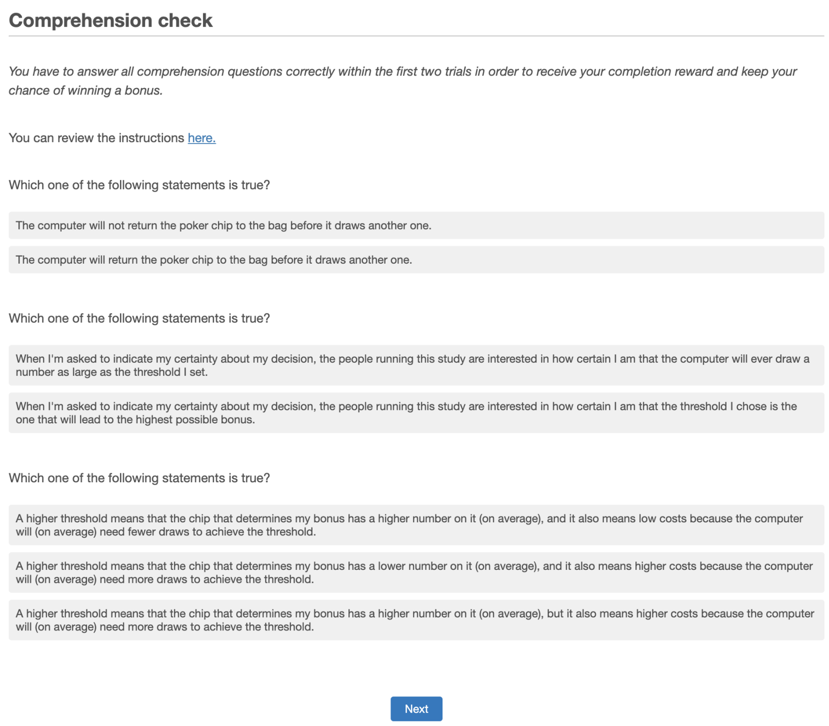


Figure 33: The comprehension screen for the SEA task.

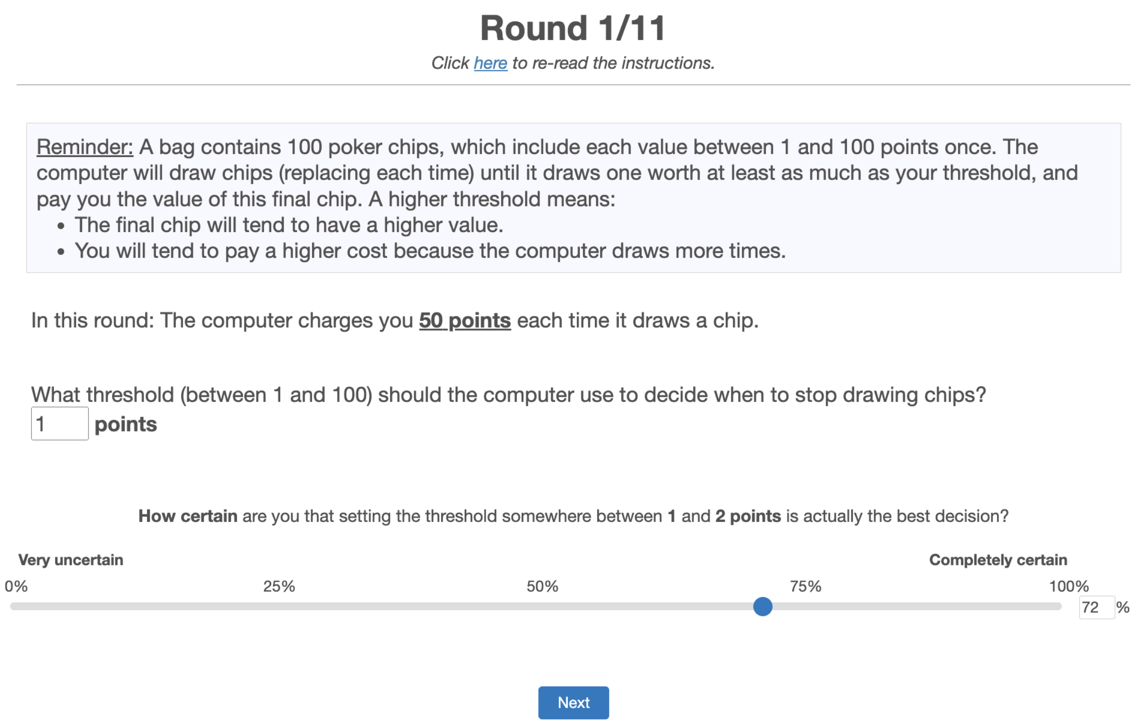
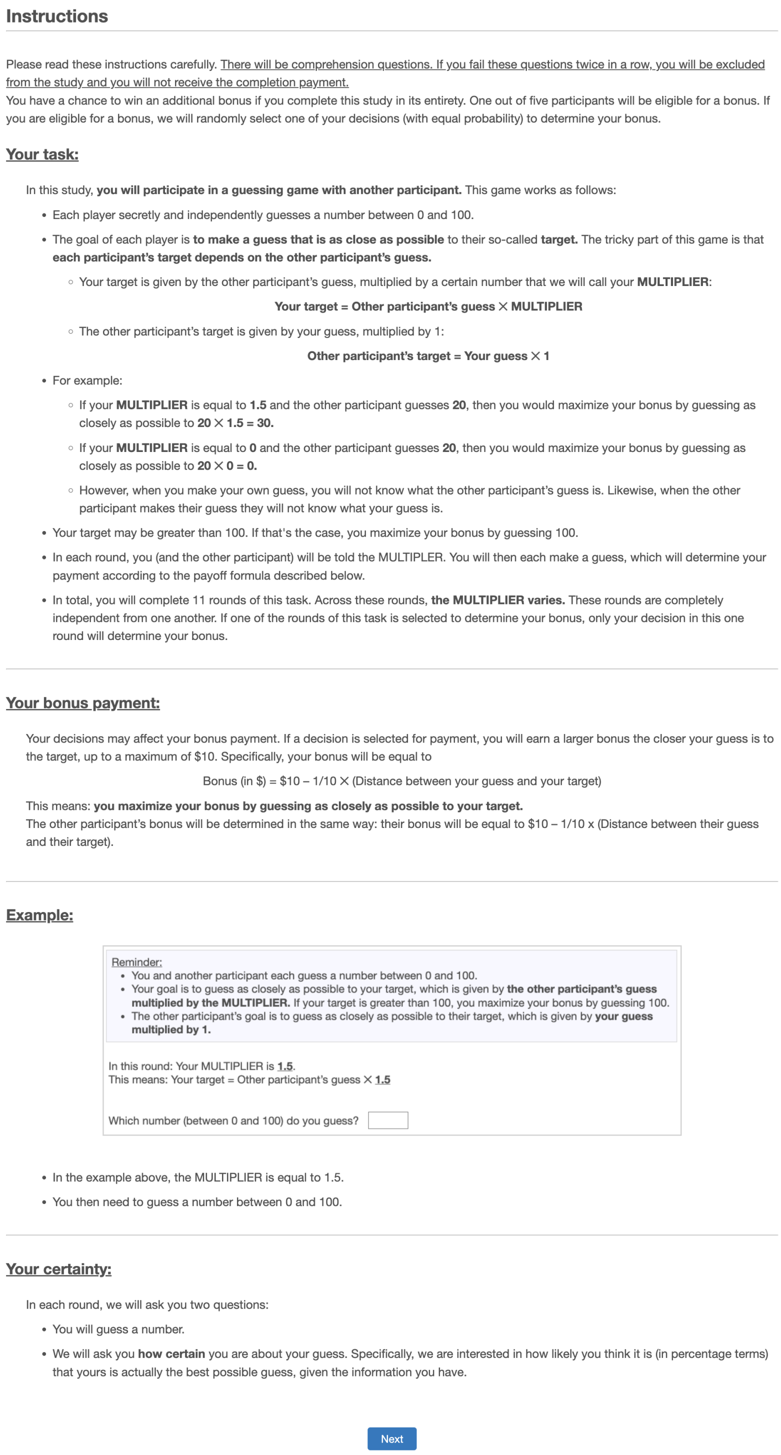


Figure 34: The decision screen for the SEA task.

D.8 GUE



Instructions

Please read these instructions carefully. There will be comprehension questions. If you fail these questions twice in a row, you will be excluded from the study and you will not receive the completion payment.
You have a chance to win an additional bonus if you complete this study in its entirety. One out of five participants will be eligible for a bonus. If you are eligible for a bonus, we will randomly select one of your decisions (with equal probability) to determine your bonus.

Your task:

In this study, **you will participate in a guessing game with another participant.** This game works as follows:

- Each player secretly and independently guesses a number between 0 and 100.
- The goal of each player is **to make a guess that is as close as possible** to their so-called **target.** The tricky part of this game is that **each participant's target depends on the other participant's guess.**
  - Your target is given by the other participant's guess, multiplied by a certain number that we will call your **MULTIPLIER**:

    Your target = Other participant's guess × MULTIPLIER
  - The other participant's target is given by your guess, multiplied by 1:

    Other participant's target = Your guess × 1
- For example:
  - If your **MULTIPLIER** is equal to **1.5** and the other participant guesses **20**, then you would maximize your bonus by guessing as closely as possible to **20 × 1.5 = 30.**
  - If your **MULTIPLIER** is equal to **0** and the other participant guesses **20**, then you would maximize your bonus by guessing as closely as possible to **20 × 0 = 0.**
  - However, when you make your own guess, you will not know what the other participant's guess is. Likewise, when the other participant makes their guess they will not know what your guess is.
- Your target may be greater than 100. If that's the case, you maximize your bonus by guessing 100.
- In each round, you (and the other participant) will be told the MULTIPLER. You will then each make a guess, which will determine your payment according to the payoff formula described below.
- In total, you will complete 11 rounds of this task. Across these rounds, **the MULTIPLIER varies.** These rounds are completely independent from one another. If one of the rounds of this task is selected to determine your bonus, only your decision in this one round will determine your bonus.

Your bonus payment:

Your decisions may affect your bonus payment. If a decision is selected for payment, you will earn a larger bonus the closer your guess is to the target, up to a maximum of $10. Specifically, your bonus will be equal to

Bonus (in $) = $10 – 1/10 × (Distance between your guess and your target)

This means: **you maximize your bonus by guessing as closely as possible to your target.**
The other participant's bonus will be determined in the same way: their bonus will be equal to $10 – 1/10 x (Distance between their guess and their target).

Example:

Reminder:
- You and another participant each guess a number between 0 and 100.
- Your goal is to guess as closely as possible to your target, which is given by **the other participant's guess multiplied by the MULTIPLIER.** If your target is greater than 100, you maximize your bonus by guessing 100.
- The other participant's goal is to guess as closely as possible to their target, which is given by **your guess multiplied by 1.**

In this round: Your MULTIPLIER is **1.5**.
This means: Your target = Other participant's guess × **1.5**

Which number (between 0 and 100) do you guess?

- In the example above, the MULTIPLIER is equal to 1.5.
- You then need to guess a number between 0 and 100.

Your certainty:

In each round, we will ask you two questions:

- You will guess a number.
- We will ask you **how certain** you are about your guess. Specifically, we are interested in how likely you think it is (in percentage terms) that yours is actually the best possible guess, given the information you have.

Next

Figure 35: The instruction screen for the GUE task.

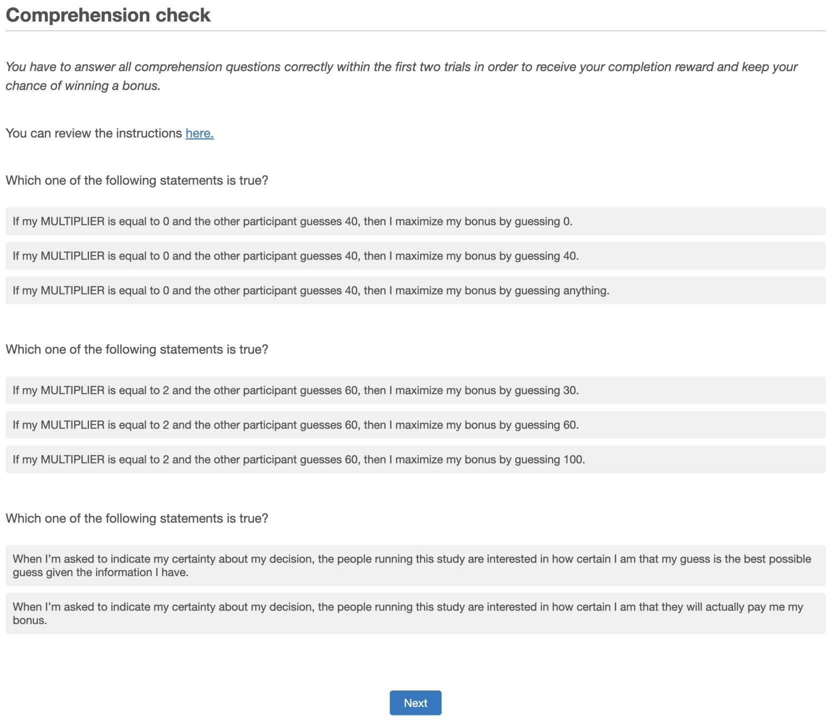


Figure 36: The comprehension screen for the GUE task.

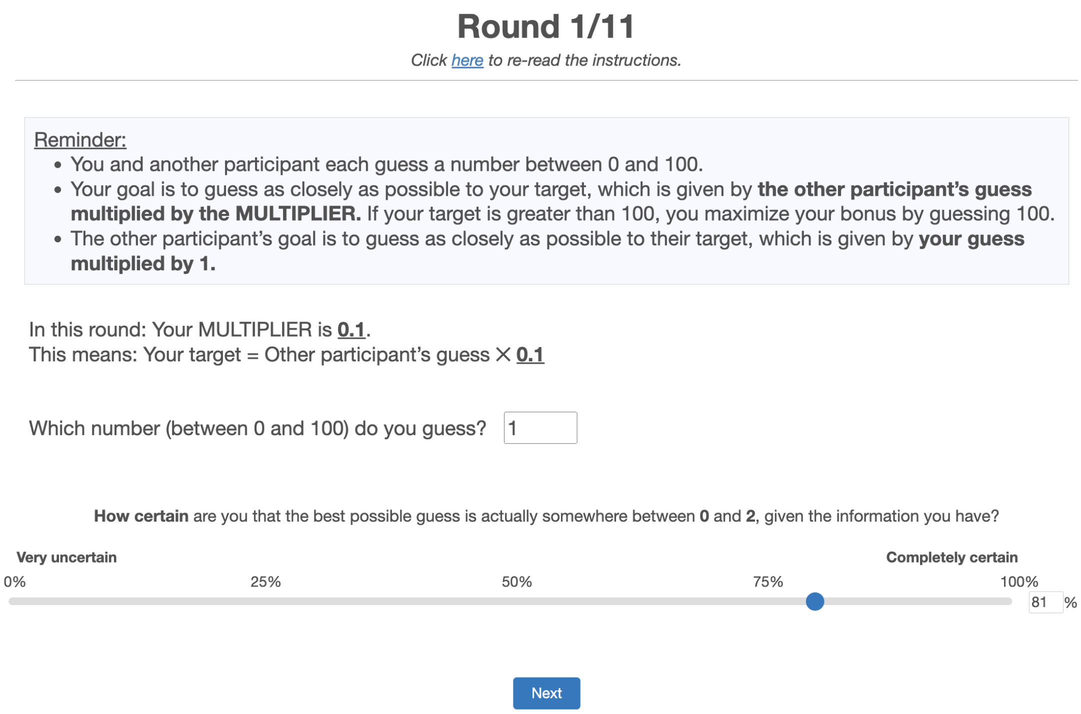


Figure 37: The decision screen for the GUE task.

D.9 GPT

Instructions

Please read these instructions carefully. There will be comprehension questions. If you fail these questions twice in a row, you will be excluded from the study and you will not receive the completion payment.

Your task:

In this study, **you will make a series of hypothetical decisions about how much you would be willing to pay for a specific quantity of a given product.**

- Imagine that you are **given a budget of $30**. You will then see **a description of the product and the quantity you would receive.**
- Your task is to indicate the **precise dollar amount (between $0 and $30) that you would at most be willing to pay.**
- Imagine that these items would be shipped to your home address without any additional shipping costs, and that you get to keep whatever amount of the $30 you don't spend.
- In each round, you will be told **what the product is and which quantity is for sale.** You will then decide how much **you would at most be willing to pay** by indicating a dollar amount.
- You can also enter digits, such as $6.78.
- In total, you will complete 11 rounds of this task. Across these rounds, the quantity of the product that is for sale varies. These rounds are completely independent from one another.

Example:

In this round:

6 packs of

Pasta: Premium Organic Penne
Italian Macaroni product made from organic durum wheat semolina
1 pound per pack

How much (out of your budget of $30) are you at most willing to pay for this product?

My maximal willingness to pay for this product is $

- In this example, you evaluate 6 packs of organic penne.
- You then need to decide how much you would at most be willing to pay for this product.

Your certainty:

In each round, we will ask you two questions:

- How much would you at most be willing to pay. We will use this answer to determine how much you value the product.
- We will ask you **how certain** you are about your decisions. Specifically, we are interested in how likely you think it is (in percentage terms) that your decisions actually reflect how much you value the product, given your personal preferences.

Next

Figure 38: The instruction screen for the GPT task.

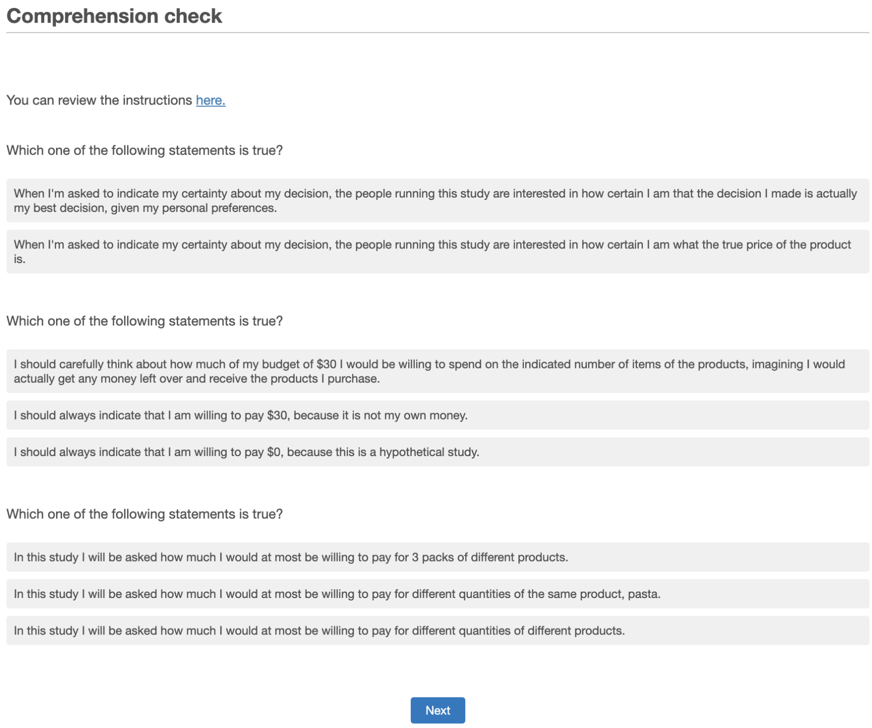


Figure 39: The comprehension screen for the GPT task.

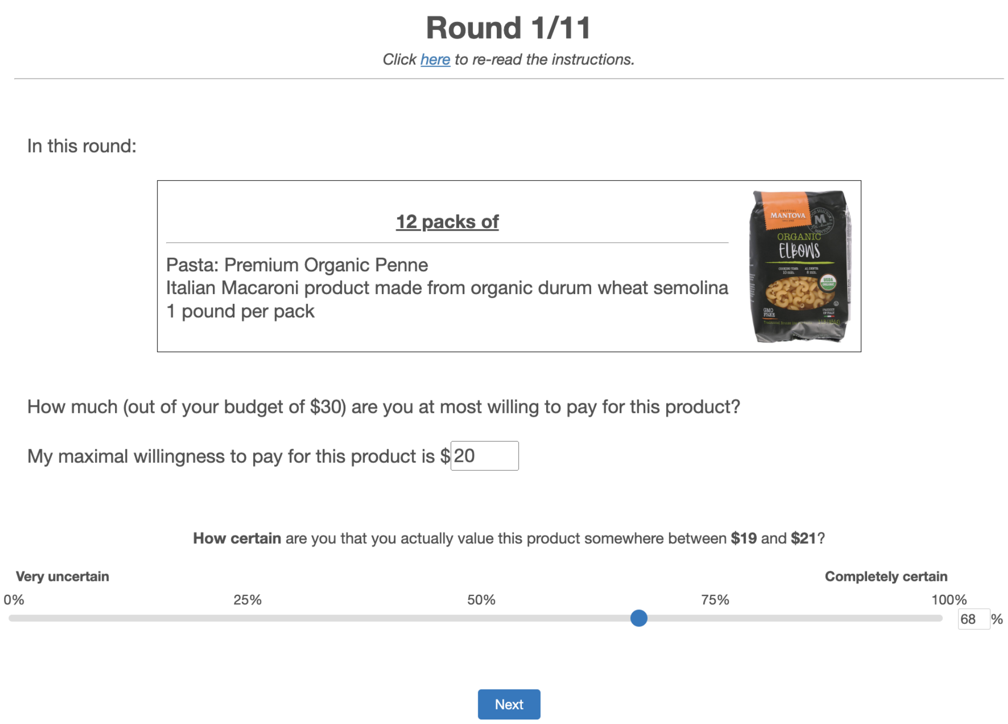


Figure 40: The decision screen for the GPT task.

D.10 PAC

Instructions

Please read these instructions carefully. There will be comprehension questions. If you fail these questions twice in a row, you will be excluded from the study and you will not receive the completion payment.
You have a chance to win an additional bonus if you complete this study in its entirety. One out of five participants will be eligible for a bonus. If you are eligible for a bonus, we will randomly select one of your decisions (with equal probability) to determine your bonus.

Your task:

In this study, you will **decide whether to participate in a lottery or not.**

- The lottery has two possible outcomes that are **equally likely, i.e. it is a 50-50 lottery.**
- One lottery outcome is a **loss**, the other lottery outcome is a **gain**. If it is a gain, you receive money. If it is a loss, you have to pay money.
- **You have a budget of 100 points** where each point is worth $0.05 in payment to you. The outcome of the lottery will be added to that budget if it is a gain, and subtracted from your budget if it is a loss.
- Your task is to decide **whether or not you want to accept the lottery** (have it played out for you to influence your payment), or reject it.
- Prior to making your decision, you can actually **find out what the randomly drawn lottery outcome is.** You can do so by verifying the correctness of math equations that will be shown to you on your screen. Specifically, 60 addition equations will be shown to you. Each equation is either correct, such as 60+29=89, or incorrect, such as 17+28=41.
    - If **50** equations are **correct** and **10** are **incorrect**, the lottery outcome is a **gain**.
    - If **10** equations are **correct** and **50** are **incorrect**, the lottery outcome is a **loss**.
- In each round, you will be told the two possible outcomes of the lottery, and 60 equations will be shown to you. You will then decide whether to accept or reject the lottery.
- In total, you will complete 11 rounds of this task. Across these rounds, the outcomes of the lottery will vary. These rounds are completely independent from one another. If one of the rounds of this task is selected to determine your bonus, only your decision in this one round will determine your bonus.

Your bonus payment:

Your decisions may affect your bonus. If a round in this study is selected for payment each point is worth $0.05. You will receive your budget of 100 points if you rejected the lottery. If you accepted the lottery, you will receive the sum of the budget and the lottery outcome:

- If the lottery outcome is a **gain**, your bonus will be **larger** than the budget.
- If the lottery outcome is a **loss**, you bonus will be **smaller** than the budget.

Example:

Reminder:
- If 50 equations are correct and 10 are wrong, the lottery outcome is the **gain**.
- If 10 equations are correct and 50 are wrong, the lottery outcome is the **loss**.
- You need to decide whether to accept or reject a lottery.

In this round:

With **50%** chance: **Get 63 points**
With **50%** chance: **Lose 37 points**

46 + 43 = 87	34 + 11 = 46	11 + 2 = 11
62 + 30 = 91	37 + 10 = 48	11 + 22 = 36
8 + 5 = 12	23 + 6 = 31	36 + 51 = 88
14 + 14 = 28	22 + 7 = 26	38 + 3 = 42
44 + 15 = 56	10 + 0 = 13	19 + 12 = 30
44 + 10 = 56	14 + 73 = 88	15 + 3 = 15
18 + 1 = 19	66 + 12 = 80	16 + 20 = 37
37 + 59 = 97	12 + 3 = 15	7 + 94 = 99
12 + 15 = 26	3 + 12 = 18	16 + 0 = 13
10 + 87 = 97	15 + 56 = 73	38 + 63 = 99
23 + 27 = 49	28 + 54 = 82	14 + 15 = 28
58 + 15 = 72	12 + 21 = 31	26 + 2 = 26
22 + 72 = 95	21 + 24 = 44	15 + 1 = 16
49 + 22 = 69	13 + 73 = 85	13 + 1 = 15
33 + 12 = 44	29 + 48 = 74	34 + 10 = 43
20 + 4 = 24	11 + 5 = 13	14 + 0 = 11
55 + 20 = 78	42 + 40 = 82	23 + 69 = 89
15 + 9 = 22	16 + 0 = 14	42 + 15 = 59
6 + 6 = 14	68 + 9 = 74	4 + 6 = 12
9 + 23 = 32	60 + 37 = 97	23 + 25 = 46

Do you accept or reject this lottery?

Accept Reject

- In this example, the possible lottery outcomes are a 63 point gain and a 37 point loss.
- You then need to decide whether to accept or reject the lottery.

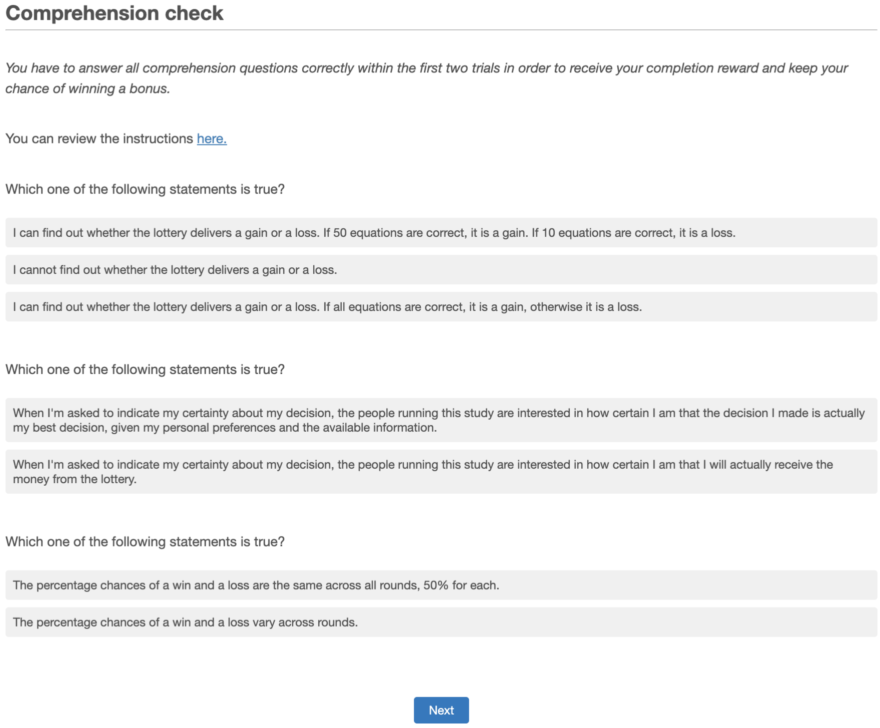
Your certainty:

In each round, we will ask you two questions:

- You will decide to accept or reject the lottery.
- We will ask you **how certain** you are about your decision. Specifically, we are interested in how likely you think it is (in percentage terms) that the decision you made is actually your best decision, given your personal preferences and the available information.

Next

Figure 41: The instruction screen for the PAC task.



Comprehension check

You have to answer all comprehension questions correctly within the first two trials in order to receive your completion reward and keep your chance of winning a bonus.

You can review the instructions here.

Which one of the following statements is true?

I can find out whether the lottery delivers a gain or a loss. If 50 equations are correct, it is a gain. If 10 equations are correct, it is a loss.

I cannot find out whether the lottery delivers a gain or a loss.

I can find out whether the lottery delivers a gain or a loss. If all equations are correct, it is a gain, otherwise it is a loss.

Which one of the following statements is true?

When I'm asked to indicate my certainty about my decision, the people running this study are interested in how certain I am that the decision I made is actually my best decision, given my personal preferences and the available information.

When I'm asked to indicate my certainty about my decision, the people running this study are interested in how certain I am that I will actually receive the money from the lottery.

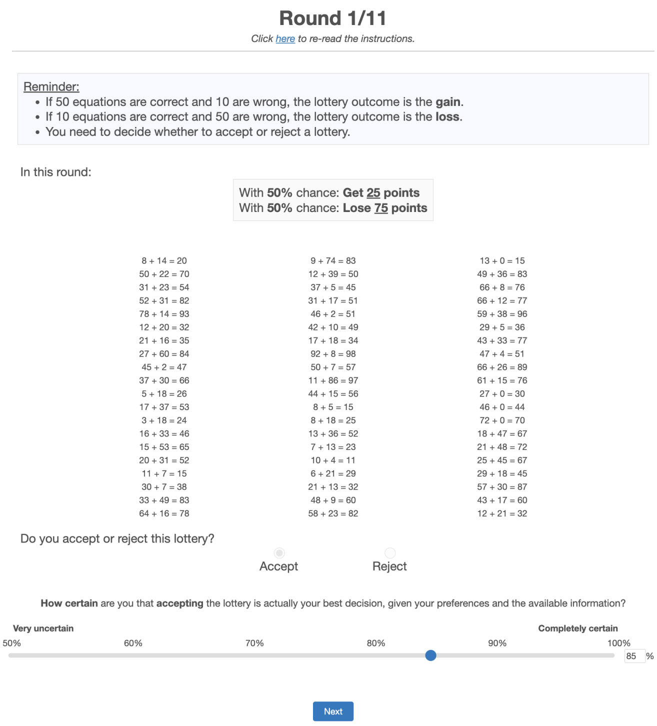
Which one of the following statements is true?

The percentage chances of a win and a loss are the same across all rounds, 50% for each.

The percentage chances of a win and a loss vary across rounds.

Next

Figure 42: The comprehension screen for the PAC task.



Round 1/11

Click here to re-read the instructions.

Reminder:
- If 50 equations are correct and 10 are wrong, the lottery outcome is the **gain**.
- If 10 equations are correct and 50 are wrong, the lottery outcome is the **loss**.
- You need to decide whether to accept or reject a lottery.

In this round:

With **50%** chance: **Get 25 points**
With **50%** chance: **Lose 75 points**

8 + 14 = 20	9 + 74 = 83	13 + 0 = 15
50 + 22 = 70	12 + 39 = 50	49 + 36 = 83
31 + 23 = 54	37 + 5 = 45	66 + 8 = 76
52 + 31 = 82	31 + 17 = 51	66 + 12 = 77
78 + 14 = 93	46 + 2 = 51	59 + 38 = 96
12 + 20 = 32	42 + 10 = 49	29 + 5 = 36
21 + 16 = 35	17 + 18 = 34	43 + 33 = 77
27 + 60 = 84	92 + 8 = 98	47 + 4 = 51
45 + 2 = 47	50 + 7 = 57	66 + 26 = 89
37 + 30 = 66	11 + 86 = 97	61 + 15 = 76
5 + 18 = 26	44 + 15 = 56	27 + 0 = 30
17 + 37 = 53	8 + 5 = 15	46 + 0 = 44
3 + 18 = 24	8 + 18 = 25	72 + 0 = 70
16 + 33 = 46	13 + 36 = 52	18 + 47 = 67
15 + 53 = 65	7 + 13 = 23	21 + 48 = 72
20 + 31 = 52	10 + 4 = 11	25 + 45 = 67
11 + 7 = 15	6 + 21 = 29	29 + 18 = 45
30 + 7 = 38	21 + 13 = 32	57 + 30 = 87
33 + 49 = 83	48 + 9 = 60	43 + 17 = 60
64 + 16 = 78	58 + 23 = 82	12 + 21 = 32

Do you accept or reject this lottery?

Accept Reject

How certain are you that **accepting** the lottery is actually your best decision, given your preferences and the available information?

Very uncertain **Completely certain**

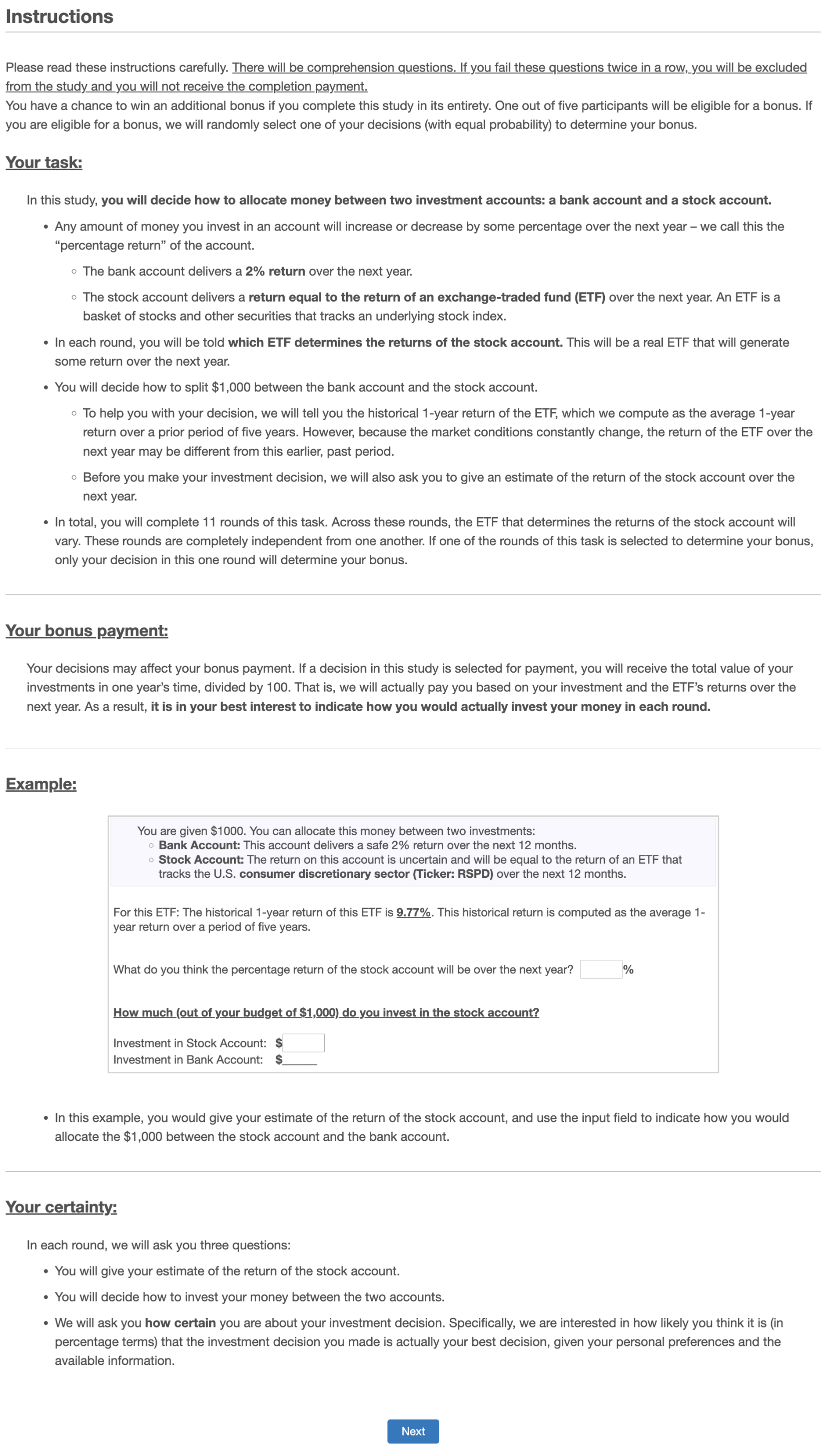
50% 60% 70% 80% 90% 100%

85 %

Next

Figure 43: The decision screen for the PAC task.

D.11 POA



Instructions

Please read these instructions carefully. There will be comprehension questions. If you fail these questions twice in a row, you will be excluded from the study and you will not receive the completion payment.
You have a chance to win an additional bonus if you complete this study in its entirety. One out of five participants will be eligible for a bonus. If you are eligible for a bonus, we will randomly select one of your decisions (with equal probability) to determine your bonus.

Your task:

In this study, **you will decide how to allocate money between two investment accounts: a bank account and a stock account.**

- Any amount of money you invest in an account will increase or decrease by some percentage over the next year – we call this the "percentage return" of the account.
    - The bank account delivers a **2% return** over the next year.
    - The stock account delivers a **return equal to the return of an exchange-traded fund (ETF)** over the next year. An ETF is a basket of stocks and other securities that tracks an underlying stock index.
- In each round, you will be told **which ETF determines the returns of the stock account.** This will be a real ETF that will generate some return over the next year.
- You will decide how to split $1,000 between the bank account and the stock account.
    - To help you with your decision, we will tell you the historical 1-year return of the ETF, which we compute as the average 1-year return over a prior period of five years. However, because the market conditions constantly change, the return of the ETF over the next year may be different from this earlier, past period.
    - Before you make your investment decision, we will also ask you to give an estimate of the return of the stock account over the next year.
- In total, you will complete 11 rounds of this task. Across these rounds, the ETF that determines the returns of the stock account will vary. These rounds are completely independent from one another. If one of the rounds of this task is selected to determine your bonus, only your decision in this one round will determine your bonus.

Your bonus payment:

Your decisions may affect your bonus payment. If a decision in this study is selected for payment, you will receive the total value of your investments in one year's time, divided by 100. That is, we will actually pay you based on your investment and the ETF's returns over the next year. As a result, **it is in your best interest to indicate how you would actually invest your money in each round.**

Example:

You are given $1000. You can allocate this money between two investments:
- **Bank Account:** This account delivers a safe 2% return over the next 12 months.
- **Stock Account:** The return on this account is uncertain and will be equal to the return of an ETF that tracks the U.S. **consumer discretionary sector (Ticker: RSPD)** over the next 12 months.

For this ETF: The historical 1-year return of this ETF is **9.77%**. This historical return is computed as the average 1-year return over a period of five years.

What do you think the percentage return of the stock account will be over the next year? ____ %

How much (out of your budget of $1,000) do you invest in the stock account?

Investment in Stock Account: $ ____
Investment in Bank Account: $____

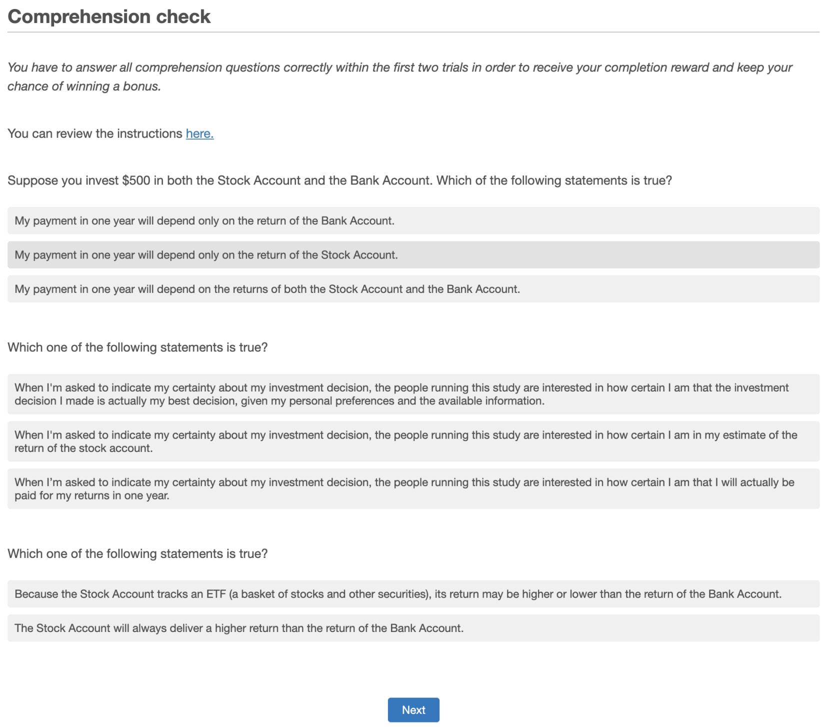
- In this example, you would give your estimate of the return of the stock account, and use the input field to indicate how you would allocate the $1,000 between the stock account and the bank account.

Your certainty:

In each round, we will ask you three questions:
- You will give your estimate of the return of the stock account.
- You will decide how to invest your money between the two accounts.
- We will ask you **how certain** you are about your investment decision. Specifically, we are interested in how likely you think it is (in percentage terms) that the investment decision you made is actually your best decision, given your personal preferences and the available information.

Next

Figure 44: The instruction screen for the POA task.



Comprehension check

You have to answer all comprehension questions correctly within the first two trials in order to receive your completion reward and keep your chance of winning a bonus.

You can review the instructions here.

Suppose you invest $500 in both the Stock Account and the Bank Account. Which of the following statements is true?

- My payment in one year will depend only on the return of the Bank Account.
- My payment in one year will depend only on the return of the Stock Account.
- My payment in one year will depend on the returns of both the Stock Account and the Bank Account.

Which one of the following statements is true?

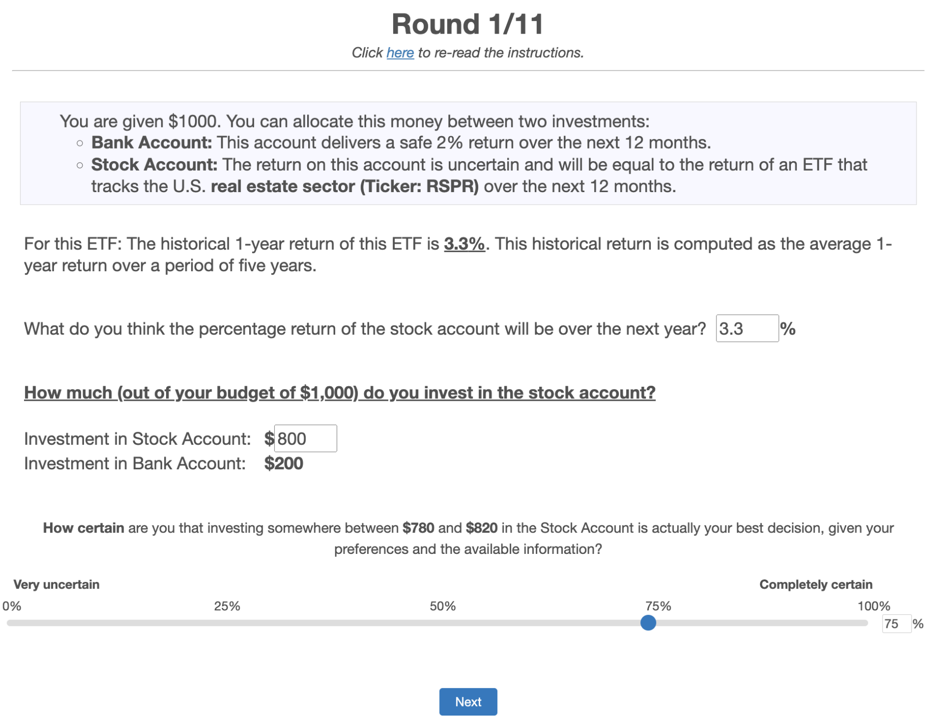
- When I'm asked to indicate my certainty about my investment decision, the people running this study are interested in how certain I am that the investment decision I made is actually my best decision, given my personal preferences and the available information.
- When I'm asked to indicate my certainty about my investment decision, the people running this study are interested in how certain I am in my estimate of the return of the stock account.
- When I'm asked to indicate my certainty about my investment decision, the people running this study are interested in how certain I am that I will actually be paid for my returns in one year.

Which one of the following statements is true?

- Because the Stock Account tracks an ETF (a basket of stocks and other securities), its return may be higher or lower than the return of the Bank Account.
- The Stock Account will always deliver a higher return than the return of the Bank Account.

Next

Figure 45: The comprehension screen for the POA task.



Round 1/11

Click here to re-read the instructions.

You are given $1000. You can allocate this money between two investments:
- **Bank Account:** This account delivers a safe 2% return over the next 12 months.
- **Stock Account:** The return on this account is uncertain and will be equal to the return of an ETF that tracks the U.S. **real estate sector (Ticker: RSPR)** over the next 12 months.

For this ETF: The historical 1-year return of this ETF is **3.3%**. This historical return is computed as the average 1-year return over a period of five years.

What do you think the percentage return of the stock account will be over the next year? 3.3 **%**

How much (out of your budget of $1,000) do you invest in the stock account?

Investment in Stock Account: **$**800
Investment in Bank Account: **$200**

How certain are you that investing somewhere between **$780** and **$820** in the Stock Account is actually your best decision, given your preferences and the available information?

Very uncertain **Completely certain**
0% 25% 50% 75% 100% 75 %

Next

Figure 46: The decision screen for the POA task.

D.12 PRD

Instructions

Please read these instructions carefully. There will be comprehension questions. If you fail these questions twice in a row, you will be excluded from the study and you will not receive the completion payment.
You have a chance to win an additional bonus if you complete this study in its entirety. One out of five participants will be eligible for a bonus. If you are eligible for a bonus, we will randomly select one of your decisions (with equal probability) to determine your bonus.

Your task:

In this study, **you will play a game with another participant. You will choose an action 'Top' or 'Bottom'.** You will be matched to **another participant in the study who will choose 'Left' or 'Right'.** The combinations of your two actions will determine each of your payments.

- Your earnings from your and the other player's choice will be shown in a payoff matrix like this one:

Other participant's choice → / Your choice↓	Left	Right
Top	**$X**, **$X**	**$1**, **$7**
Bottom	**$7**, **$1**	**$2**, **$2**

  - Your choice determines the row of the matrix determining the payments (top row or bottom row); the other player's choice determines the column of the matrix (left column or right column). **Together they determine which one cell of the matrix determines both of your payments.**
  - In each cell of the table (each combination of your and the other player's choices), the **first number (shown in blue) gives the amount you would earn** and **the second number (shown in red) the amount the other player would earn.**
  - The amount '**X**', i.e. the payment that occurs if you choose Top and the other player Left, **will vary from round to round in the task.**
- In each round, you (and the other player) will be told what X is. You will then each choose an action, which will determine your payment according to the payoff matrix.
- In total, you will complete 11 rounds of this task. Across these rounds, the payment X varies. These rounds are completely independent from one another. If one of the rounds of this task is selected to determine your bonus, only your decision in this one round will determine your bonus.

Your bonus payment:

Your decisions may affect your bonus payment. If a decision in this study is selected for payment, you and and the other player will earn the amounts in the matrix shown above that corresponds to your and the other player's choices.

Example:

Which action do you choose (click a button next to the table)?

	Other participant's choice → / Your choice↓	Left	Right
○	Top	**$3.3**, **$3.3**	**$1**, **$7**
○	Bottom	**$7**, **$1**	**$2**, **$2**

- In the example above, X is equal to $3.30.
- You then need to decide whether to choose Top or Bottom.

Your certainty:

In each round, we will ask you two questions:

- You will choose an action, either Top or Bottom.
- We will ask you **how certain** you are about your decision. Specifically, we are interested in how likely you think it is (in percentage terms) that the decision you made is actually your best decision, given your personal preferences and the available information.

Next

Figure 47: The instruction screen for the PRD task.

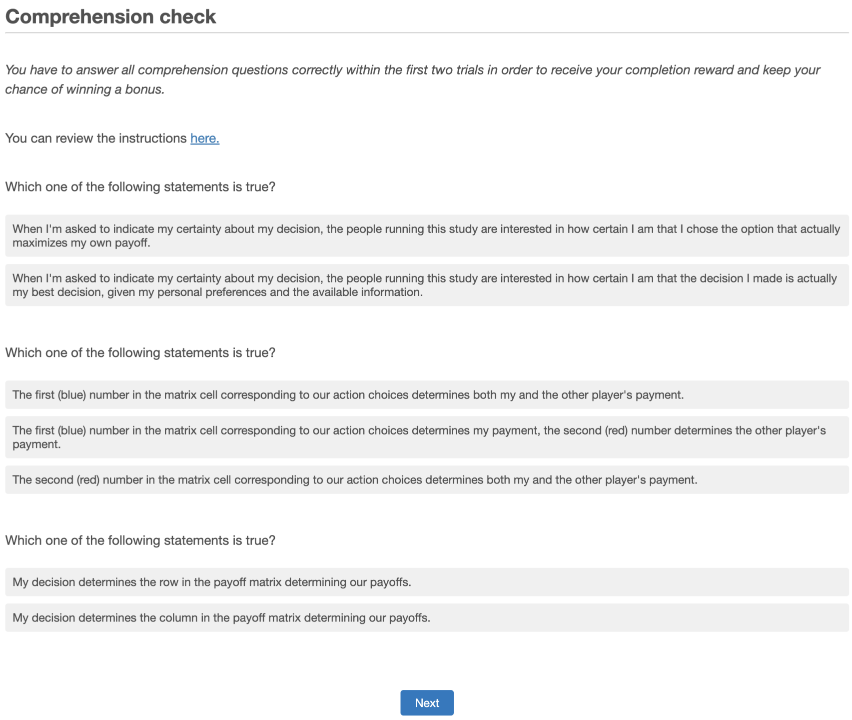


Figure 48: The comprehension screen for the PRD task.

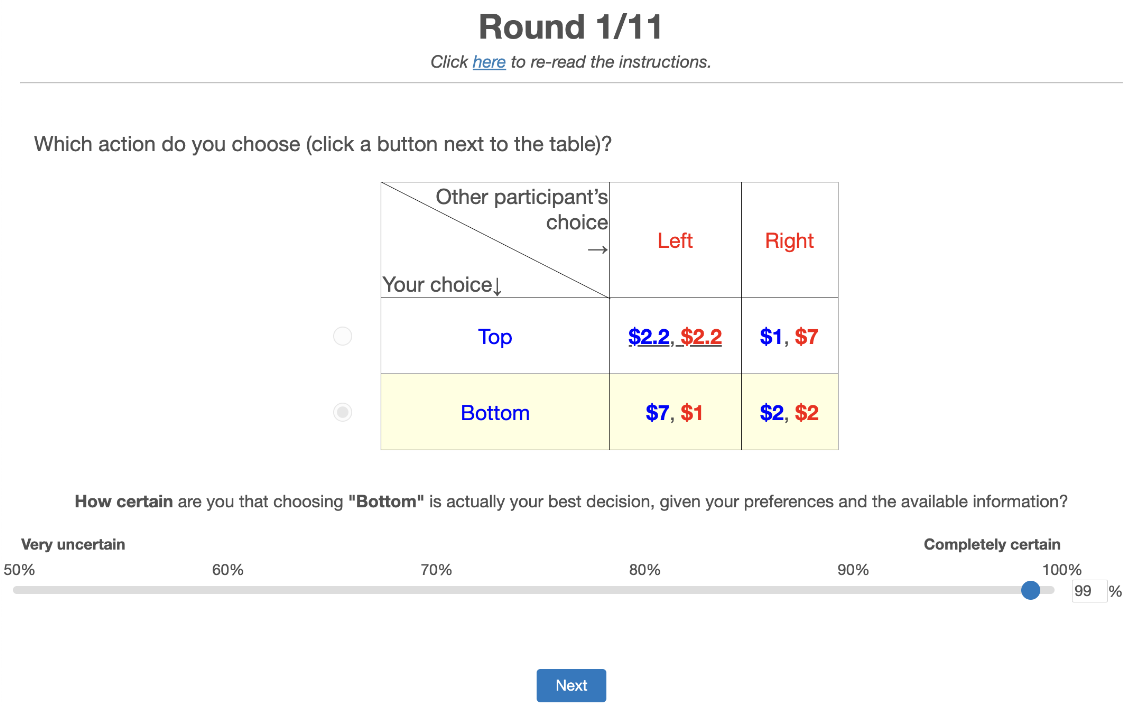


Figure 49: The decision screen for the PRD task.

D.13 PRE

Instructions

Please read these instructions carefully. There will be comprehension questions. If you fail these questions twice in a row, you will be excluded from the study and you will not receive the completion payment.
You have a chance to win an additional bonus if you complete this study in its entirety. One out of five participants will be eligible for a bonus. If you are eligible for a bonus, we will randomly select one of your decisions (with equal probability) to determine your bonus.

Your task:

In this study, you will **decide between a lottery ticket and a safe payment.**

- A lottery ticket pays **$18 with some percentage chance, and $0 otherwise.**
- A safe payment is paid with certainty.
- In each round, you will be told **the amount of the safe payment.** You will then decide between the safe payment and lottery tickets with different percentage chances of paying $18.
- In total, you will complete 11 rounds of this task. Across these rounds, the safe payment will vary. These rounds are completely independent from one another. If one of the rounds of this task is selected to determine your bonus, only your decision in this one round will determine your bonus.

Your bonus payment:

Your decisions may affect your bonus.

- If you picked the lottery, you will receive the outcome of the lottery, implemented by the computer.
- If you picked the safe payment, you will receive that payment.

This means that it is in your best interest to **choose the option (lottery or safe payment) you actually prefer in each case.**

Example:

Safe payment			Lottery
$12	◉	○	With **5%** chance: **Get $18.**
	◉	○	With **10%** chance: **Get $18.**
	◉	○	With **15%** chance: **Get $18.**
	◉	○	With **20%** chance: **Get $18.**
	◉	○	With **25%** chance: **Get $18.**
	◉	○	With **30%** chance: **Get $18.**
	◉	○	With **35%** chance: **Get $18.**
	◉	○	With **40%** chance: **Get $18.**
	◉	○	With **45%** chance: **Get $18.**
	◉	○	With **50%** chance: **Get $18.**
	◉	○	With **55%** chance: **Get $18.**
	◉	○	With **60%** chance: **Get $18.**
	○	◉	With **65%** chance: **Get $18.**
	○	◉	With **70%** chance: **Get $18.**
	○	◉	With **75%** chance: **Get $18.**
	○	◉	With **80%** chance: **Get $18.**
	○	◉	With **85%** chance: **Get $18.**
	○	◉	With **90%** chance: **Get $18.**
	○	◉	With **95%** chance: **Get $18.**

- In this example, the safe payment is $12.
- You then need to decide whether you prefer this safe payment or a lottery ticket with a specific percentage chance of winning $18.
- You will make your decisions in a choice list, **where each row is a separate choice.**
  - In every list, the left-hand option is a safe payment that is identical in all rows. The right-hand option is a lottery ticket. The percentage chance of the lottery ticket paying $18 increases from row-to-row as you go down the list.
  - To make a choice just click on the radio button you prefer for each choice (i.e. for each row).
  - **An effective way to complete these choice lists is to determine in which row you would prefer to switch from choosing the safe payment to choosing the lottery.** You can click on that row and we will automatically fill out the rest of the list for you, by selecting the safe payment in all rows above and the lottery in all rows below your selected row.
  - Based on where you switch from the safe payment to the lottery in this list, we assess which percentage chance of winning $18 you value as much as the safe payment.
  - For example, in the choice list above, your choice suggests that you value the safe payment as much as a lottery ticket that pays $18 with a percentage chance between 60% and 65% because this is where you switched.
  - If a round in this study is selected for bonus payment, the computer will randomly select one of your choices from that choice list, and you will receive the option you selected in that choice.

Your certainty:

In each round, we will ask you two questions:

- You will decide between a safe payment and different lottery tickets. We will use these decisions to assess which winning probability you value as much as the safe payment.
- We will ask you **how certain** you are about your decisions. Specifically, we are interested in how likely you think it is (in percentage terms) that your decisions actually reflect which winning probability you value as much as the safe payment.

Next

Figure 50: The instruction screen for the PRE task.

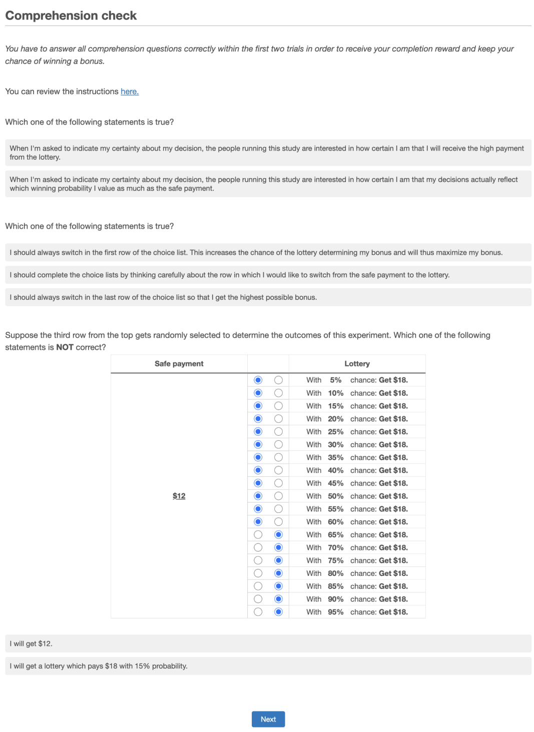


Figure 51: The comprehension screen for the PRE task.

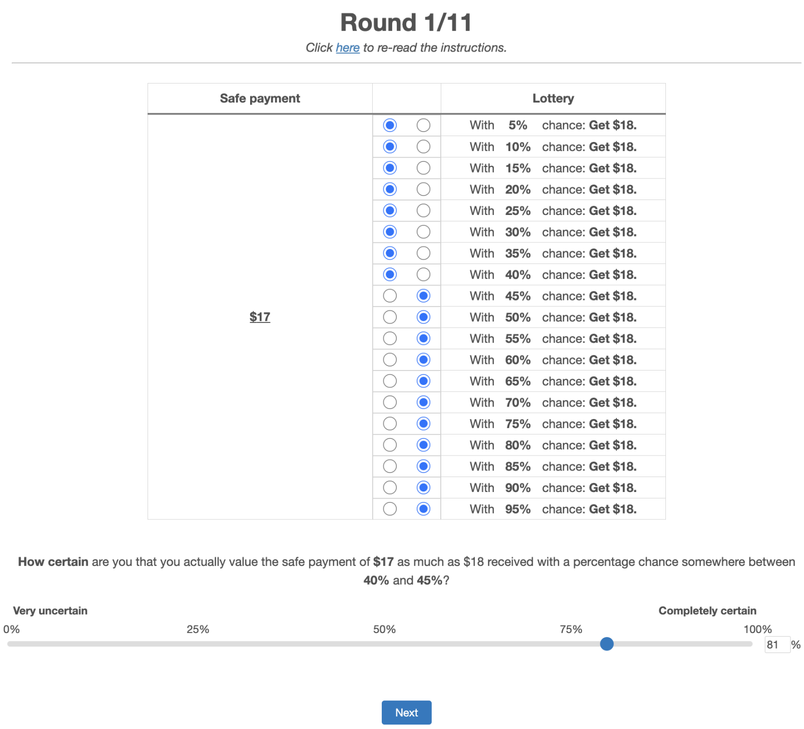
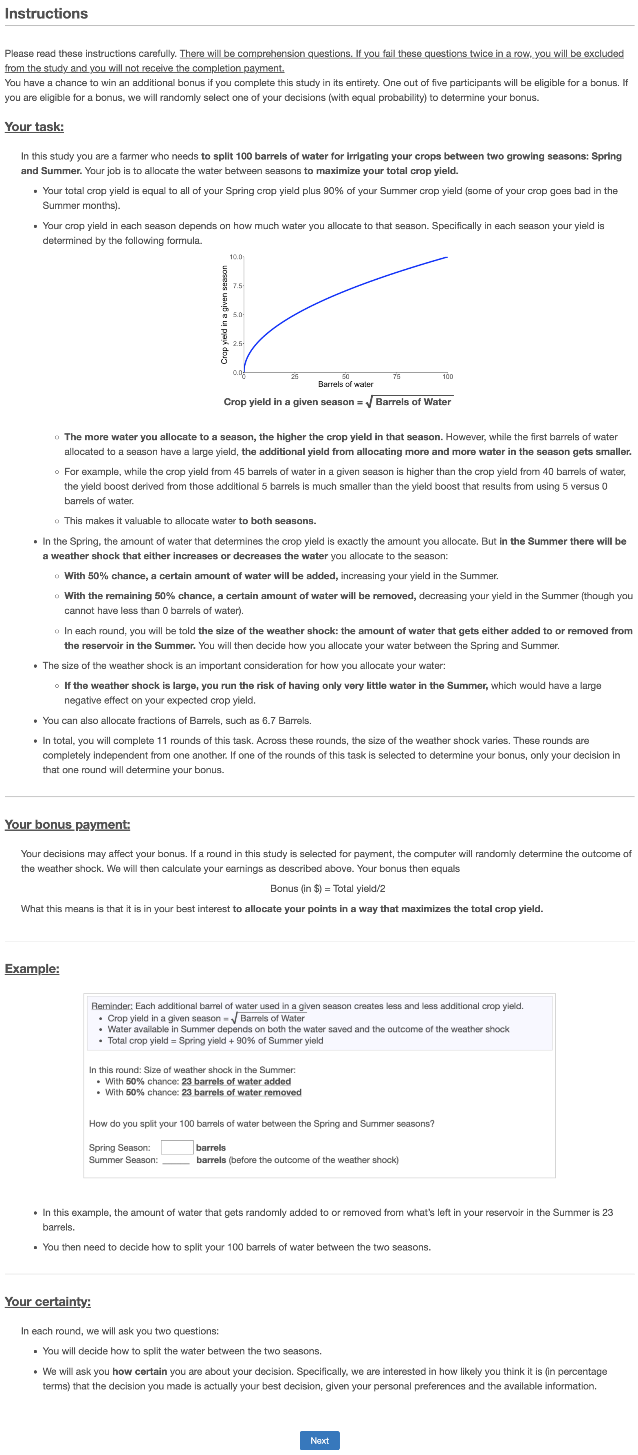


Figure 52: The decision screen for the PRE task.

D.14 PRS



Instructions

Please read these instructions carefully. There will be comprehension questions. If you fail these questions twice in a row, you will be excluded from the study and you will not receive the completion payment.
You have a chance to win an additional bonus if you complete this study in its entirety. One out of five participants will be eligible for a bonus. If you are eligible for a bonus, we will randomly select one of your decisions (with equal probability) to determine your bonus.

Your task:

In this study you are a farmer who needs **to split 100 barrels of water for irrigating your crops between two growing seasons: Spring and Summer.** Your job is to allocate the water between seasons **to maximize your total crop yield.**

- Your total crop yield is equal to all of your Spring crop yield plus 90% of your Summer crop yield (some of your crop goes bad in the Summer months).
- Your crop yield in each season depends on how much water you allocate to that season. Specifically in each season your yield is determined by the following formula.

Crop yield in a given season = $\sqrt{\text{Barrels of Water}}$

  - **The more water you allocate to a season, the higher the crop yield in that season.** However, while the first barrels of water allocated to a season have a large yield, **the additional yield from allocating more and more water in the season gets smaller.**
  - For example, while the crop yield from 45 barrels of water in a given season is higher than the crop yield from 40 barrels of water, the yield boost derived from those additional 5 barrels is much smaller than the yield boost that results from using 5 versus 0 barrels of water.
  - This makes it valuable to allocate water **to both seasons.**
- In the Spring, the amount of water that determines the crop yield is exactly the amount you allocate. But **in the Summer there will be a weather shock that either increases or decreases the water** you allocate to the season:
  - **With 50% chance, a certain amount of water will be added,** increasing your yield in the Summer.
  - **With the remaining 50% chance, a certain amount of water will be removed,** decreasing your yield in the Summer (though you cannot have less than 0 barrels of water).
  - In each round, you will be told **the size of the weather shock: the amount of water that gets either added to or removed from the reservoir in the Summer.** You will then decide how you allocate your water between the Spring and Summer.
- The size of the weather shock is an important consideration for how you allocate your water:
  - **If the weather shock is large, you run the risk of having only very little water in the Summer,** which would have a large negative effect on your expected crop yield.
- You can also allocate fractions of Barrels, such as 6.7 Barrels.
- In total, you will complete 11 rounds of this task. Across these rounds, the size of the weather shock varies. These rounds are completely independent from one another. If one of the rounds of this task is selected to determine your bonus, only your decision in that one round will determine your bonus.

Your bonus payment:

Your decisions may affect your bonus. If a round in this study is selected for payment, the computer will randomly determine the outcome of the weather shock. We will then calculate your earnings as described above. Your bonus then equals

Bonus (in $) = Total yield/2

What this means is that it is in your best interest **to allocate your points in a way that maximizes the total crop yield.**

Example:

Reminder: Each additional barrel of water used in a given season creates less and less additional crop yield.
- Crop yield in a given season = $\sqrt{\text{Barrels of Water}}$
- Water available in Summer depends on both the water saved and the outcome of the weather shock
- Total crop yield = Spring yield + 90% of Summer yield

In this round: Size of weather shock in the Summer:
- With **50%** chance: **23 barrels of water added**
- With **50%** chance: **23 barrels of water removed**

How do you split your 100 barrels of water between the Spring and Summer seasons?

Spring Season: [ ] **barrels**
Summer Season: ____ **barrels** (before the outcome of the weather shock)

- In this example, the amount of water that gets randomly added to or removed from what's left in your reservoir in the Summer is 23 barrels.
- You then need to decide how to split your 100 barrels of water between the two seasons.

Your certainty:

In each round, we will ask you two questions:

- You will decide how to split the water between the two seasons.
- We will ask you **how certain** you are about your decision. Specifically, we are interested in how likely you think it is (in percentage terms) that the decision you made is actually your best decision, given your personal preferences and the available information.

Next

Figure 53: The instruction screen for the PRS task.

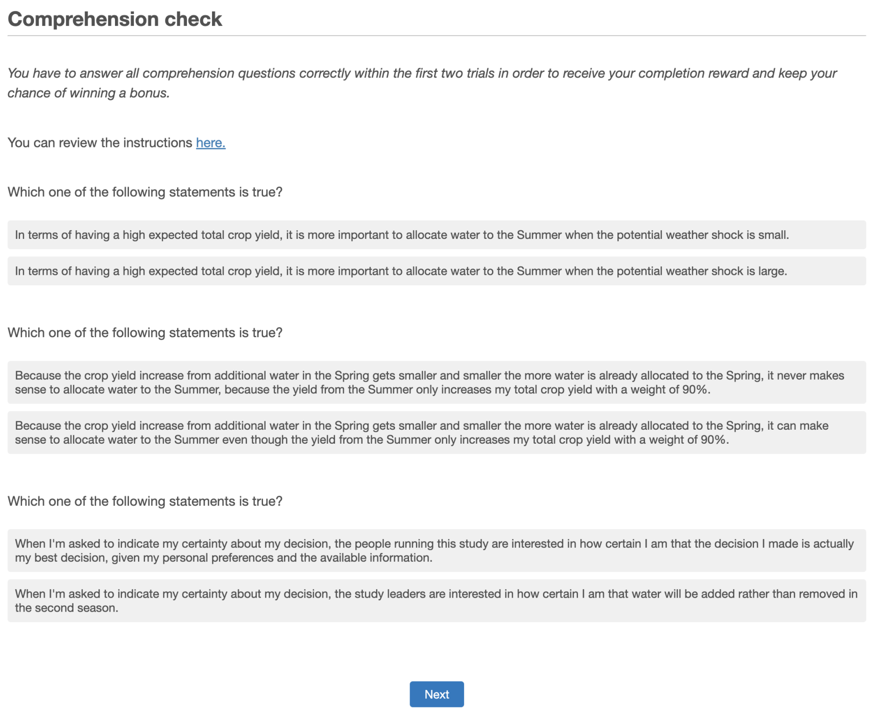


Figure 54: The comprehension screen for the PRS task.

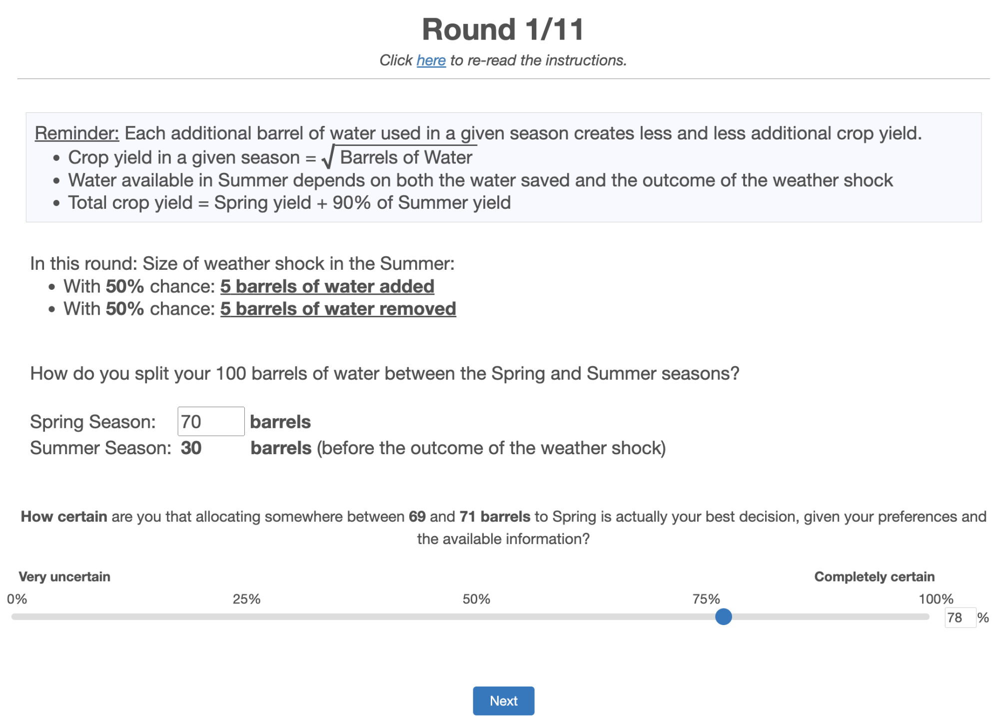
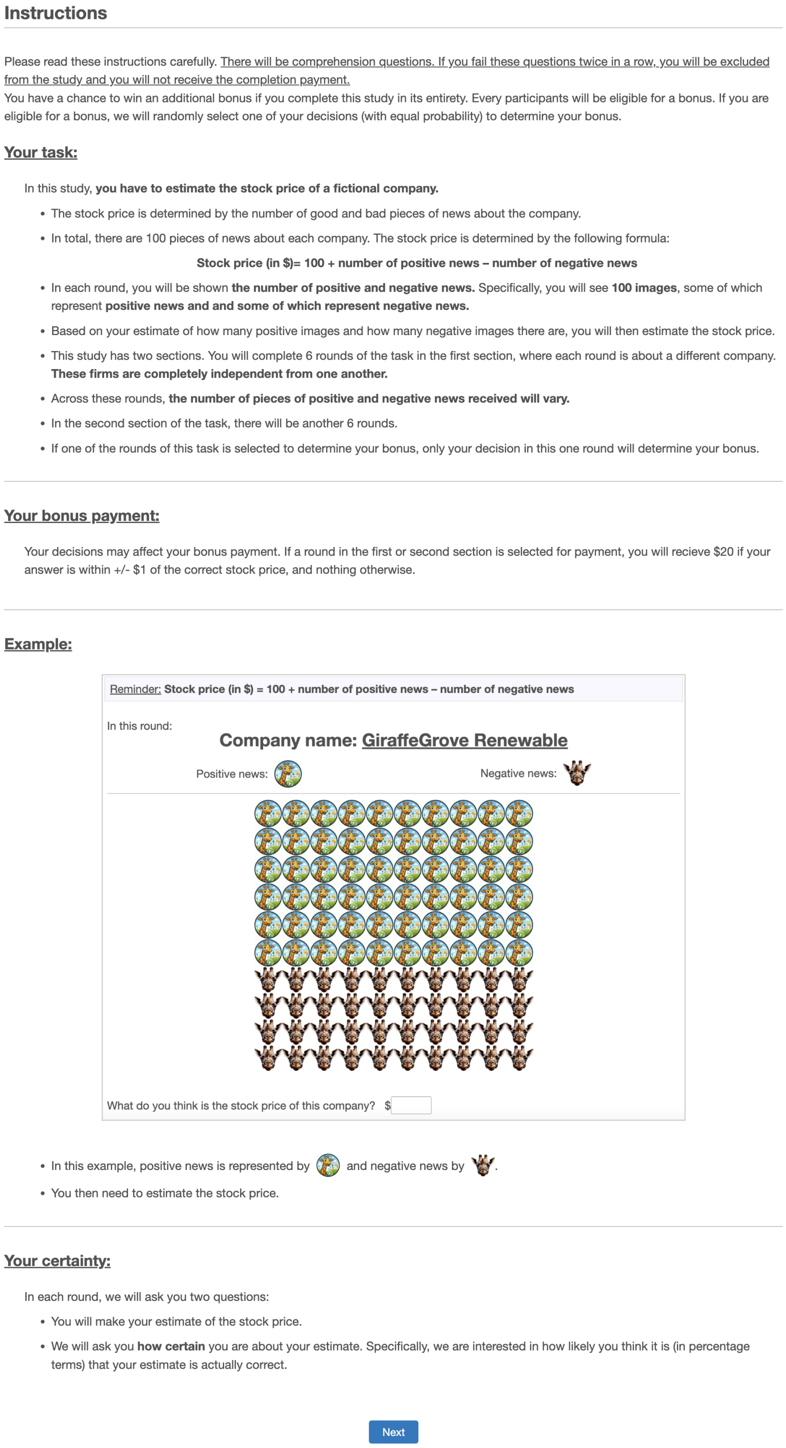


Figure 55: The decision screen for the PRS task.

D.15 REC



Instructions

Please read these instructions carefully. There will be comprehension questions. If you fail these questions twice in a row, you will be excluded from the study and you will not receive the completion payment.
You have a chance to win an additional bonus if you complete this study in its entirety. Every participants will be eligible for a bonus. If you are eligible for a bonus, we will randomly select one of your decisions (with equal probability) to determine your bonus.

Your task:

In this study, **you have to estimate the stock price of a fictional company.**

- The stock price is determined by the number of good and bad pieces of news about the company.
- In total, there are 100 pieces of news about each company. The stock price is determined by the following formula:

Stock price (in $)= 100 + number of positive news – number of negative news

- In each round, you will be shown **the number of positive and negative news.** Specifically, you will see **100 images**, some of which represent **positive news and and some of which represent negative news.**
- Based on your estimate of how many positive images and how many negative images there are, you will then estimate the stock price.
- This study has two sections. You will complete 6 rounds of the task in the first section, where each round is about a different company. **These firms are completely independent from one another.**
- Across these rounds, **the number of pieces of positive and negative news received will vary.**
- In the second section of the task, there will be another 6 rounds.
- If one of the rounds of this task is selected to determine your bonus, only your decision in this one round will determine your bonus.

Your bonus payment:

Your decisions may affect your bonus payment. If a round in the first or second section is selected for payment, you will recieve $20 if your answer is within +/- $1 of the correct stock price, and nothing otherwise.

Example:

Reminder: **Stock price (in $) = 100 + number of positive news – number of negative news**

In this round:

Company name: GiraffeGrove Renewable

Positive news: Negative news:

What do you think is the stock price of this company? $

- In this example, positive news is represented by and negative news by .
- You then need to estimate the stock price.

Your certainty:

In each round, we will ask you two questions:

- You will make your estimate of the stock price.
- We will ask you **how certain** you are about your estimate. Specifically, we are interested in how likely you think it is (in percentage terms) that your estimate is actually correct.

Next

Figure 56: The instruction screen for the REC task.

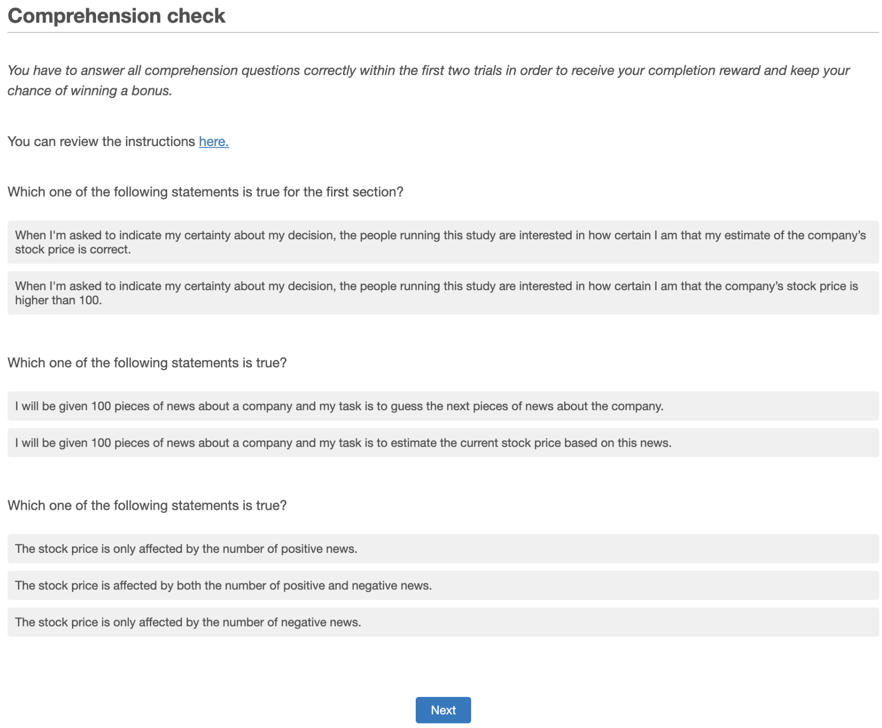


Figure 57: The comprehension screen for the REC task.

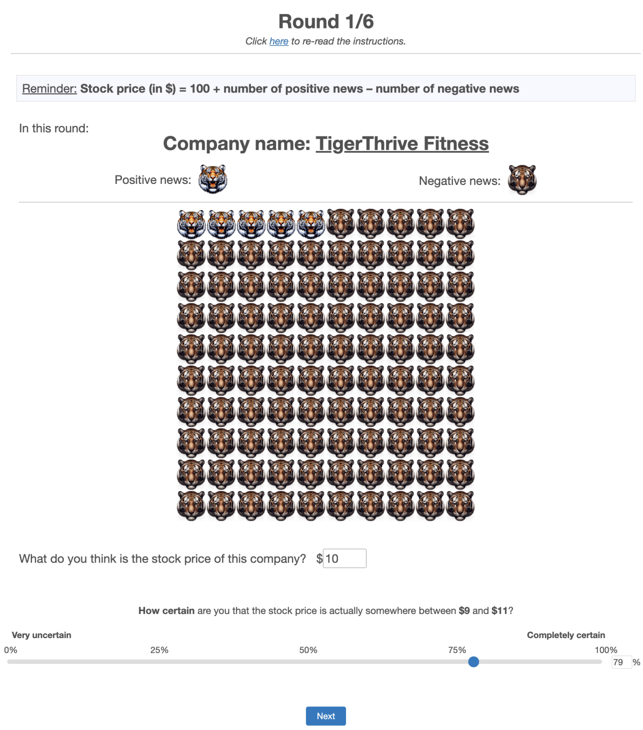


Figure 58: The decision screen for the REC task.

D.16 SIA

Instructions

Please read these instructions carefully. <u>There will be comprehension questions. If you fail these questions twice in a row, you will be excluded from the study and you will not receive the completion payment.</u>
You have a chance to win an additional bonus if you complete this study in its entirety. One out of five participants will be eligible for a bonus. If you are eligible for a bonus, we will randomly select one of your decisions (with equal probability) to determine your bonus.

<u>Your task:</u>

In this study, you will be asked to **estimate the weight of a bucket.** You will not get to see the bucket yourself. Rather, **you will have to rely on the estimates of others.**

- There are two different types of people: **2 Communicators** and **100 Estimators.**
  - The **Communicators** are called **Ann** and **Bob**. Neither of them gets to see the bucket, either.
  - The **Estimators**, on the other hand, have all **independently seen the bucket and are all equally good at estimating its weight.** Each estimator produces their own estimate of the weight of the bucket. **The actual weight of the bucket is the average of these 100 estimates.**
  - Each of the 100 Estimators transmits their individual estimate either to Ann or to Bob.
  - Ann and Bob each **compute the average of the estimates they individually observe,** and then communicate the averages to you.
- In each round, Ann and Bob report these two averages to you. You will also be told **how many of the 100 Estimators reported their estimates to Ann and to Bob,** respectively. Based on what you find out from Ann and Bob, your task is to **estimate the weight of the bucket.**
- In total, you will complete 11 rounds of this task. Across these rounds, the number of Estimators reporting to Ann and Bob as well as their estimates vary. These rounds are completely independent from one another. The weight of the bucket is determined anew in each round. If one of the rounds of this task is selected to determine your bonus, only your decision in this one round will determine your bonus.

<u>Your bonus payment:</u>

Your decisions may affect your bonus payment. For each round, there is a correct answer for the weight of the bucket. If a decision in this study is selected for payment, you will receive $10 if your estimate is within +/-1 pound of the correct answer, and nothing otherwise.

<u>Example:</u>

<u>Reminder:</u> **100** Estimators observe the bucket. Some share their estimate with Ann and some with Bob.

In this round: **<u>30 Estimators</u>** reported their estimates to Ann, and **<u>70 Estimators</u>** reported their estimates to Bob.
The reports of Ann and Bob are given below:

Ann reports **<u>55 pounds.</u>**
Bob reports **<u>35 pounds.</u>**

What do you think the weight of the bucket is, given the information above? ____ **pounds**

- In this example, 30 of the 100 estimators reported to Ann, who computes an average estimate of 55 pounds, and 70 of the 100 estimators reported to Bob, who computes an average estimate of 35 pounds
- You would then give your estimate of the weight of the bucket in pounds, based on the information provided.

<u>Your certainty:</u>

In each round, we will ask you two questions:

- You will estimate the weight of the bucket.
- We will ask you **how certain** you are about your estimate. Specifically, we are interested in how likely you think it is (in percentage terms) that your estimate is actually correct.

Next

Figure 59: The instruction screen for the SIA task.

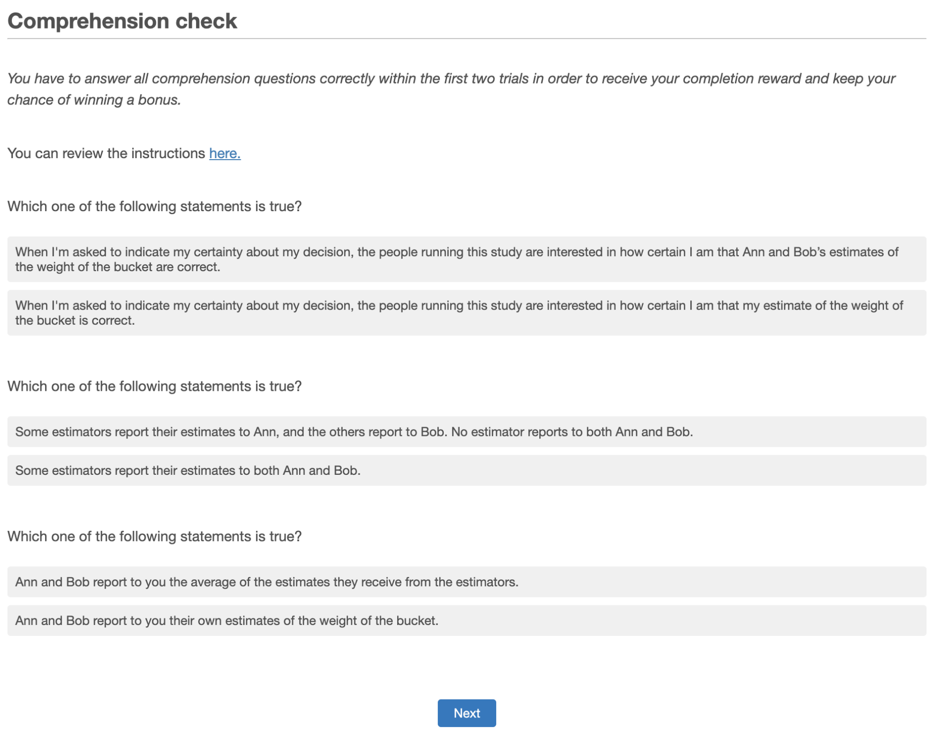


Figure 60: The comprehension screen for the SIA task.

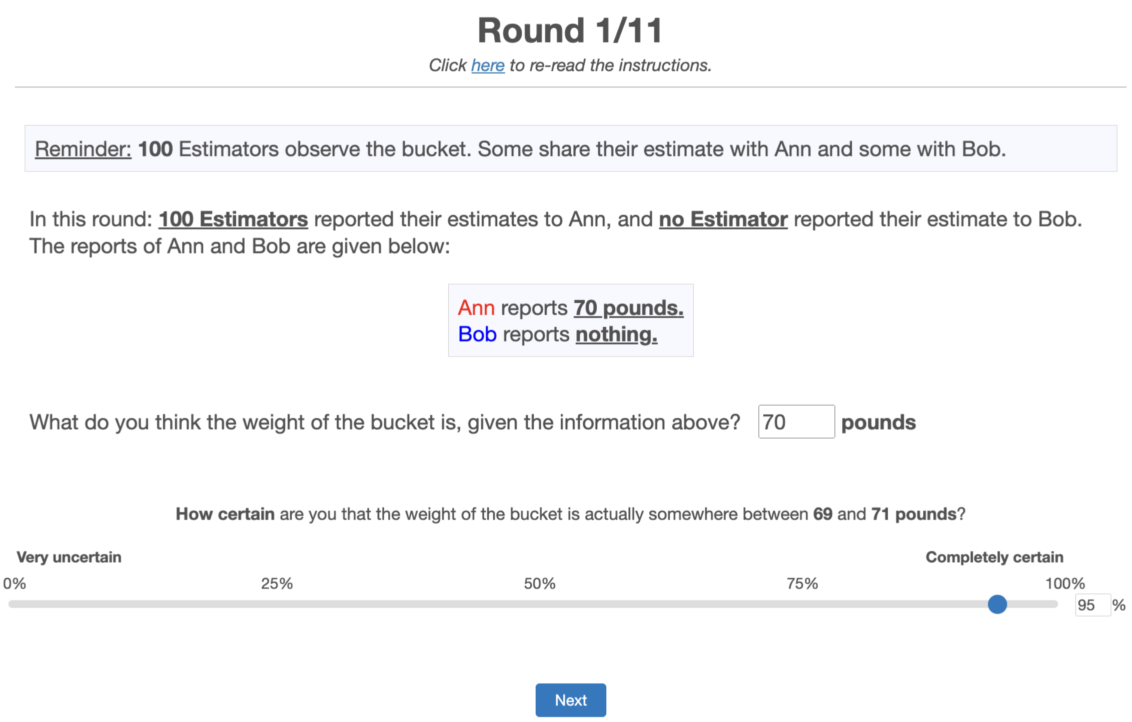


Figure 61: The decision screen for the SIA task.

D.17 TAX

Instructions

Please read these instructions carefully. There will be comprehension questions. If you fail these questions twice in a row, you will be excluded from the study and you will not receive the completion payment.
You have a chance to win an additional bonus if you complete this study in its entirety. One out of five participants will be eligible for a bonus. If you are eligible for a bonus, we will randomly select one of your decisions (with equal probability) to determine your bonus.

Your task:

In this study, **you will estimate the income taxes owed by a hypothetical taxpayer named Fred.**

- Fred's income is subject to two taxes: a **federal tax** and **a state tax.**
- The federal income tax contains 5 tax brackets and the state income tax contains 3 tax brackets:

Federal Tax Rate	Income Bracket
12%	$0 to $20,000
18%	$20,000 to $50,000
26%	$50,000 to $80,000
32%	$80,000 to $120,000
42%	$120,000 and above

State Tax Rate	Income Bracket
3%	$0 to $30,000
7%	$30,000 to $70,000
10%	$70,000 and above

- These brackets work just as actual U.S. tax brackets do. Specifically, when Fred's income jumps to a higher tax bracket, he doesn't pay the higher rate on his entire income. **He pays the higher rate only on the portion of his income that's in the new tax bracket.**
  - For instance, if Fred's income is $35,000, he would pay federal taxes equal to 12% on the $20,000 portion of his income in the first bracket, plus 18% on the $15,000 portion of his income in the second bracket.
  - Similarly, in the scenario above Fred would pay state taxes equal to 3% on the $30,000 portion of his income in the first bracket, plus 7% on the $5,000 portion of his income in the second bracket.
- In each round, we will ask you to estimate the total income tax **(state plus federal)** that Fred would have to pay for different levels of income.
- In total, you will complete 11 rounds of this task. Across these rounds, the income of Fred varies. These rounds are completely independent from one another. If one of the rounds of this task is selected to determine your bonus, only your decision in this one round will determine your bonus.

Your bonus payment:

Your decisions in this part of the study may affect your bonus payment. If a decision in this part is selected for payment, you will receive $10 if your answer is within +/-$300 of the correct answer.

Example:

Reminder: Fred's income is subject to a federal and state income tax, which have the following tax brackets:

Federal Tax Rate	Income Bracket
12%	$0 to $20,000
18%	$20,000 to $50,000
26%	$50,000 to $80,000
32%	$80,000 to $120,000
42%	$120,000 and above

State Tax Rate	Income Bracket
3%	$0 to $30,000
7%	$30,000 to $70,000
10%	$70,000 and above

Fred pays each tax rate only on the portion of his income that's in the corresponding tax bracket.

In this round: Fred's annual income is **$65,000**.

How much does he have to pay in total income taxes? **$**

- In this example, Fred's income is $65,000.
- You then need to estimate how much Fred would have to pay in total income taxes (state income taxes plus federal income taxes).

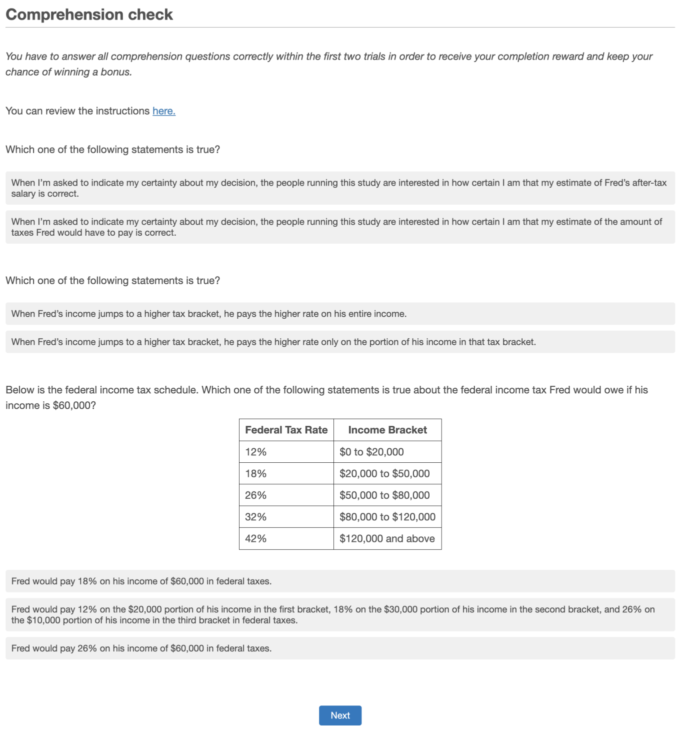
Your certainty:

In each round, we will ask you two questions:

- You will estimate how much Fred would have to pay in total income taxes.
- We will ask you **how certain** you are about your answer. Specifically, we are interested in how likely you think it is (in percentage terms) that your answer is actually correct.

Next

Figure 62: The instruction screen for the TAX task.



Comprehension check

You have to answer all comprehension questions correctly within the first two trials in order to receive your completion reward and keep your chance of winning a bonus.

You can review the instructions here.

Which one of the following statements is true?

When I'm asked to indicate my certainty about my decision, the people running this study are interested in how certain I am that my estimate of Fred's after-tax salary is correct.

When I'm asked to indicate my certainty about my decision, the people running this study are interested in how certain I am that my estimate of the amount of taxes Fred would have to pay is correct.

Which one of the following statements is true?

When Fred's income jumps to a higher tax bracket, he pays the higher rate on his entire income.

When Fred's income jumps to a higher tax bracket, he pays the higher rate only on the portion of his income in that tax bracket.

Below is the federal income tax schedule. Which one of the following statements is true about the federal income tax Fred would owe if his income is $60,000?

Federal Tax Rate	Income Bracket
12%	$0 to $20,000
18%	$20,000 to $50,000
26%	$50,000 to $80,000
32%	$80,000 to $120,000
42%	$120,000 and above

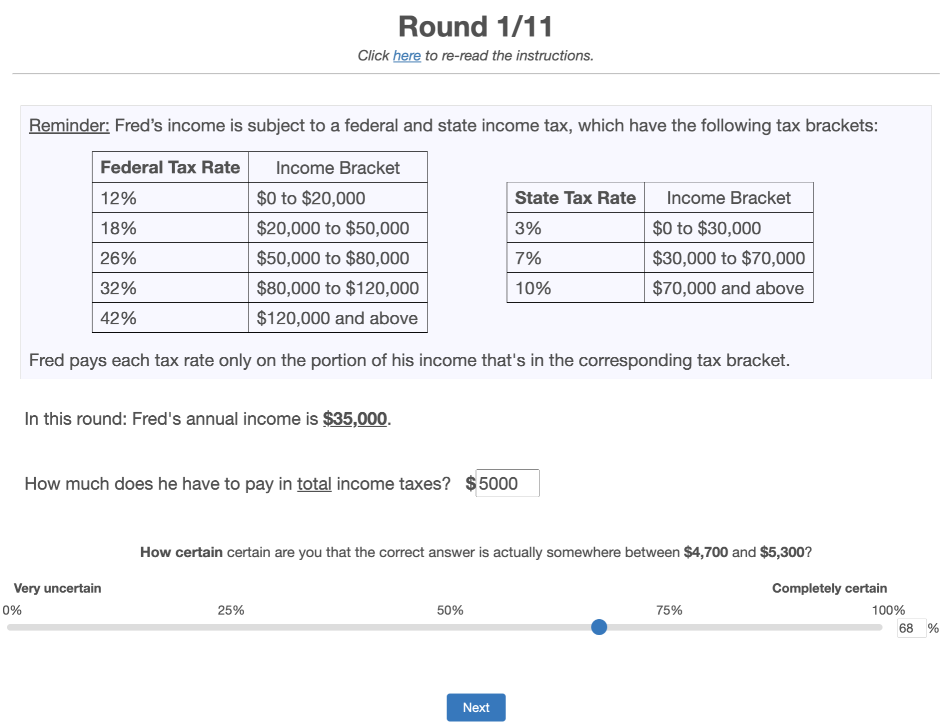
Fred would pay 18% on his income of $60,000 in federal taxes.

Fred would pay 12% on the $20,000 portion of his income in the first bracket, 18% on the $30,000 portion of his income in the second bracket, and 26% on the $10,000 portion of his income in the third bracket in federal taxes.

Fred would pay 26% on his income of $60,000 in federal taxes.

Next

Figure 63: The comprehension screen for the TAX task.



Round 1/11

Click here to re-read the instructions.

Reminder: Fred's income is subject to a federal and state income tax, which have the following tax brackets:

Federal Tax Rate	Income Bracket
12%	$0 to $20,000
18%	$20,000 to $50,000
26%	$50,000 to $80,000
32%	$80,000 to $120,000
42%	$120,000 and above

State Tax Rate	Income Bracket
3%	$0 to $30,000
7%	$30,000 to $70,000
10%	$70,000 and above

Fred pays each tax rate only on the portion of his income that's in the corresponding tax bracket.

In this round: Fred's annual income is **$35,000**.

How much does he have to pay in total income taxes? **$** 5000

How certain certain are you that the correct answer is actually somewhere between **$4,700** and **$5,300**?

Very uncertain **Completely certain**

0% 25% 50% 75% 100%

68 %

Next

Figure 64: The decision screen for the TAX task.

D.18 VOT

Instructions

Please read these instructions carefully. There will be comprehension questions. If you fail these questions twice in a row, you will be excluded from the study and you will not receive the completion payment.
You have a chance to win an additional bonus if you complete this study in its entirety. One out of five participants will be eligible for a bonus. If you are eligible for a bonus, we will randomly select one of your decisions (with equal probability) to determine your bonus.

Your task:

In this study **you will decide whether or not to submit a vote in an election for option A or option B.**

- In each round, you **start out with a wealth of $10.** If **option B wins** the election, you **must pay $8 in taxes**, leaving you with $2. But if **option A** wins the election, you won't be taxed and **will keep your entire $10**. **Submitting a vote (for option A) costs you $1**.
  - There are some number of other robot voters in the election. Each robot voter **has a 50% chance of randomly voting for A vs. B**. You will know how many other voters there are, but you won't know which way each of them is voting when you make your decision.
  - We will add up all of the votes for A and B (including yours if you submit one), and **declare A the winner if A receives strictly more votes than B.** If both get equally many votes, B is the winner.
  - Your decision is simply whether to pay $1 to submit a vote for A, or instead to not vote.
  - The outcome of the election will matter for your earnings, whether or not you decided to vote.
- In each round, you will be told **the number of other robot voters.** You will then decide **whether you would would like to pay $1 to vote for A**, or instead not vote.
- In total, you will complete 11 rounds of this task. Across these rounds, the number of other voters varies. These rounds are completely independent from one another. If one of the rounds of this task is selected to determine your bonus, only your decision in this one round will influence your bonus.

Your bonus payment:

Your decisions in this part of the study may affect your bonus payment. If a decision in this part is selected for payment, you will start out with $10. You will be taxed $8 if B wins the election and pay $1 if you submitted a vote.

Example:

Reminder: You have a wealth of $10. Whether or not you vote, **you must pay $8 in taxes if B wins** the election, but you **pay no taxes if A wins the election**. The price of voting is **$1.** Each one of the other voters randomly votes for A or B with **equal probability**. A wins the election if it has more votes than B.

In this round: The number of other voters is **35**.

Which option do you prefer?

I would like to pay $1 to vote for A. | I would not like to submit a vote.

- In this example, the number of other voters is 35.
- You then need to decide whether to pay $1 to submit a vote for A.

Your certainty:

In each round, we will ask you two questions:

- Would you like to pay $1 to submit a vote for A?
- We will ask you **how certain** you are about your decision. Specifically, we are interested in how likely you think it is (in percentage terms) that the decision you made is actually your best decision, given your personal preferences and the available information.

Next

Figure 65: The instruction screen for the VOT task.

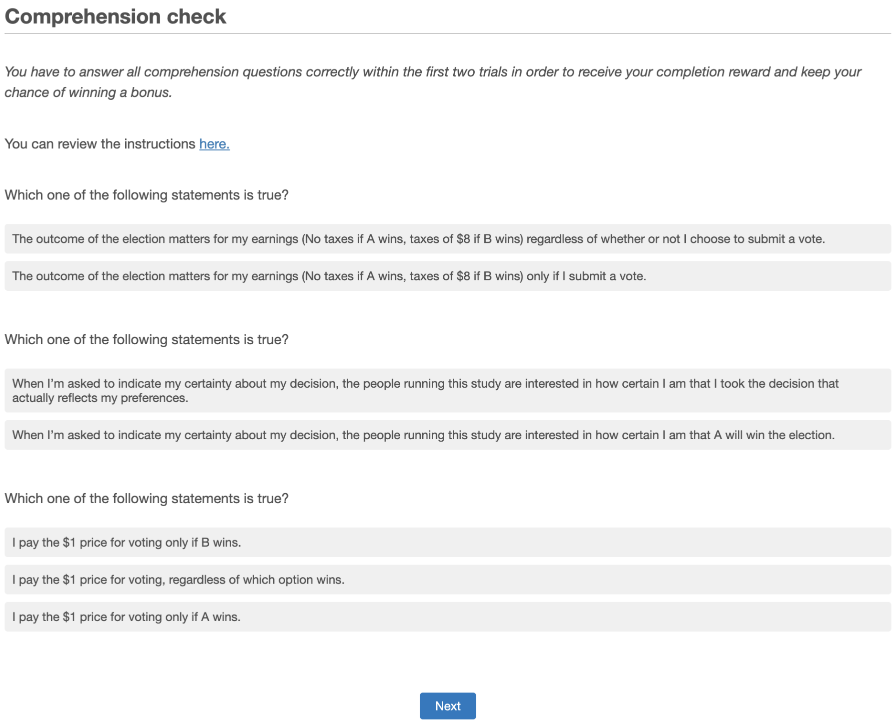


Figure 66: The comprehension screen for the VOT task.

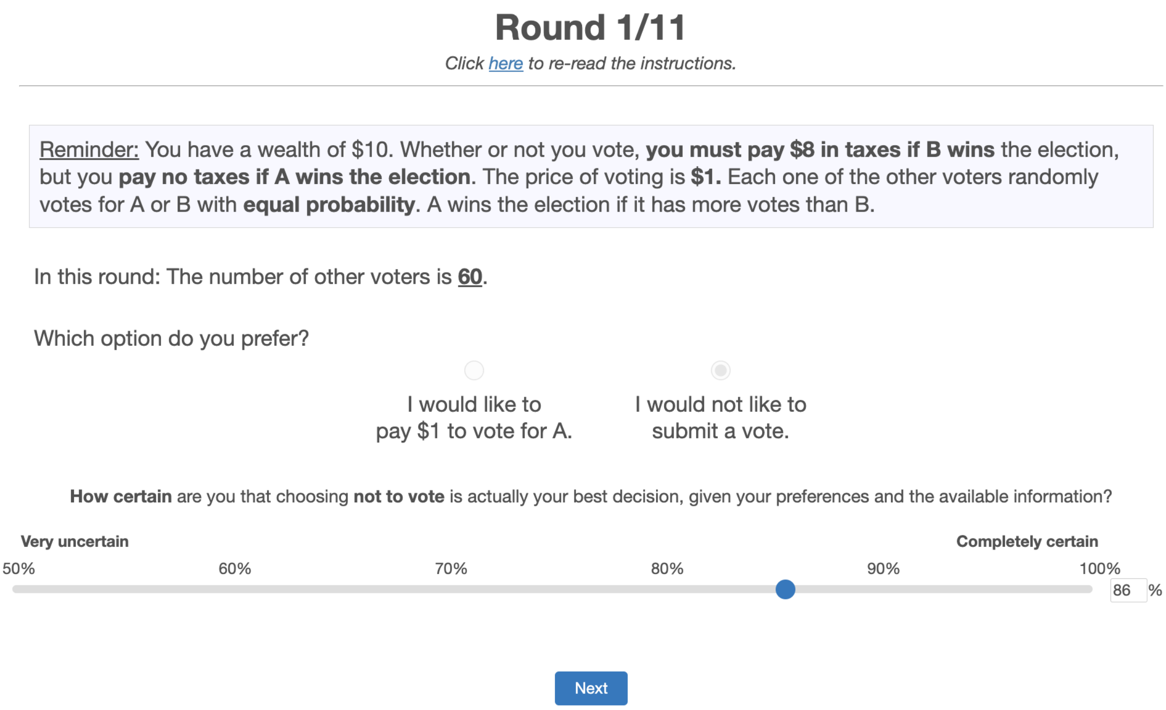


Figure 67: The decision screen for the VOT task.

D.19 PGG

Instructions

Please read these instructions carefully. There will be comprehension questions. If you fail these questions twice in a row, you will be excluded from the study and you will not receive the completion payment.
You have a chance to win an additional bonus if you complete this study in its entirety. One out of five participants will be eligible for a bonus. If you are eligible for a bonus, we will randomly select one of your decisions (with equal probability) to determine your bonus.

Your task:

In this study, you will **play a game with 2 other participants**. This game works as follows:

- Each of you will be given **100 points**. At the end of the study, each participant will be paid 10 cent for each point they have.
- Each of you simultaneously and independently decides **how many points to transfer into a shared account.**
- Whichever number of points each player transfers into **the shared account gets multiplied by a number** that we will call the **Multiplier**. For example, if the Multiplier is 2 and you transfer 30 of your points into the shared account, then 60 points will end up in the shared account.
- This means: **the higher the Multiplier, the more points you and the other participants will get from the shared account for each point any of you transfer into the shared account.**
- After all participants have decided how many points to transfer, **all points in the shared account get distributed equally among the three participants.** For example, if there are 90 points in the shared account in total, then you each get 30 points from the shared account, regardless of how many points each of you transferred into the shared account.
- You will also each keep any of the 100 points you didn't put in the shared account.
- Your total point score is thus calculated as follows:

Total points =
Points not transferred into shared account + One third of total number of points in shared account

- In each round you will be told the Multiplier that determines how many points end up in the shared account for each point that you transfer. You will then decide how many points to transfer to the shared account (you will not see how many points the other participants sent to the shared account until the end of the study).
- In total, you will complete 11 rounds of this task. Across these rounds, the Multiplier varies. These rounds are completely independent from one another. If one of the rounds of this task is selected to determine your bonus, only your decision in this one round will determine your (and the other participants') bonus.

Your bonus payment:

Your decisions in this part of the study may affect your bonus payment and the bonus payment of the other participants. If a decision in this part is selected for payment you will be paid 10 cents for each point you have.

Example:

Reminder: Three participants simultaneously decide how many of their 100 points to transfer into a shared account.
- **Each point that gets transfered into the shared account will get multiplied by the Multiplier**, and the total will be distributed equally among all three of you.
- Each point you don't transfer, you keep.

In this round: The Multiplier is **1.7**.

How many points (out of 100) do you want to transfer into the shared account?

- In this example, the Multiplier is 1.7.
- You then need to decide how many points to transfer to the shared account.

Your certainty:

In each round, we will ask you two questions:

- How many points you want to transfer into the shared account.
- We will ask you **how certain** you are about your decision. Specifically, we are interested in how likely you think it is (in percentage terms) that the decision you made is actually your best decision, given your personal preferences and the available information.

Next

Figure 68: The instruction screen for the PGG task.

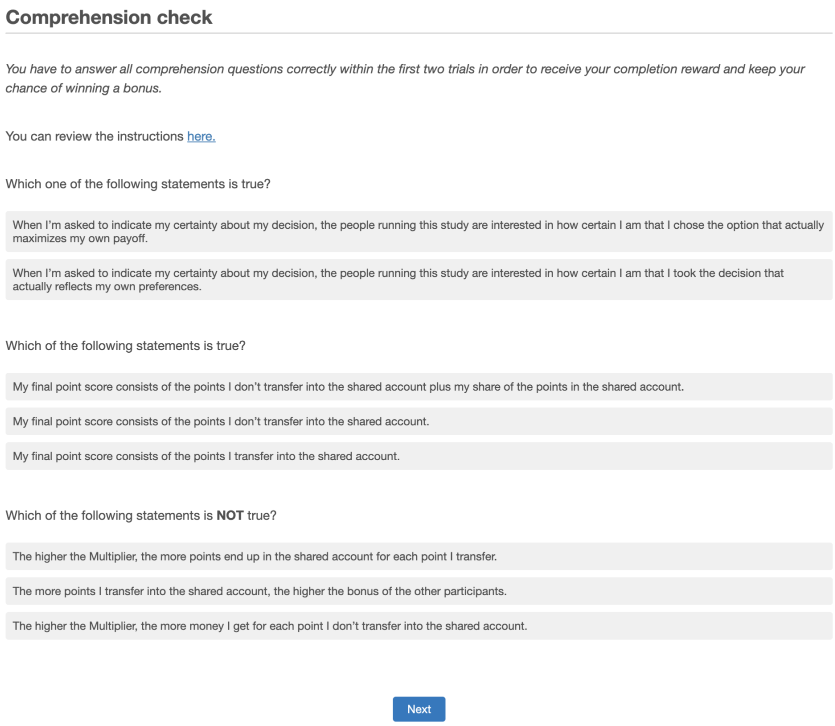


Figure 69: The comprehension screen for the PGG task.

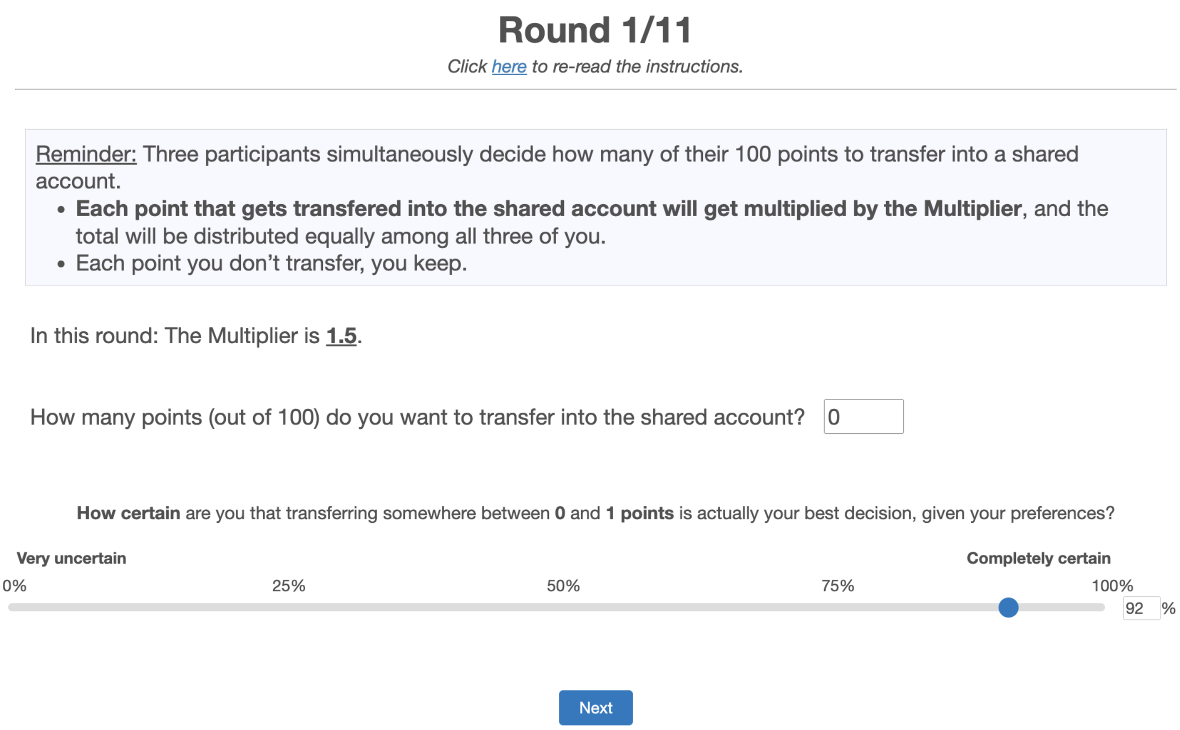


Figure 70: The decision screen for the PGG task.

D.20 POL

Instructions

Please read these instructions carefully. There will be comprehension questions. If you fail these questions twice in a row, you will be excluded from the study and you will not receive the completion payment.

<u>Your task:</u>

In this study, **you will be asked to evaluate a hypothetical policy.**

- In a bipartisan effort, Democrats and Republicans cobbled together a new bill that would **increase the income of each household in the U.S. next year by $10,000.** If the bill is not passed, incomes do not increase.
- However, the bill would also **lead to inflation next year**. The prices of all goods, including groceries and gas, would increase. The estimates of how much prices would increase vary. Experts agree that if the bill is not passed, there will be no inflation over the next year.
- In each round, we will tell you how much inflation there would be. You will then be asked to indicate **how much you would support the policy** (on a scale from 0 to 100).
- In total, you will complete 11 rounds of this task. Across these rounds, the degree of inflation varies. These rounds are completely independent from one another.

<u>Example:</u>

<u>Reminder:</u> A proposed bill would **increase the annual income of each U.S. household next year by $10,000**. However, implementing the policy would also **produce inflation.**

In this round: Inflation next year would be **<u>6%</u>**.

On a scale from 0 to 100, how strongly do you support the policy?

- In this example, inflation would be 6%.
- You then need to indicate your support for the policy.

<u>Your certainty:</u>

In each round, we will ask you two questions:

- How much you would support the policy.
- We will ask you **how certain** you are about your decision. Specifically, we are interested in how likely you think it is (in percentage terms) that the decision you made is actually your best decision, given your personal preferences and the available information.

Next

Figure 71: The instruction screen for the POL task.

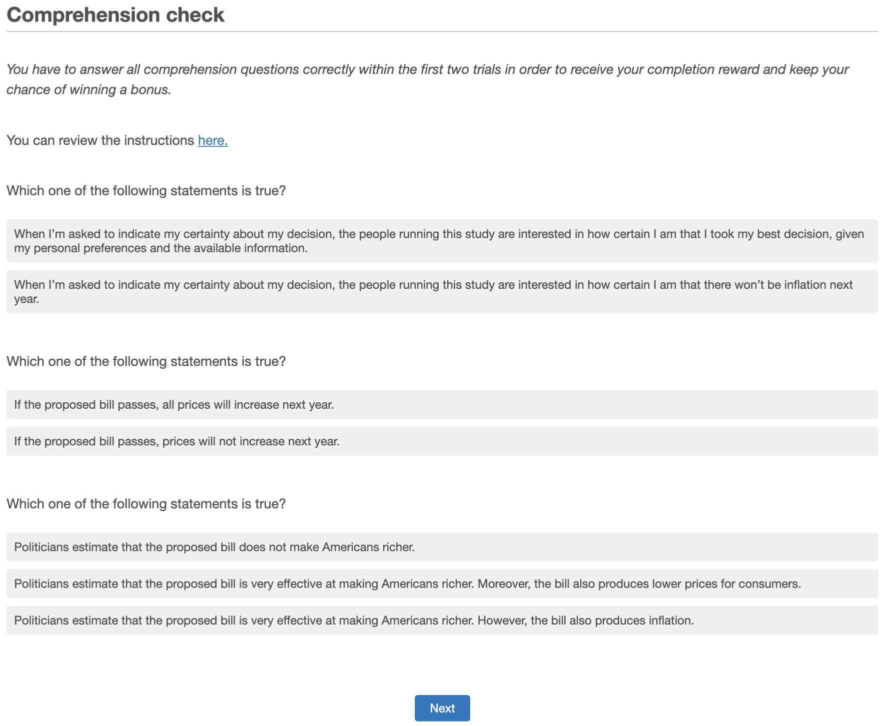


Figure 72: The comprehension screen for the POL task.

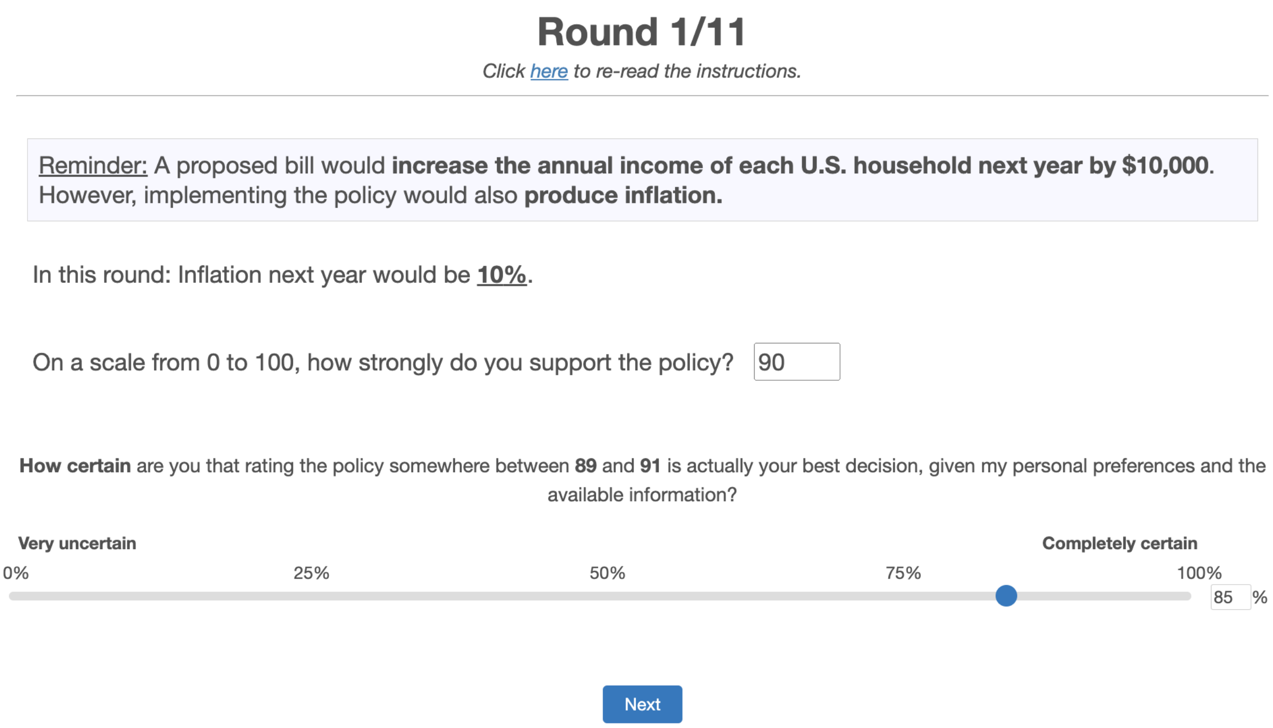
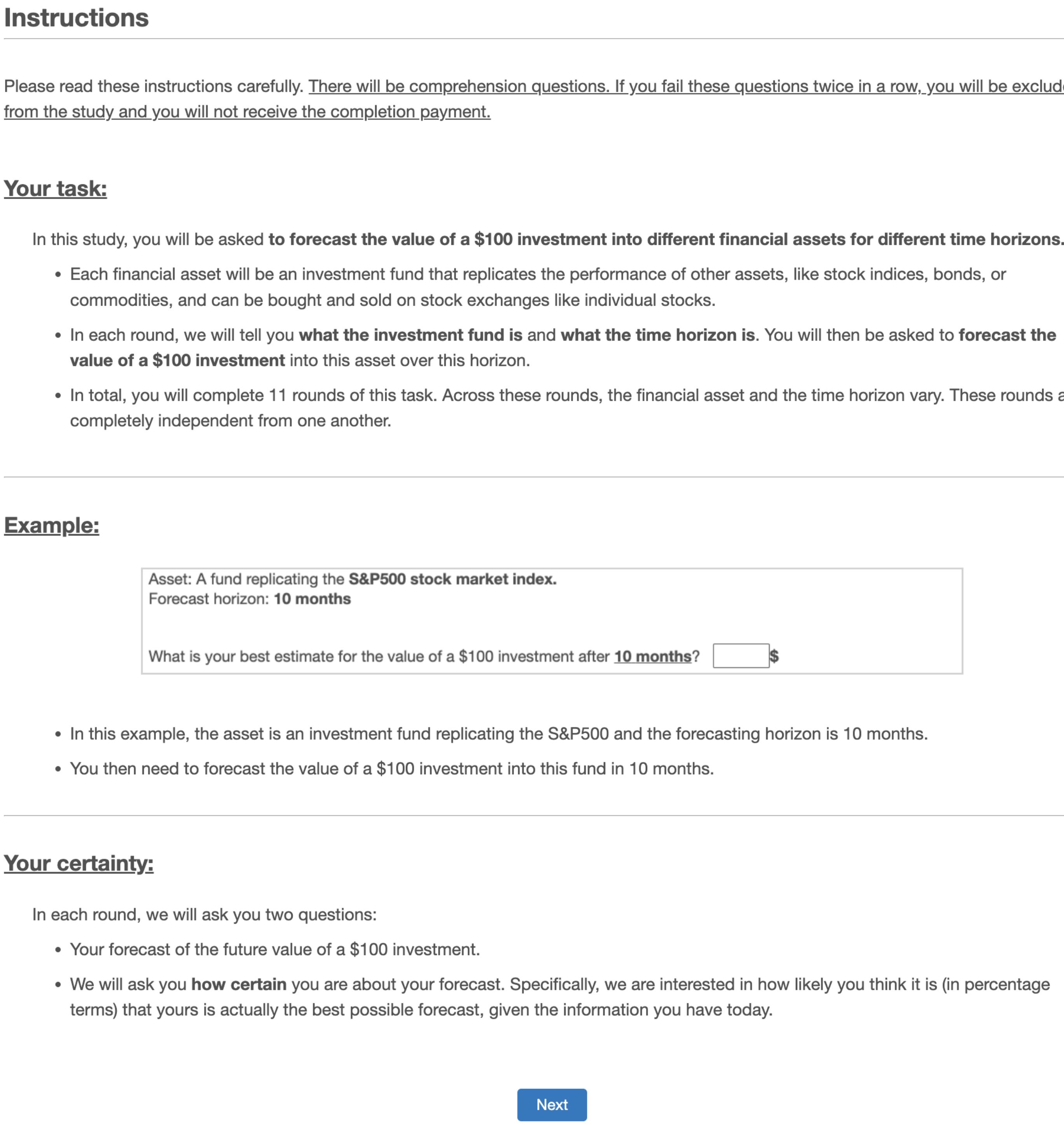


Figure 73: The decision screen for the POL task.

D.21 STO



Instructions

Please read these instructions carefully. There will be comprehension questions. If you fail these questions twice in a row, you will be exclud
from the study and you will not receive the completion payment.

Your task:

In this study, you will be asked **to forecast the value of a $100 investment into different financial assets for different time horizons.**

- Each financial asset will be an investment fund that replicates the performance of other assets, like stock indices, bonds, or commodities, and can be bought and sold on stock exchanges like individual stocks.
- In each round, we will tell you **what the investment fund is** and **what the time horizon is**. You will then be asked to **forecast the value of a $100 investment** into this asset over this horizon.
- In total, you will complete 11 rounds of this task. Across these rounds, the financial asset and the time horizon vary. These rounds a
completely independent from one another.

Example:

Asset: A fund replicating the **S&P500 stock market index.**
Forecast horizon: **10 months**

What is your best estimate for the value of a $100 investment after **10 months**? [ ] **$**

- In this example, the asset is an investment fund replicating the S&P500 and the forecasting horizon is 10 months.
- You then need to forecast the value of a $100 investment into this fund in 10 months.

Your certainty:

In each round, we will ask you two questions:

- Your forecast of the future value of a $100 investment.
- We will ask you **how certain** you are about your forecast. Specifically, we are interested in how likely you think it is (in percentage terms) that yours is actually the best possible forecast, given the information you have today.

Next

Figure 74: The instruction screen for the STO task.

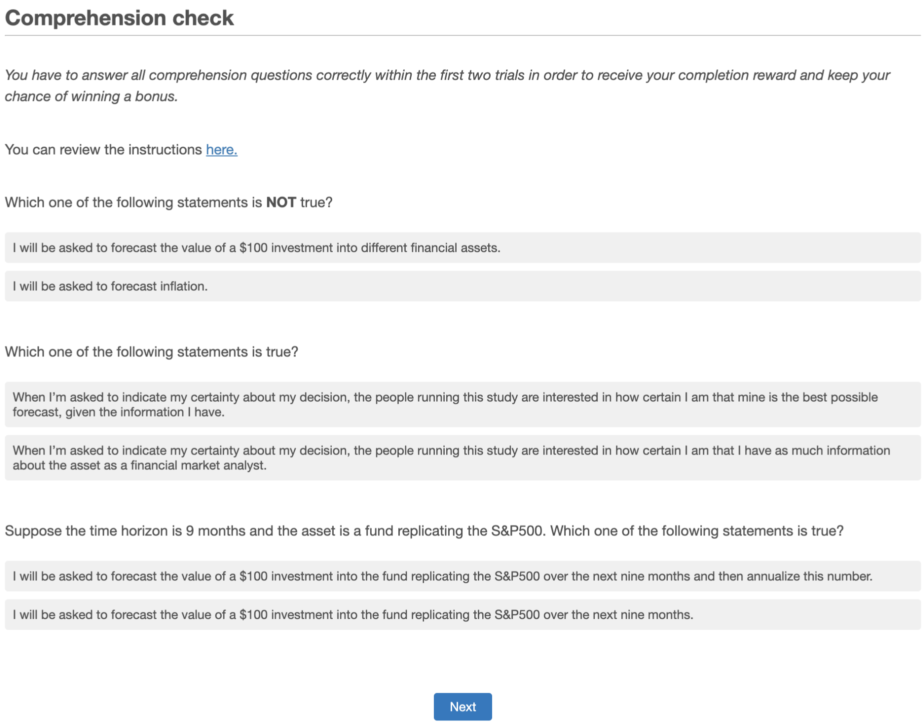


Figure 75: The comprehension screen for the STO task.

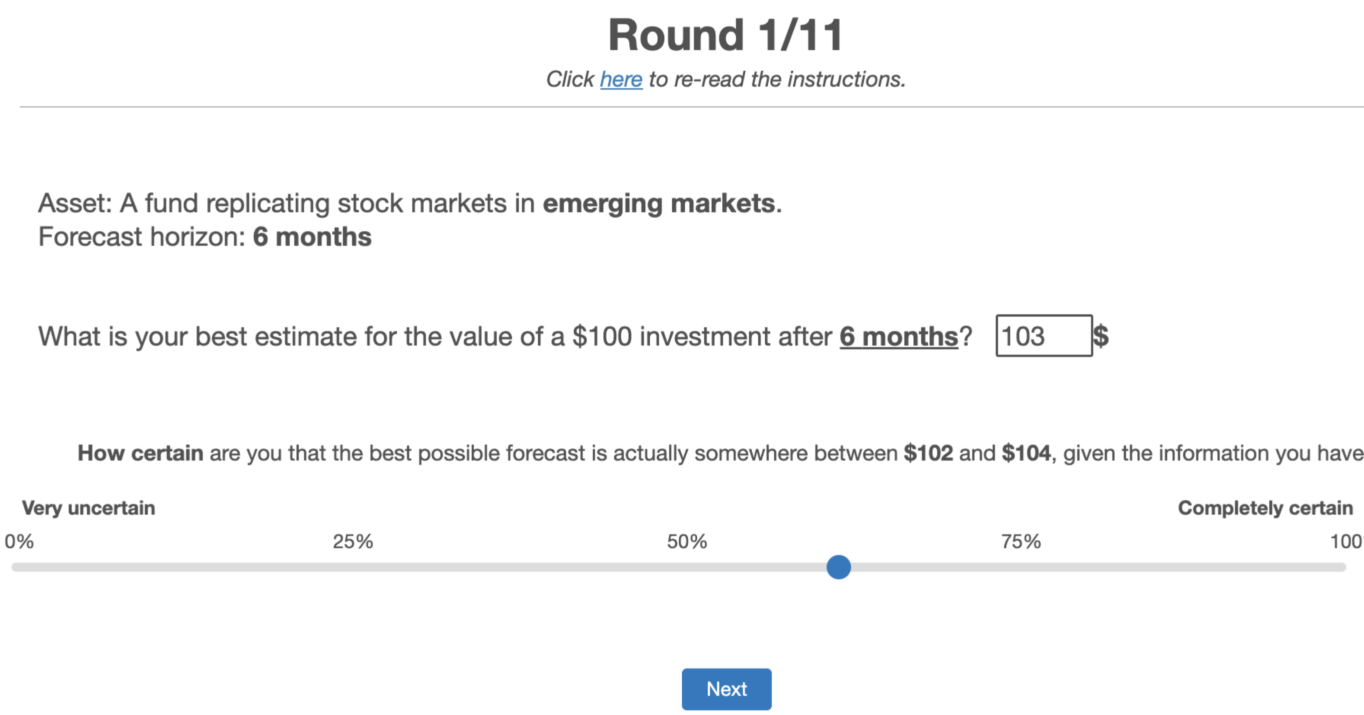


Figure 76: The decision screen for the STO task.

D.22 TID

Instructions

Please read these instructions carefully. There will be comprehension questions. If you fail these questions twice in a row, you will be excluded from the study and you will not receive the completion payment.

Your task:

In this study, **you will decide between two hypothetical payments.**

- The **"future payment"** pays $100 **at some point in the future (i.e., with some specific delay).**
- The **"immediate payment"** pays **a specific amount now.**
- For all hypothetical payments in this study, **please treat them as if you know you will receive them with certainty,** even if they are delayed. That is, please assume there is no risk that you wouldn't actually get paid.
- In each round, you will be told the **delay of the future payment (of $100) as well as the amount of the immediate payment.** You will then decide between the two payments.
- In total, you will complete 11 rounds of this task. Across these rounds, the delay of the future payment will vary. These rounds are completely independent from one another.

Example:

Delayed payment			Immediate payment
	●	○	**$5** now
	●	○	**$10** now
	●	○	**$15** now
	●	○	**$20** now
	●	○	**$25** now
	●	○	**$30** now
	○	●	**$35** now
	○	●	**$40** now
	○	●	**$45** now
$100 in **10 months**	○	●	**$50** now
	○	●	**$55** now
	○	●	**$60** now
	○	●	**$65** now
	○	●	**$70** now
	○	●	**$75** now
	○	●	**$80** now
	○	●	**$85** now
	○	●	**$90** now
	○	●	**$95** now

- In this example, the delay of the future payment is 10 months.
- You then need to decide whether you prefer this delayed payment or a given immediate payment.
- You will make your decisions in a choice list, **where each row is a separate choice.**
  - In every list, the left-hand option is a delayed payment that is identical in all rows. The right-hand option is an immediate payment. The immediate payment increases from row-to-row as you go down the list.
  - To make a choice just click on the radio button you prefer for each choice (i.e. for each row).
  - **An effective way to complete these choice lists is to determine in which row you would prefer to switch from choosing the delayed payment to choosing the immediate payment.** You can click on that row and we will automatically fill out the rest of the list for you, by selecting the delayed payment in all rows above and immediate payment in all rows below your selected row.
  - Based on where you switch from the delayed payment to the immediate payment in this list, we assess which immediate payment you value as much as the future payment.
  - For example, in the choice list above, your choice suggests that you value the future payment as much as an immediate payment between $30 and $35 because this is where you switched.

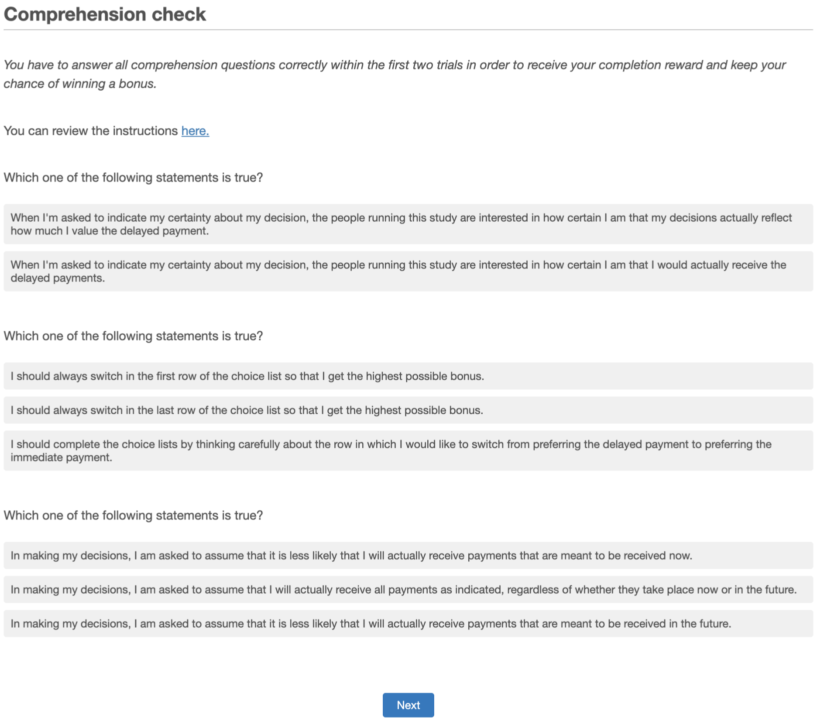
Your certainty:

In each round, we will ask you two questions:

- You will decide between a future payment and different immediate payments. We will use these decisions to assess how much the delayed payment is worth to you.
- We will ask you **how certain** you are about your decisions. Specifically, we are interested in how likely you think it is (in percentage terms) that your decisions actually reflect how much you value the delayed payment.

Next

Figure 77: The instruction screen for the TID task.



Comprehension check

You have to answer all comprehension questions correctly within the first two trials in order to receive your completion reward and keep your chance of winning a bonus.

You can review the instructions here.

Which one of the following statements is true?

When I'm asked to indicate my certainty about my decision, the people running this study are interested in how certain I am that my decisions actually reflect how much I value the delayed payment.

When I'm asked to indicate my certainty about my decision, the people running this study are interested in how certain I am that I would actually receive the delayed payments.

Which one of the following statements is true?

I should always switch in the first row of the choice list so that I get the highest possible bonus.

I should always switch in the last row of the choice list so that I get the highest possible bonus.

I should complete the choice lists by thinking carefully about the row in which I would like to switch from preferring the delayed payment to preferring the immediate payment.

Which one of the following statements is true?

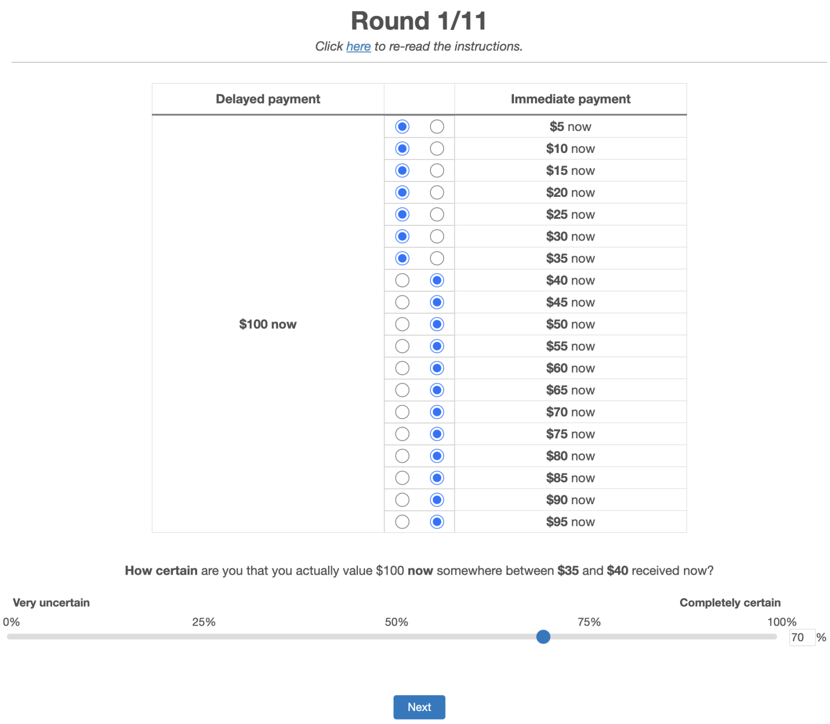
In making my decisions, I am asked to assume that it is less likely that I will actually receive payments that are meant to be received now.

In making my decisions, I am asked to assume that I will actually receive all payments as indicated, regardless of whether they take place now or in the future.

In making my decisions, I am asked to assume that it is less likely that I will actually receive payments that are meant to be received in the future.

Next

Figure 78: The comprehension screen for the TID task.



Round 1/11

Click here to re-read the instructions.

Delayed payment			Immediate payment
	◉	○	**$5** now
	◉	○	**$10** now
	◉	○	**$15** now
	◉	○	**$20** now
	◉	○	**$25** now
	◉	○	**$30** now
	◉	○	**$35** now
	○	◉	**$40** now
	○	◉	**$45** now
$100 now	○	◉	**$50** now
	○	◉	**$55** now
	○	◉	**$60** now
	○	◉	**$65** now
	○	◉	**$70** now
	○	◉	**$75** now
	○	◉	**$80** now
	○	◉	**$85** now
	○	◉	**$90** now
	○	◉	**$95** now

How certain are you that you actually value $100 **now** somewhere between **$35** and **$40** received now?

Very uncertain **Completely certain**

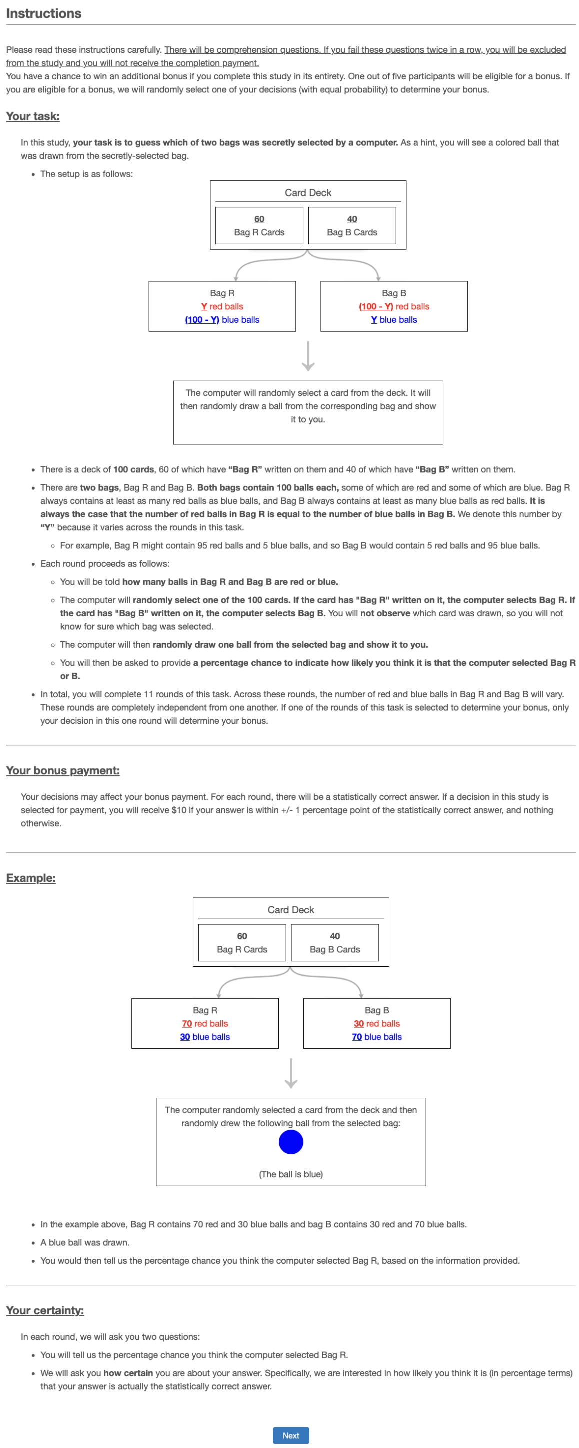
0% 25% 50% 75% 100%

70 %

Next

Figure 79: The decision screen for the TID task.

D.23 BEU



Instructions

Please read these instructions carefully. There will be comprehension questions. If you fail these questions twice in a row, you will be excluded from the study and you will not receive the completion payment.
You have a chance to win an additional bonus if you complete this study in its entirety. One out of five participants will be eligible for a bonus. If you are eligible for a bonus, we will randomly select one of your decisions (with equal probability) to determine your bonus.

Your task:

In this study, **your task is to guess which of two bags was secretly selected by a computer.** As a hint, you will see a colored ball that was drawn from the secretly-selected bag.

- The setup is as follows:

- There is a deck of **100 cards**, 60 of which have **“Bag R”** written on them and 40 of which have **“Bag B”** written on them.
- There are **two bags**, Bag R and Bag B. **Both bags contain 100 balls each,** some of which are red and some of which are blue. Bag R always contains at least as many red balls as blue balls, and Bag B always contains at least as many blue balls as red balls. **It is always the case that the number of red balls in Bag R is equal to the number of blue balls in Bag B.** We denote this number by **“Y”** because it varies across the rounds in this task.
  - For example, Bag R might contain 95 red balls and 5 blue balls, and so Bag B would contain 5 red balls and 95 blue balls.
- Each round proceeds as follows:
  - You will be told **how many balls in Bag R and Bag B are red or blue.**
  - The computer will **randomly select one of the 100 cards. If the card has "Bag R" written on it, the computer selects Bag R. If the card has "Bag B" written on it, the computer selects Bag B.** You will **not observe** which card was drawn, so you will not know for sure which bag was selected.
  - The computer will then **randomly draw one ball from the selected bag and show it to you.**
  - You will then be asked to provide **a percentage chance to indicate how likely you think it is that the computer selected Bag R or B.**
- In total, you will complete 11 rounds of this task. Across these rounds, the number of red and blue balls in Bag R and Bag B will vary. These rounds are completely independent from one another. If one of the rounds of this task is selected to determine your bonus, only your decision in this one round will determine your bonus.

Your bonus payment:

Your decisions may affect your bonus payment. For each round, there will be a statistically correct answer. If a decision in this study is selected for payment, you will receive $10 if your answer is within +/- 1 percentage point of the statistically correct answer, and nothing otherwise.

Example:

- In the example above, Bag R contains 70 red and 30 blue balls and bag B contains 30 red and 70 blue balls.
- A blue ball was drawn.
- You would then tell us the percentage chance you think the computer selected Bag R, based on the information provided.

Your certainty:

In each round, we will ask you two questions:

- You will tell us the percentage chance you think the computer selected Bag R.
- We will ask you **how certain** you are about your answer. Specifically, we are interested in how likely you think it is (in percentage terms) that your answer is actually the statistically correct answer.

Next

Figure 80: The instruction screen for the BEU task.

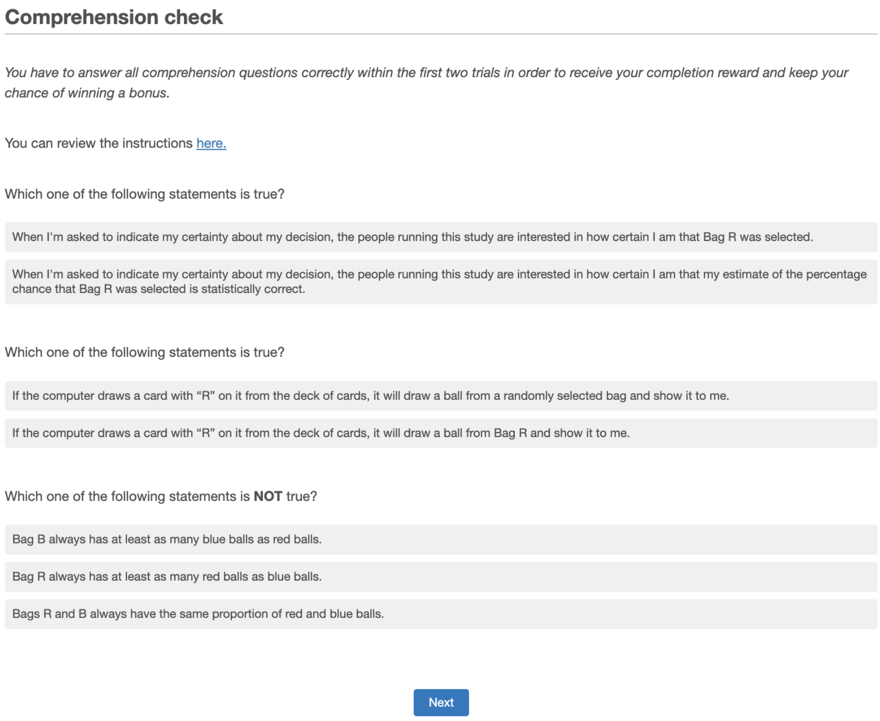


Figure 81: The comprehension screen for the BEU task.

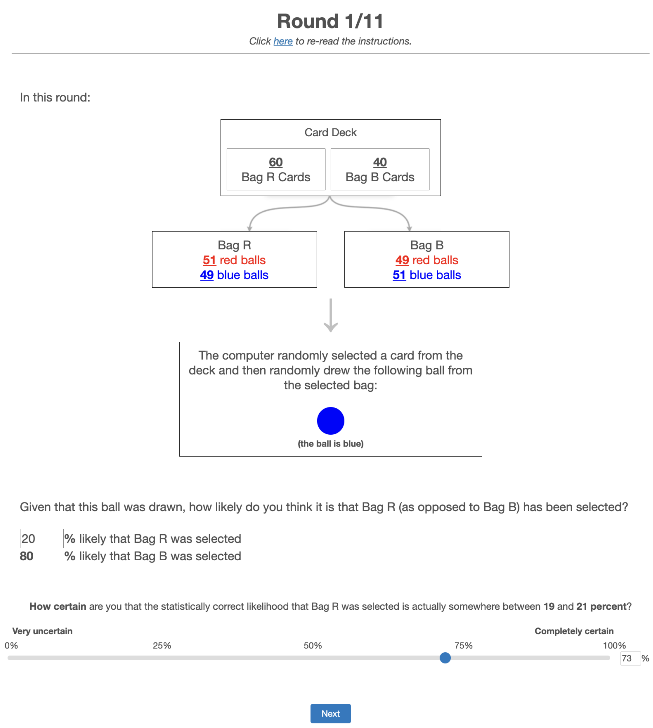


Figure 82: The decision screen for the BEU task.

D.24 CEE

Instructions

Please read these instructions carefully. <u>There will be comprehension questions. If you fail these questions twice in a row, you will be excluded from the study and you will not receive the completion payment.</u>
You have a chance to win an additional bonus if you complete this study in its entirety. One out of five participants will be eligible for a bonus. If you are eligible for a bonus, we will randomly select one of your decisions (with equal probability) to determine your bonus.

<u>Your task:</u>

In this study, you will **decide between a lottery ticket and a safe payment.**

- A lottery ticket pays **$18 with some percentage chance, and $0 otherwise.**
- A safe payment is paid with certainty.
- In each round, you will be told the **percentage chance of getting $18 from the lottery ticket.** You will then decide between the lottery ticket and different safe payment amounts.
- In total, you will complete 11 rounds of this task. Across these rounds, the percentage chance the lottery ticket pays $18 varies. These rounds are completely independent from one another. If one of the rounds of this task is selected to determine your bonus, only your decision in this one round will determine your bonus.

<u>Your bonus payment:</u>

Your decisions may affect your bonus.

- If you picked the lottery ticket, you will receive the outcome of the lottery, implemented by the computer.
- If you picked the safe payment, you will receive that payment.

This means that it is in your best interest to **choose the option (lottery ticket or safe payment) you actually prefer in each case.**

<u>Example:</u>

Lottery			Safe payment
	●	○	$1
	●	○	$2
	●	○	$3
	●	○	$4
	●	○	$5
	●	○	$6
	●	○	$7
With **80%** chance: **Get $18**	●	○	$8
With **20%** chance: **Get $0**	●	○	$9
	●	○	$10
	●	○	$11
	●	○	$12
	●	○	$13
	○	●	$14
	○	●	$15
	○	●	$16
	○	●	$17

- In this example, the percentage chance of winning $18 is 80%.
- You then need to decide whether you prefer this lottery ticket or a given safe payment.
- You will make your decisions in a choice list, **where each row is a separate choice.**
  - In every list, the left-hand option is a lottery that is identical in all rows. The right-hand option is a safe payment. The safe payment increases as you go down the list.
  - To make a choice just click on the radio button you prefer for each choice (i.e. for each row).
  - **An effective way to complete these choice lists is to determine in which row you would prefer to switch from choosing the lottery to choosing the safe payment.** You can click on the radio button in that row and we will automatically fill out the rest of the list for you, by selecting the lottery in all rows above and safe payment in all rows below your selected row.
  - Based on where you switch from the lottery to the safe payment in this list, we assess which safe payment you value as much as the lottery.
  - For example, in the choice list above, your choice suggests that you value the lottery as much as a safe payment between $13 and $14 because this is where you switched.
  - If a round in this study is selected for bonus payment, the computer will randomly select one of your choices from that choice list, and you will receive the option you selected in that choice.

<u>Your certainty:</u>

In each round, we will ask you two questions:

- You will decide between a lottery ticket and different safe payments. We will use these decisions to assess how much you value the lottery ticket.
- We will ask you **how certain** you are about your decisions. Specifically, we are interested in how likely you think it is (in percentage terms) that your decisions actually reflect how much you value the lottery ticket.

Next

Figure 83: The instruction screen for the CEE task.

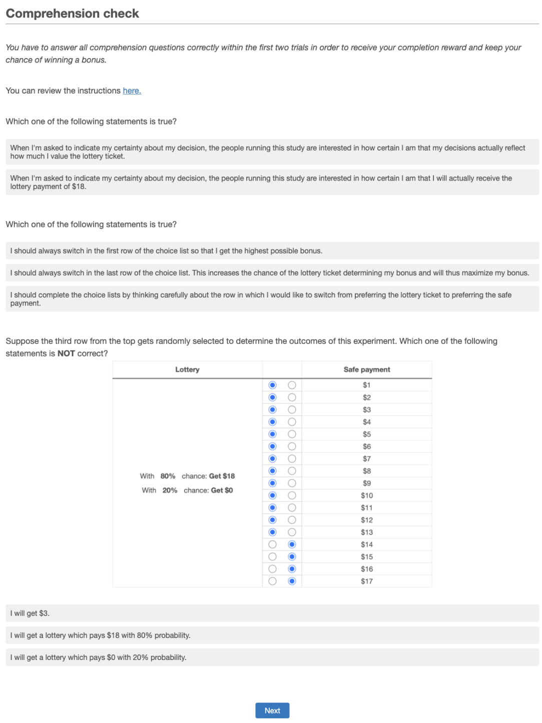


Figure 84: The comprehension screen for the CEE task.

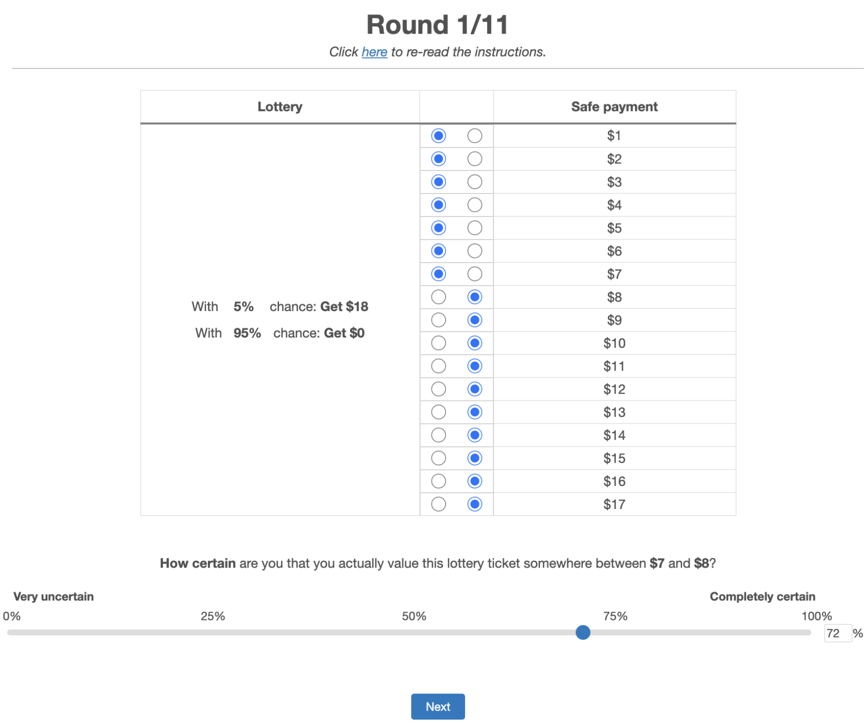
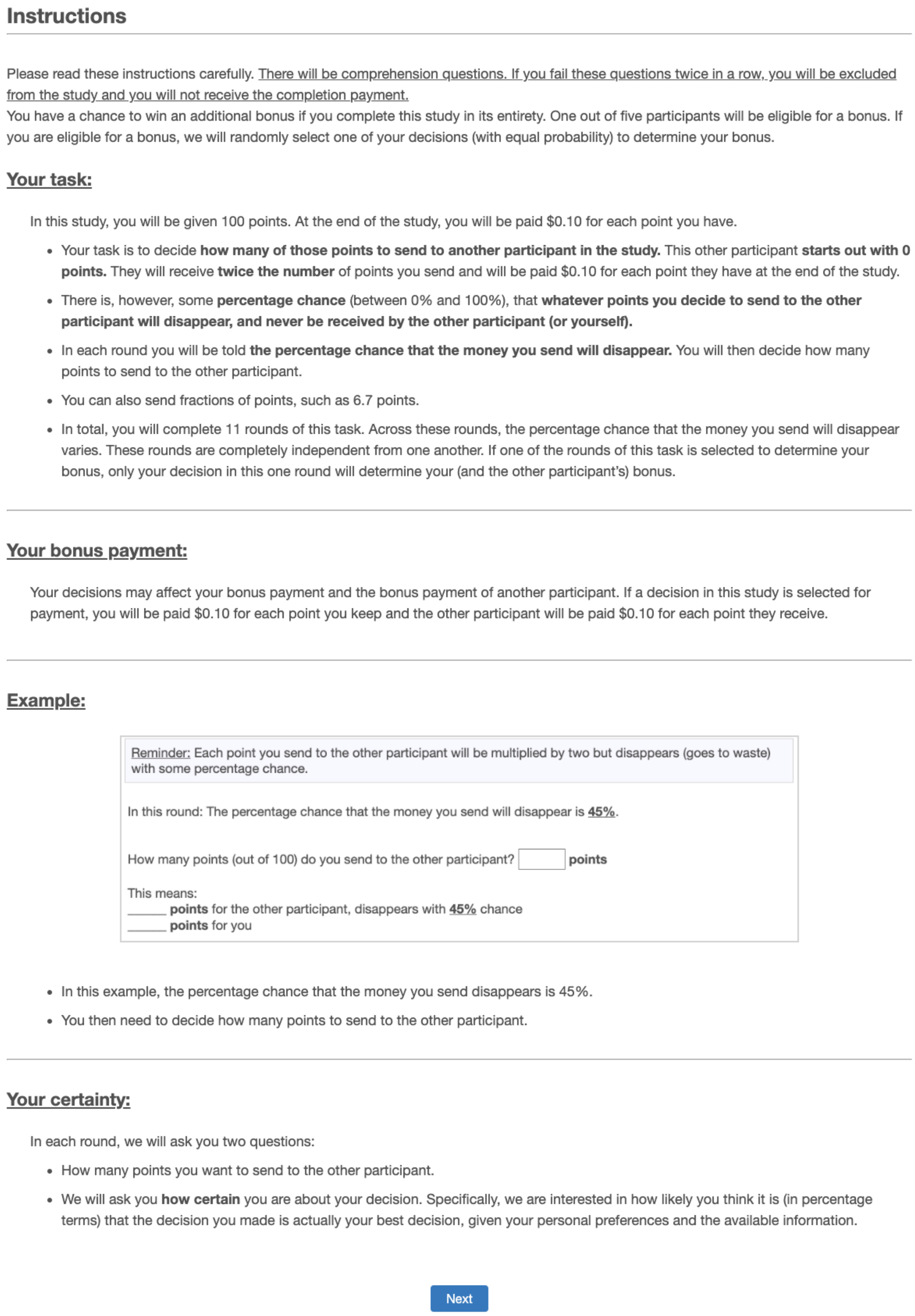


Figure 85: The decision screen for the CEE task.

D.25 DIG



Instructions

Please read these instructions carefully. There will be comprehension questions. If you fail these questions twice in a row, you will be excluded from the study and you will not receive the completion payment.
You have a chance to win an additional bonus if you complete this study in its entirety. One out of five participants will be eligible for a bonus. If you are eligible for a bonus, we will randomly select one of your decisions (with equal probability) to determine your bonus.

Your task:

In this study, you will be given 100 points. At the end of the study, you will be paid $0.10 for each point you have.

- Your task is to decide **how many of those points to send to another participant in the study.** This other participant **starts out with 0 points.** They will receive **twice the number** of points you send and will be paid $0.10 for each point they have at the end of the study.
- There is, however, some **percentage chance** (between 0% and 100%), that **whatever points you decide to send to the other participant will disappear, and never be received by the other participant (or yourself).**
- In each round you will be told **the percentage chance that the money you send will disappear.** You will then decide how many points to send to the other participant.
- You can also send fractions of points, such as 6.7 points.
- In total, you will complete 11 rounds of this task. Across these rounds, the percentage chance that the money you send will disappear varies. These rounds are completely independent from one another. If one of the rounds of this task is selected to determine your bonus, only your decision in this one round will determine your (and the other participant's) bonus.

Your bonus payment:

Your decisions may affect your bonus payment and the bonus payment of another participant. If a decision in this study is selected for payment, you will be paid $0.10 for each point you keep and the other participant will be paid $0.10 for each point they receive.

Example:

Reminder: Each point you send to the other participant will be multiplied by two but disappears (goes to waste) with some percentage chance.

In this round: The percentage chance that the money you send will disappear is **45%**.

How many points (out of 100) do you send to the other participant? ____ **points**

This means:
_____ **points** for the other participant, disappears with **45%** chance
_____ **points** for you

- In this example, the percentage chance that the money you send disappears is 45%.
- You then need to decide how many points to send to the other participant.

Your certainty:

In each round, we will ask you two questions:

- How many points you want to send to the other participant.
- We will ask you **how certain** you are about your decision. Specifically, we are interested in how likely you think it is (in percentage terms) that the decision you made is actually your best decision, given your personal preferences and the available information.

Next

Figure 86: The instruction screen for the DIG task.

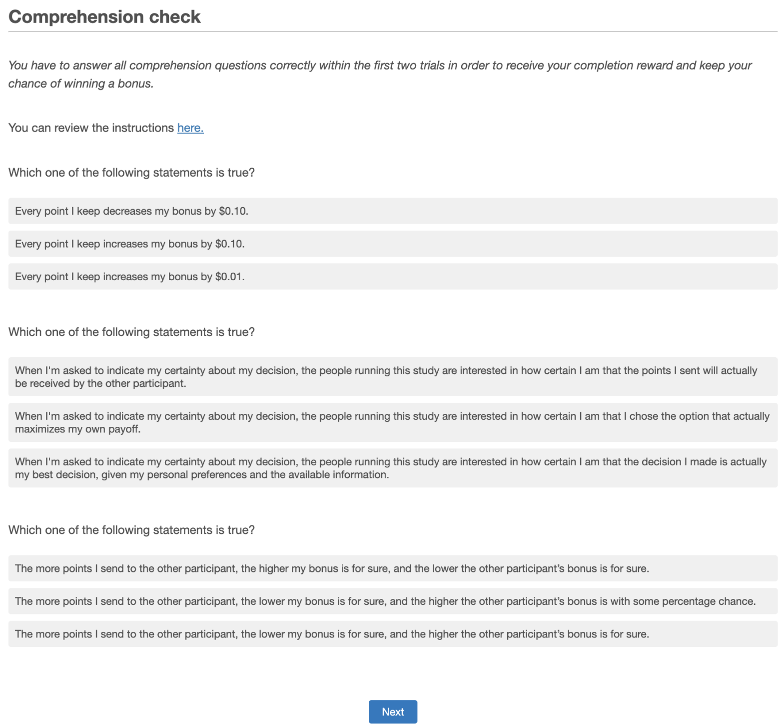


Figure 87: The comprehension screen for the DIG task.

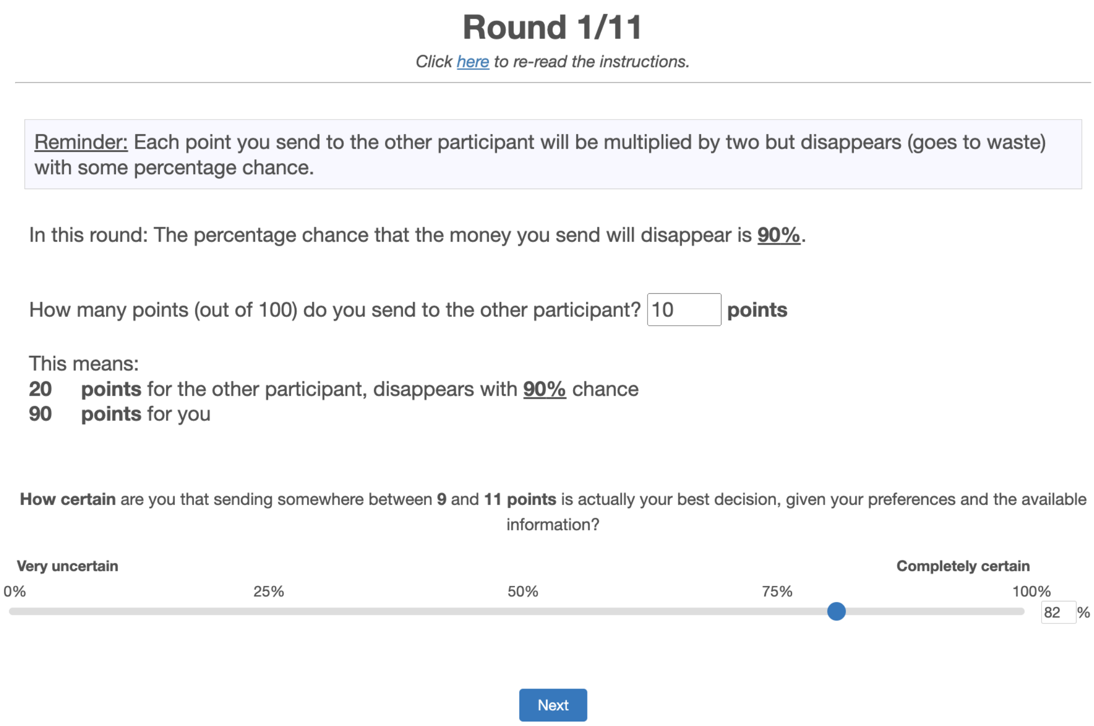


Figure 88: The decision screen for the DIG task.

D.26 EFF

Instructions

Please read these instructions carefully. <u>There will be comprehension questions. If you fail these questions twice in a row, you will be excluded from the study and you will not receive the completion payment.</u>
You have a chance to win an additional bonus if you complete this study in its entirety. One out of five participants will be eligible for a bonus. If you are eligible for a bonus, we will randomly select one of your decisions (with equal probability) to determine your bonus.

<u>Your task:</u>

In this study, you will **decide how many tasks you want to complete for a given wage.**

- You will be offered a wage for every task you complete. You then decide how many tasks you would like to be assigned. Your payment for the work assignment equals the **wage times the number of tasks you complete.**
- Each task you are assigned will require you to count the number of 1s in a table with 64 cells such as the one below:

6	5	4	2	0	5	7	0
6	0	7	4	7	6	3	8
7	3	2	5	8	8	9	2
8	6	7	3	4	9	6	8
2	3	3	1	5	6	4	8
8	6	5	4	5	1	5	8
5	9	6	7	8	4	1	9
0	8	6	3	9	3	8	6

- To complete a task successfully, you have to **correctly count the number of 1s.**
- A task that is not completed successfully will not count towards the total of tasks you need to complete for the assignment. Instead, **if you do not successfully complete a task, the computer will generate a new one.**
- The average time to complete a task is about 20 seconds.
- In each round, you will be told the wage per task. You will then decide how many tasks your work assignment should include.
- In total, you will complete 11 rounds of this task. Across these rounds, the wage varies. These rounds are completely independent from one another. If one of the rounds of this task is selected to determine your bonus, only your decision in this one round will determine your bonus.

<u>Your bonus payment:</u>

Your decisions may affect your bonus payment as well as how many tasks you will have to work on to receive your bonus. If a decision in this study is selected for payment, you will have to complete the number of tasks you selected and you will receive the total payment for the assignment. If you do not complete the total number of tasks your assignment includes, you will not receive any bonus payment. There is no partial payment for partially completed assignments.

<u>Example:</u>

<u>Reminder:</u>
- To complete a task successfully, you have to count the number of 1s in a table with 64 cells.
- For each task you choose to complete, you receive a wage. You will have to complete all tasks to receive a bonus payment, there are no partial payments.
- The average time to complete a task is about 20 seconds.

In this round: Your wage per completed task is **<u>$0.22</u>**.

How many tasks do you want to be assigned? [ ] **tasks**.

- In this example, the wage per completed task is $0.22.
- You then need to decide how many tasks to complete.

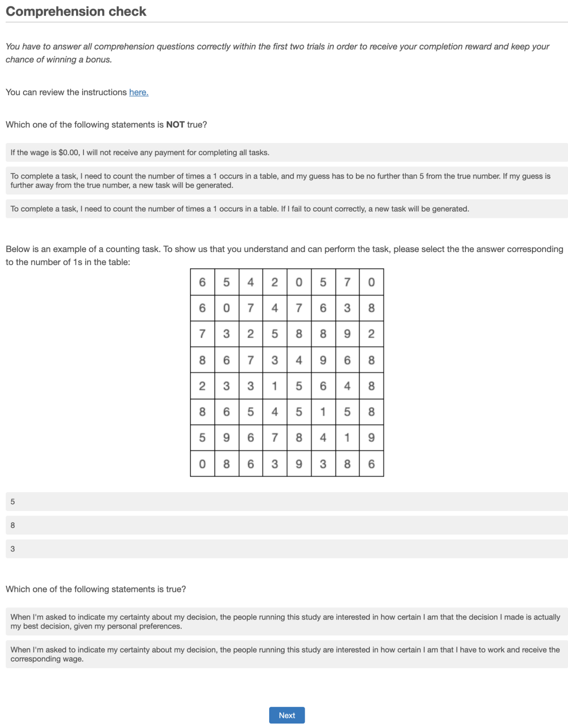
<u>Your certainty:</u>

In each round, we will ask you two questions:

- You will decide how many tasks you would like to complete given the wage you are offered.
- We will ask you **how certain** you are about your decision. Specifically, we are interested in how likely you think it is (in percentage terms) that the decision you made is actually your best decision, given your personal preferences.

Next

Figure 89: The instruction screen for the EFF task.



Comprehension check

You have to answer all comprehension questions correctly within the first two trials in order to receive your completion reward and keep your chance of winning a bonus.

You can review the instructions here.

Which one of the following statements is **NOT** true?

- If the wage is $0.00, I will not receive any payment for completing all tasks.
- To complete a task, I need to count the number of times a 1 occurs in a table, and my guess has to be no further than 5 from the true number. If my guess is further away from the true number, a new task will be generated.
- To complete a task, I need to count the number of times a 1 occurs in a table. If I fail to count correctly, a new task will be generated.

Below is an example of a counting task. To show us that you understand and can perform the task, please select the the answer corresponding to the number of 1s in the table:

6	5	4	2	0	5	7	0
6	0	7	4	7	6	3	8
7	3	2	5	8	8	9	2
8	6	7	3	4	9	6	8
2	3	3	1	5	6	4	8
8	6	5	4	5	1	5	8
5	9	6	7	8	4	1	9
0	8	6	3	9	3	8	6

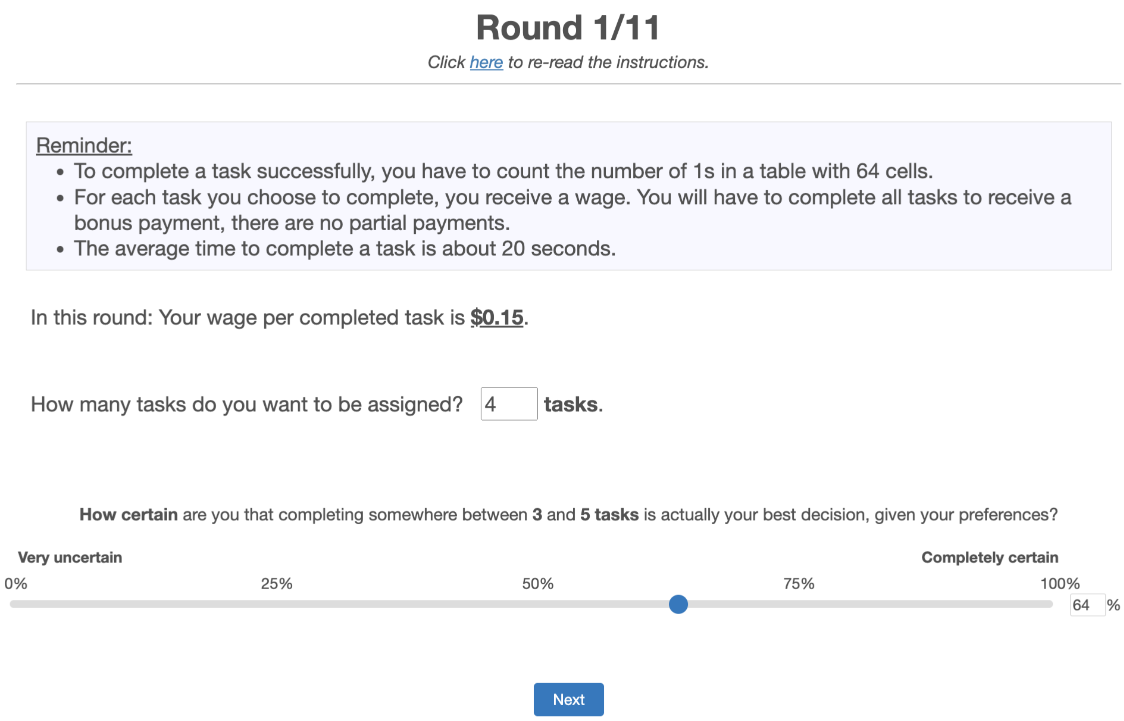
- 5
- 8
- 3

Which one of the following statements is true?

- When I'm asked to indicate my certainty about my decision, the people running this study are interested in how certain I am that the decision I made is actually my best decision, given my personal preferences.
- When I'm asked to indicate my certainty about my decision, the people running this study are interested in how certain I am that I have to work and receive the corresponding wage.

Next

Figure 90: The comprehension screen for the EFF task.



Round 1/11

Click here to re-read the instructions.

Reminder:

- To complete a task successfully, you have to count the number of 1s in a table with 64 cells.
- For each task you choose to complete, you receive a wage. You will have to complete all tasks to receive a bonus payment, there are no partial payments.
- The average time to complete a task is about 20 seconds.

In this round: Your wage per completed task is **$0.15**.

How many tasks do you want to be assigned? 4 **tasks**.

How certain are you that completing somewhere between **3** and **5 tasks** is actually your best decision, given your preferences?

Very uncertain **Completely certain**

0% 25% 50% 75% 100% 64 %

Next

Figure 91: The decision screen for the EFF task.

D.27 FOR

Instructions

Please read these instructions carefully. There will be comprehension questions. If you fail these questions twice in a row, you will be excluded from the study and you will not receive the completion payment.
You have a chance to win an additional bonus if you complete this study in its entirety. One out of five participants will be eligible for a bonus. If you are eligible for a bonus, we will randomly select one of your decisions (with equal probability) to determine your bonus.

Your task:

In this study, **your task is to forecast the end-of-year earnings of a fictional firm** for the year 2024, based on the firm's earnings over the previous two years.

- The 2024 earnings of the firm are partly predictable. Specifically, the change in the firm's earnings from 2023 to 2024 is determined by two components:
  - A **predictable change** equal to the previous change in the firm's earnings from 2022 to 2023.
  - An **unpredictable change** that will be a random draw from the numbers
    (-8, -7, -6, -5, -4, -3, -2, -1, 0, 1, 2, 3, 4, 5, 6, 7, 8),
    where each number is **equally likely to be drawn.**
- The relative importance of these two components is given by the predictability level P, a fraction between 0 and 1. In particular, the earnings change is given by the formula

  2024 earnings – 2023 earnings =
  P × (2023 earnings – 2022 earnings) + (1 – **P**) × (Unpredictable change).

- If you know the change in the firm's earnings from 2023 to 2024, the earnings of the firm in 2024 is simply the firm's earnings in 2023 plus that change in earnings.
- In each round, you will be given a different firm to forecast. You will be told the earnings of that firm over the last two years, as well as the predictability level P. Your task is to **forecast the earnings of the firm in 2024.**
- In total, you will complete 11 rounds of this task. Across these rounds, the predictability level P will vary. These rounds are completely independent from one another. If one of the rounds of this task is selected to determine your bonus, only your decision in this one round will determine your bonus.

Your bonus payment:

Your decisions may affect your bonus payment. For each round, there will be a statistically correct forecast of the earnings of the firm. If a decision in this part is selected for payment, you will receive $10 if your answer is within +/- $1 of the statistically correct forecast, and nothing otherwise.

Example:

Reminder: The earnings change between 2023 and 2024 is determined by two components:
- A **predictable change** equal to the previous change in the firm's earnings between 2022 and 2023
- A **unpredictable change** equal to a random draw from the numbers between -8 and +8, with each number equally likely to be drawn

The importance of these two components is determined by the predictability level **P**.

In this round: The predictability level **P** is 0.80, which means:

2024 earnings - 2023 earnings =
0.80 × (2023 earnings - 2022 earnings) + 0.20 × (Unpredictable change)

The firm's earnings over the previous two years are given below:

2024 Earnings	?
2023 Earnings	**$127**
2022 Earnings	**$109**

What is your forecast of the earnings of this firm in 2024? **$**

- In this example, the predictability level is 0.8, and the firm's earnings over the last two years (2022 and 2023) are $109 and $127, respectively.
- You would give your forecast of the 2024 earnings of this firm, based on the information provided.

Your certainty:

In each round, we will ask you two questions:

- You will forecast the 2024 earnings of the firm.
- We will ask you **how certain** you are about your forecast. Specifically, we are interested in how likely you think it is (in percentage terms) that your forecast is actually the statistically correct forecast.

Next

Figure 92: The instruction screen for the FOR task.

Comprehension check

You have to answer all comprehension questions correctly within the first two trials in order to receive your completion reward and keep your chance of winning a bonus.

You can review the instructions here.

Which one of the following statements is true?

My task is to forecast the 2024 earnings of the firm, which is equal to the firm's 2023 earnings plus the predictable and unpredictable change.

My task is to forecast the 2023 earnings change of the firm.

Which one of the following statements is true?

When I'm asked to indicate my certainty about my decision, the people running this study are interested in how certain I am that my forecast of the firm's earnings is statistically correct, given the available information.

When I'm asked to indicate my certainty about my decision, the people running this study are interested in how predictable I think the firm's earnings will be.

Which one of the following statements is true?

The unpredictable change is a random draw from the numbers between -8 and +8, with each number equally likely to be drawn.

The unpredictable change is a random draw from the numbers between -8 and +8, with positive numbers more likely to be drawn than negative numbers.

Next

Figure 93: The comprehension screen for the FOR task.

Round 1/11

Click here to re-read the instructions.

Reminder: The earnings change between 2023 and 2024 is determined by two components:
- A **predictable change** equal to the previous change in the firm's earnings between 2022 and 2023
- A **unpredictable change** equal to a random draw from the numbers between -8 and +8, with each number equally likely to be drawn

The importance of these two components is determined by the predictability level **P**.

In this round: The predictability level **P** is 0.75, which means:

2024 earnings - 2023 earnings =
0.75 × (2023 earnings - 2022 earnings) + 0.25 × (Unpredictable change)

The firm's earnings over the previous two years are given below:

2024 Earnings	?
2023 Earnings	**$127**
2022 Earnings	**$109**

What is your forecast of the earnings of this firm in 2024? **$** 145

How certain are you that the statistically correct forecast of the firm's 2024 earnings is actually somewhere **$144** and **$146**?

Very uncertain **Completely certain**

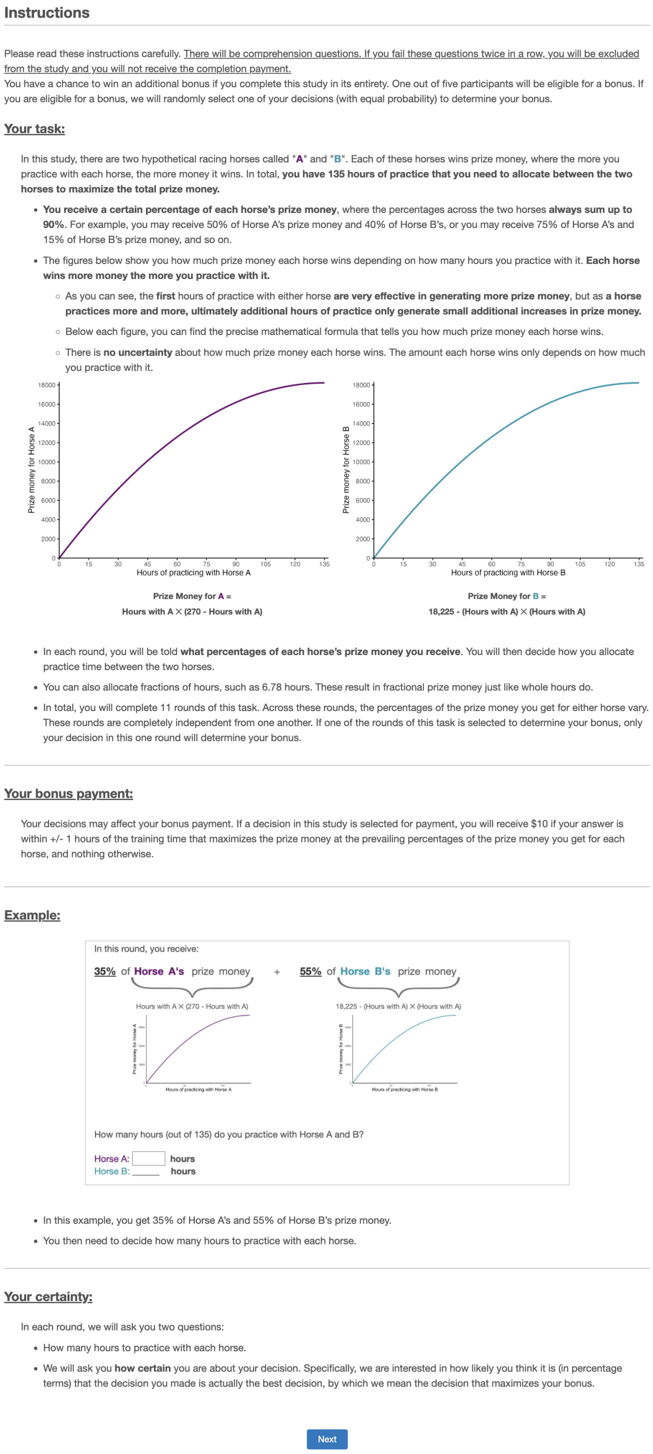
0% 25% 50% 75% 100%

67 %

Next

Figure 94: The decision screen for the FOR task.

D.28 MUL



Instructions

Please read these instructions carefully. There will be comprehension questions. If you fail these questions twice in a row, you will be excluded from the study and you will not receive the completion payment.
You have a chance to win an additional bonus if you complete this study in its entirety. One out of five participants will be eligible for a bonus. If you are eligible for a bonus, we will randomly select one of your decisions (with equal probability) to determine your bonus.

Your task:

In this study, there are two hypothetical racing horses called "**A**" and "**B**". Each of these horses wins prize money, where the more you practice with each horse, the more money it wins. In total, **you have 135 hours of practice that you need to allocate between the two horses to maximize the total prize money.**

- **You receive a certain percentage of each horse's prize money**, where the percentages across the two horses **always sum up to 90%**. For example, you may receive 50% of Horse A's prize money and 40% of Horse B's, or you may receive 75% of Horse A's and 15% of Horse B's prize money, and so on.
- The figures below show you how much prize money each horse wins depending on how many hours you practice with it. **Each horse wins more money the more you practice with it.**
  - As you can see, the **first** hours of practice with either horse **are very effective in generating more prize money**, but as **a horse practices more and more, ultimately additional hours of practice only generate small additional increases in prize money.**
  - Below each figure, you can find the precise mathematical formula that tells you how much prize money each horse wins.
  - There is **no uncertainty** about how much prize money each horse wins. The amount each horse wins only depends on how much you practice with it.

Prize Money for A =
Hours with A × (270 - Hours with A)

Prize Money for B =
18,225 - (Hours with A) × (Hours with A)

- In each round, you will be told **what percentages of each horse's prize money you receive**. You will then decide how you allocate practice time between the two horses.
- You can also allocate fractions of hours, such as 6.78 hours. These result in fractional prize money just like whole hours do.
- In total, you will complete 11 rounds of this task. Across these rounds, the percentages of the prize money you get for either horse vary. These rounds are completely independent from one another. If one of the rounds of this task is selected to determine your bonus, only your decision in this one round will determine your bonus.

Your bonus payment:

Your decisions may affect your bonus payment. If a decision in this study is selected for payment, you will receive $10 if your answer is within +/- 1 hours of the training time that maximizes the prize money at the prevailing percentages of the prize money you get for each horse, and nothing otherwise.

Example:

In this round, you receive:

35% of **Horse A's** prize money + 55% of **Horse B's** prize money

Hours with A × (270 - Hours with A)

18,225 - (Hours with A) × (Hours with A)

How many hours (out of 135) do you practice with Horse A and B?

Horse A: ______ **hours**
Horse B: ______ **hours**

- In this example, you get 35% of Horse A's and 55% of Horse B's prize money.
- You then need to decide how many hours to practice with each horse.

Your certainty:

In each round, we will ask you two questions:

- How many hours to practice with each horse.
- We will ask you **how certain** you are about your decision. Specifically, we are interested in how likely you think it is (in percentage terms) that the decision you made is actually the best decision, by which we mean the decision that maximizes your bonus.

Next

Figure 95: The instruction screen for the MUL task.

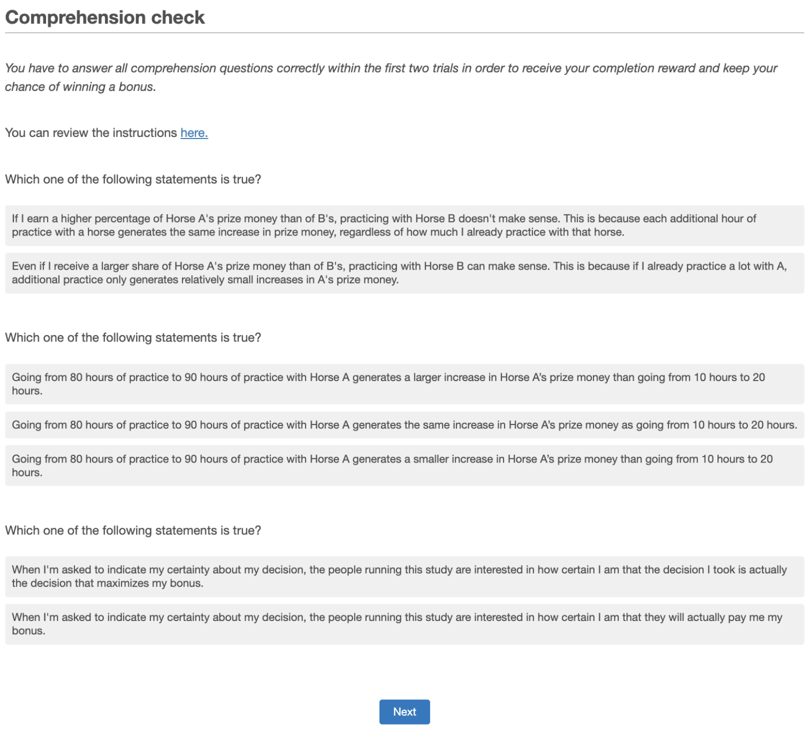


Figure 96: The comprehension screen for the MUL task.

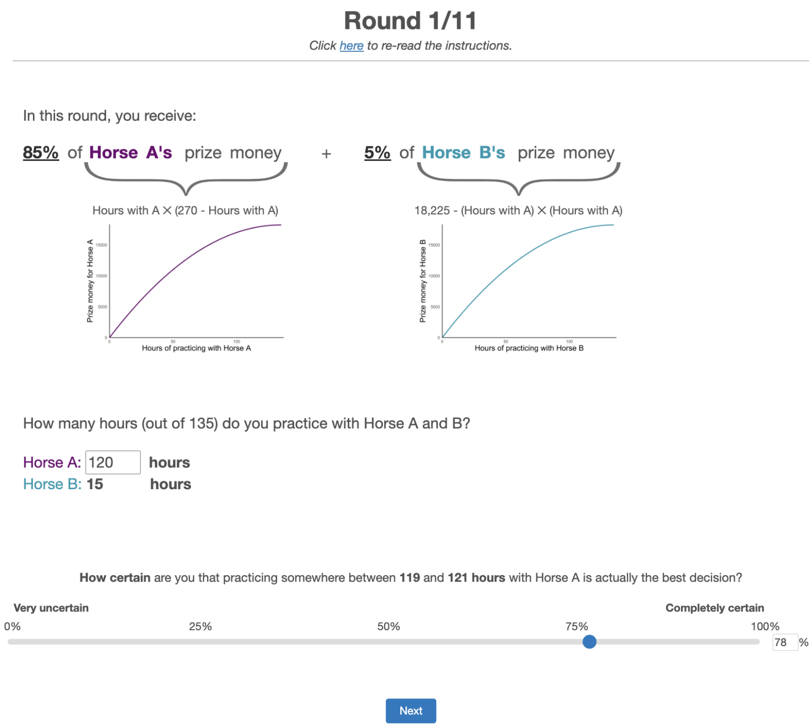


Figure 97: The decision screen for the MUL task.

D.29 NEW

Instructions

Please read these instructions carefully. There will be comprehension questions. If you fail these questions twice in a row, you will be excluded from the study and you will not receive the completion payment.
You have a chance to win an additional bonus if you complete this study in its entirety. One out of five participants will be eligible for a bonus. If you are eligible for a bonus, we will randomly select one of your decisions (with equal probability) to determine your bonus.

Your task:

In this study, you will act as a **fictional firm that produces and sells a single product**: gallons of cola.

- You will choose how much cola to produce, between 0 and 100 gallons. You can **sell cola at a sales price of $12 per gallon.**
- Each gallon will cost you a certain amount to produce.
- In each round, you will be told how much each gallon costs to produce. You will then decide **how many gallons to produce.**
- You must decide how many gallons to produce **before** you know for certain the "demand" quantity: the amount of cola your customers actually want to buy. The computer **randomly selects the demand from a range of 0 to 100 gallons**, with each whole number in the range **equally likely**. Gallons that you produce but for which there is no demand go to waste.
- This means:
  - If you produce **fewer** gallons than the available demand, you sell **all gallons that you produced,** but you also **lose sales you would have made if you'd produced more.**
  - If you produce **more** gallons than the available demand, you only sell **those gallons that meet the available demand.** The remaining gallons that **can't be sold go to waste,** and you still need to **pay the cost of producing them.**
- The **firm's profit** is equal to the number of gallons you sell times the sales price of $12, minus the cost of producing gallons:

  Firm profit = Gallons sold × $12 – Gallons produced × Cost of producing each gallon
- You can also produce fractions of gallons, such as 6.78 gallons. These result in fractional revenue just like whole gallons do.
- In total, you will complete 11 rounds of this task. Across these rounds, **the cost of producing cola varies.** These rounds are completely independent from one another. If one of the rounds of this task is selected to determine your bonus, only your decision in this one round will determine your bonus.

Your bonus payment:

Your decisions may affect your bonus payment. If a decision in this study is selected for payment, we will calculate your profit as described above. Your bonus then equals:

Bonus (in $) = 4 + 1/300 × Firm profit (or loss)

While this may sound complicated, all it means is that it is in your best interest to **truthfully indicate the amount of cola you want to produce.**

Example:

Reminder: You can sell each gallon at a sales price of **$12**, but only to the extent that there is available demand.
The number of gallons demanded is equally likely to be any number **between 0 and 100.**

In this round: The cost of producing each gallon is **$5**.

How many gallons (out of 100) do you produce? ______ gallons

- In this example, the cost of producing each gallon is $5.
- You then need to decide how many gallons to produce.

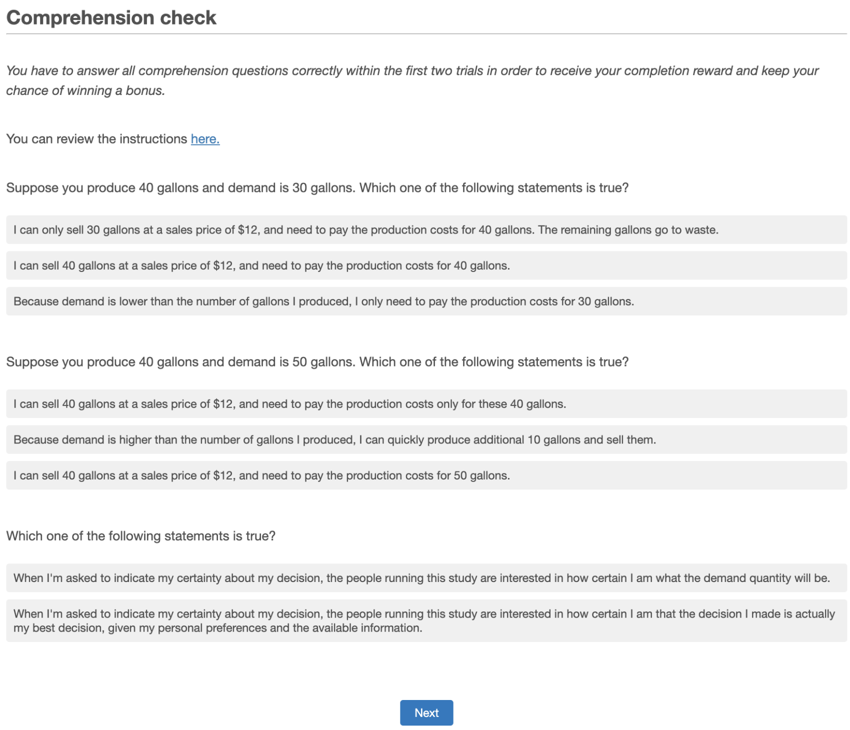
Your certainty:

In each round, we will ask you two questions:

- How many gallons you want to produce.
- We will ask you **how certain** you are about your decision. Specifically, we are interested in how likely you think it is (in percentage terms) that the decision you made is actually your best decision, given your personal preferences and the available information.

Next

Figure 98: The instruction screen for the NEW task.



Comprehension check

You have to answer all comprehension questions correctly within the first two trials in order to receive your completion reward and keep your chance of winning a bonus.

You can review the instructions here.

Suppose you produce 40 gallons and demand is 30 gallons. Which one of the following statements is true?

I can only sell 30 gallons at a sales price of $12, and need to pay the production costs for 40 gallons. The remaining gallons go to waste.

I can sell 40 gallons at a sales price of $12, and need to pay the production costs for 40 gallons.

Because demand is lower than the number of gallons I produced, I only need to pay the production costs for 30 gallons.

Suppose you produce 40 gallons and demand is 50 gallons. Which one of the following statements is true?

I can sell 40 gallons at a sales price of $12, and need to pay the production costs only for these 40 gallons.

Because demand is higher than the number of gallons I produced, I can quickly produce additional 10 gallons and sell them.

I can sell 40 gallons at a sales price of $12, and need to pay the production costs for 50 gallons.

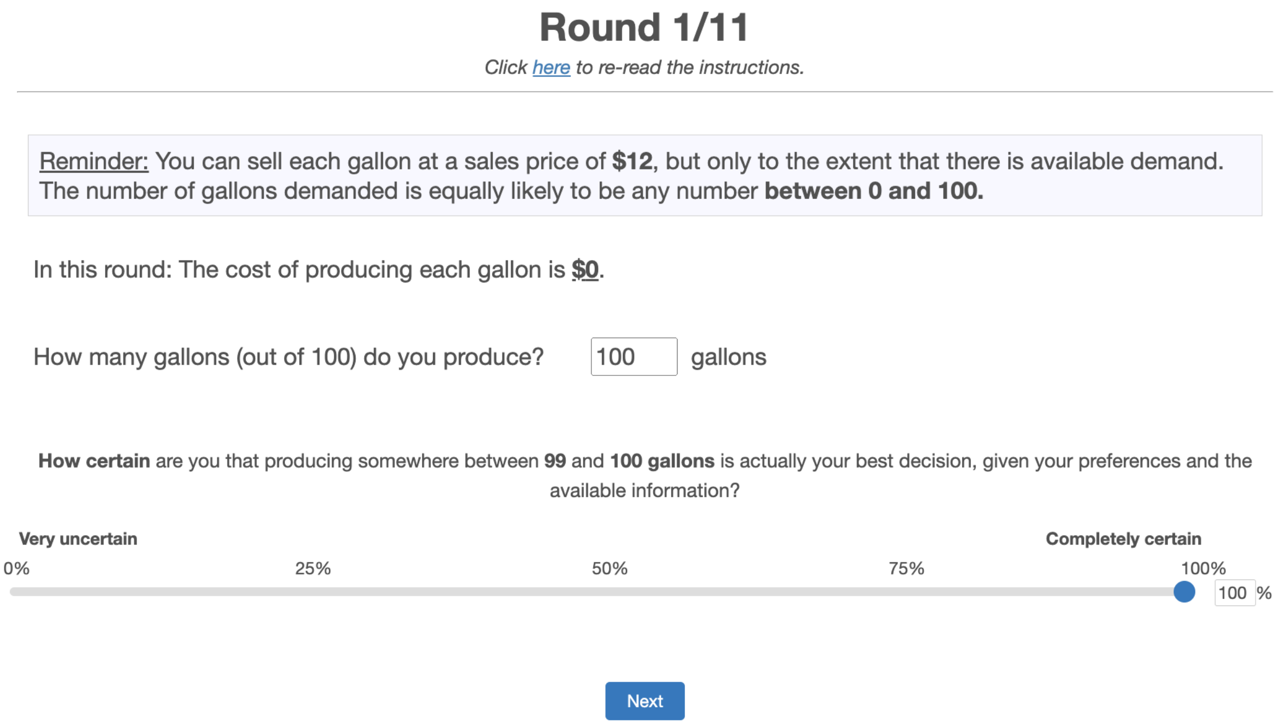
Which one of the following statements is true?

When I'm asked to indicate my certainty about my decision, the people running this study are interested in how certain I am what the demand quantity will be.

When I'm asked to indicate my certainty about my decision, the people running this study are interested in how certain I am that the decision I made is actually my best decision, given my personal preferences and the available information.

Next

Figure 99: The comprehension screen for the NEW task.



Round 1/11

Click here to re-read the instructions.

Reminder: You can sell each gallon at a sales price of **$12**, but only to the extent that there is available demand. The number of gallons demanded is equally likely to be any number **between 0 and 100.**

In this round: The cost of producing each gallon is **$0**.

How many gallons (out of 100) do you produce? 100 gallons

How certain are you that producing somewhere between **99** and **100 gallons** is actually your best decision, given your preferences and the available information?

Very uncertain **Completely certain**

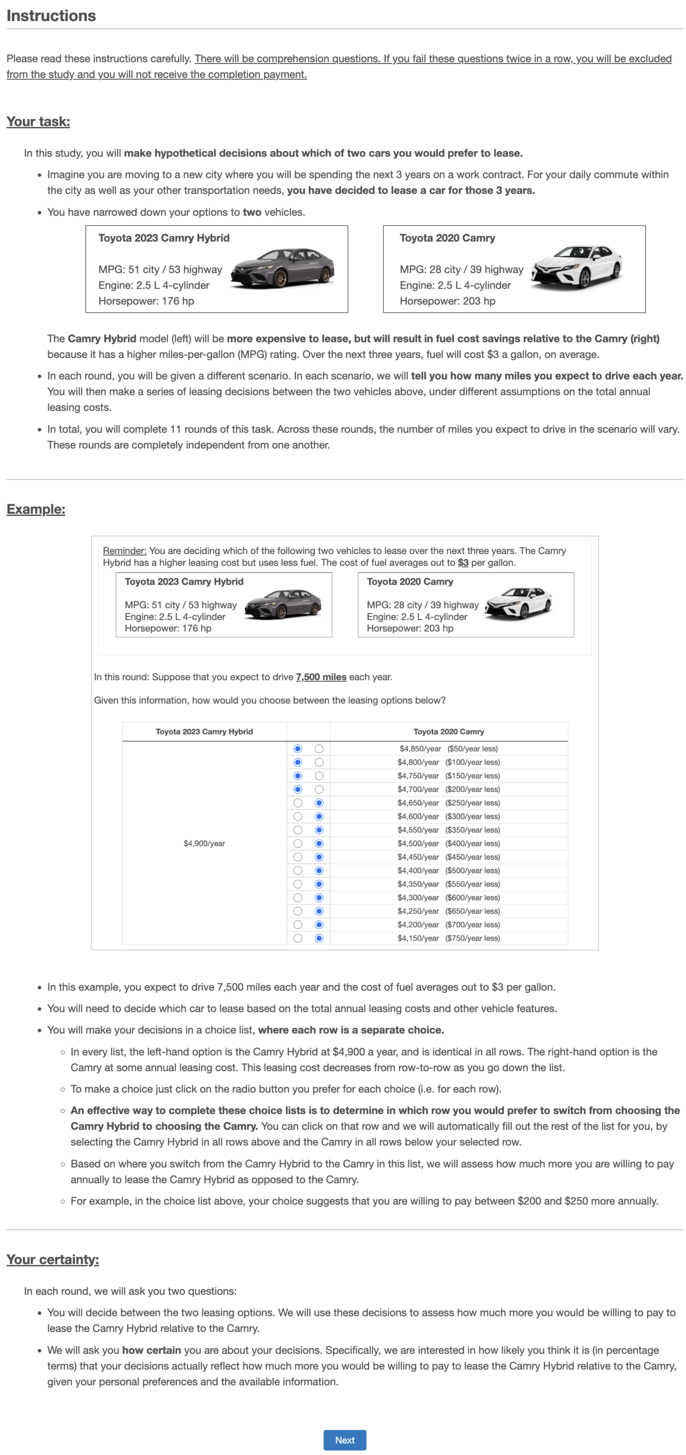
0% 25% 50% 75% 100%

100 %

Next

Figure 100: The decision screen for the NEW task.

D.30 ENS



Instructions

Please read these instructions carefully. There will be comprehension questions. If you fail these questions twice in a row, you will be excluded from the study and you will not receive the completion payment.

Your task:

In this study, you will **make hypothetical decisions about which of two cars you would prefer to lease.**

- Imagine you are moving to a new city where you will be spending the next 3 years on a work contract. For your daily commute within the city as well as your other transportation needs, **you have decided to lease a car for those 3 years.**
- You have narrowed down your options to **two** vehicles.

Toyota 2023 Camry Hybrid
MPG: 51 city / 53 highway
Engine: 2.5 L 4-cylinder
Horsepower: 176 hp

Toyota 2020 Camry
MPG: 28 city / 39 highway
Engine: 2.5 L 4-cylinder
Horsepower: 203 hp

The **Camry Hybrid** model (left) will be **more expensive to lease, but will result in fuel cost savings relative to the Camry (right)** because it has a higher miles-per-gallon (MPG) rating. Over the next three years, fuel will cost $3 a gallon, on average.

- In each round, you will be given a different scenario. In each scenario, we will **tell you how many miles you expect to drive each year.** You will then make a series of leasing decisions between the two vehicles above, under different assumptions on the total annual leasing costs.
- In total, you will complete 11 rounds of this task. Across these rounds, the number of miles you expect to drive in the scenario will vary. These rounds are completely independent from one another.

Example:

Reminder: You are deciding which of the following two vehicles to lease over the next three years. The Camry Hybrid has a higher leasing cost but uses less fuel. The cost of fuel averages out to **$3** per gallon.

Toyota 2023 Camry Hybrid
MPG: 51 city / 53 highway
Engine: 2.5 L 4-cylinder
Horsepower: 176 hp

Toyota 2020 Camry
MPG: 28 city / 39 highway
Engine: 2.5 L 4-cylinder
Horsepower: 203 hp

In this round: Suppose that you expect to drive **7,500 miles** each year.

Given this information, how would you choose between the leasing options below?

Toyota 2023 Camry Hybrid			Toyota 2020 Camry
	●	○	$4,850/year ($50/year less)
	●	○	$4,800/year ($100/year less)
	●	○	$4,750/year ($150/year less)
	●	○	$4,700/year ($200/year less)
	○	●	$4,650/year ($250/year less)
	○	●	$4,600/year ($300/year less)
	○	●	$4,550/year ($350/year less)
$4,900/year	○	●	$4,500/year ($400/year less)
	○	●	$4,450/year ($450/year less)
	○	●	$4,400/year ($500/year less)
	○	●	$4,350/year ($550/year less)
	○	●	$4,300/year ($600/year less)
	○	●	$4,250/year ($650/year less)
	○	●	$4,200/year ($700/year less)
	○	●	$4,150/year ($750/year less)

- In this example, you expect to drive 7,500 miles each year and the cost of fuel averages out to $3 per gallon.
- You will need to decide which car to lease based on the total annual leasing costs and other vehicle features.
- You will make your decisions in a choice list, **where each row is a separate choice.**
  - In every list, the left-hand option is the Camry Hybrid at $4,900 a year, and is identical in all rows. The right-hand option is the Camry at some annual leasing cost. This leasing cost decreases from row-to-row as you go down the list.
  - To make a choice just click on the radio button you prefer for each choice (i.e. for each row).
  - **An effective way to complete these choice lists is to determine in which row you would prefer to switch from choosing the Camry Hybrid to choosing the Camry.** You can click on that row and we will automatically fill out the rest of the list for you, by selecting the Camry Hybrid in all rows above and the Camry in all rows below your selected row.
  - Based on where you switch from the Camry Hybrid to the Camry in this list, we will assess how much more you are willing to pay annually to lease the Camry Hybrid as opposed to the Camry.
  - For example, in the choice list above, your choice suggests that you are willing to pay between $200 and $250 more annually.

Your certainty:

In each round, we will ask you two questions:

- You will decide between the two leasing options. We will use these decisions to assess how much more you would be willing to pay to lease the Camry Hybrid relative to the Camry.
- We will ask you **how certain** you are about your decisions. Specifically, we are interested in how likely you think it is (in percentage terms) that your decisions actually reflect how much more you would be willing to pay to lease the Camry Hybrid relative to the Camry, given your personal preferences and the available information.

Next

Figure 101: The instruction screen for the ENS task.

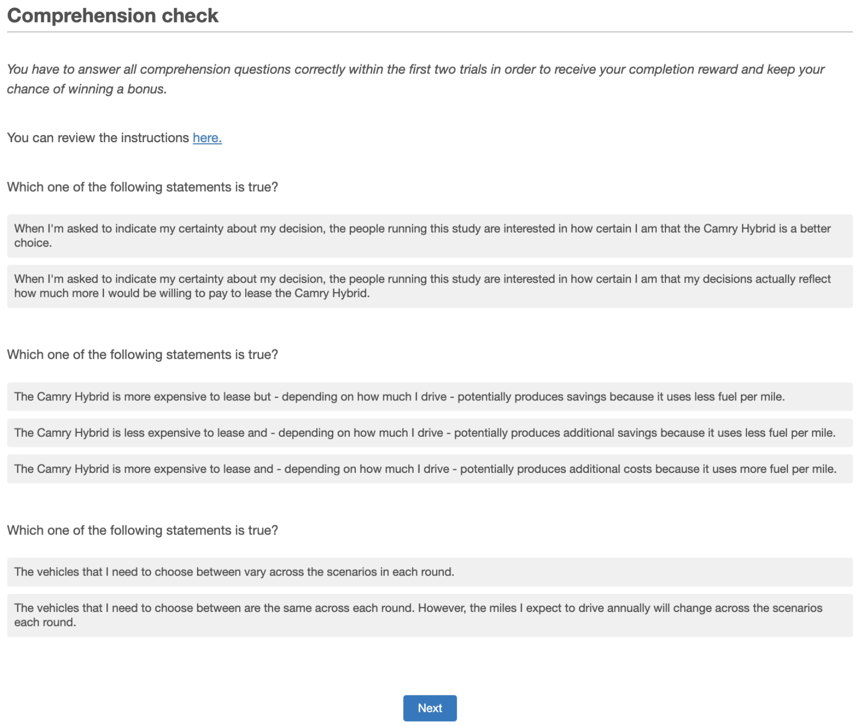


Figure 102: The comprehension screen for the ENS task.

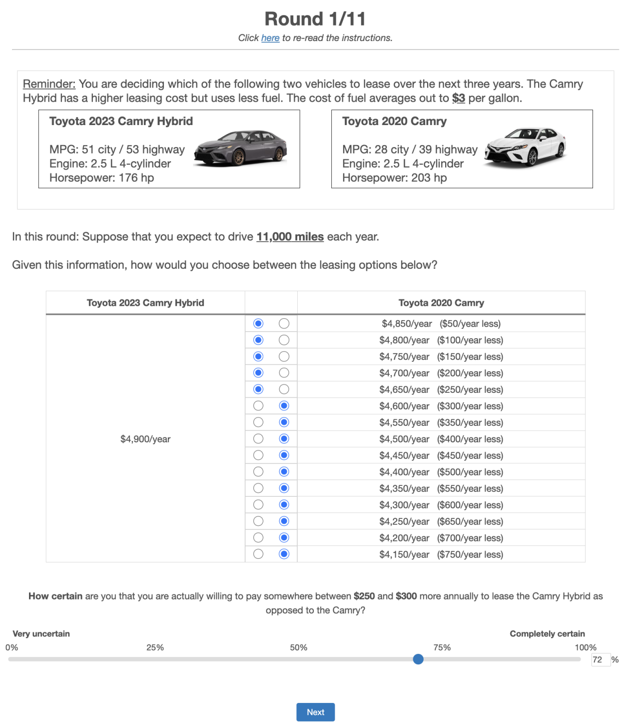


Figure 103: The decision screen for the ENS task.

D.31 HEA

Instructions

Please read these instructions carefully. There will be comprehension questions. If you fail these questions twice in a row, you will be excluded from the study and you will not receive the completion payment.

Your task:

In this study, we will describe a hypothetical scenario in which some number of people are expected to be sick for one month due to a new disease. **You will decide how much money you think the government should spend on curing the disease.**

- In each round, you will be told **how many people are expected to be sick for a month due to the disease**. During their sickness, people cannot work and are generally heavily constrained in their activities. There are no secondary damages of the disease.
- Your task is to decide **how much money, between $0 and $1 million, the government should be willing to spend** to cure the disease, preventing people from being sick.
- In total, you will complete 11 rounds of this task. Across these rounds, the number of people expected to suffer from the disease varies. These rounds are completely independent from one another.

Example:

Reminder: Some number of people are expected to be sick for a month due to a disease. You will decide how much money the government should be willing to spend to cure the disease, preventing people from getting sick.

In this round: **5 people** are expected to get sick.

How much (between $0 and $1,000,000) should the government be willing to pay to cure the disease? $

- In this example, there are 5 people expected to get sick.
- You then need to type into the box the number (between 0 and 1,000,000) of dollars you think the government should spend to cure the disease.

Your certainty:

In each round, we will ask you two questions:

- How many dollars you think the government should be willing to spend.
- We will ask you **how certain** you are about your decision. Specifically, we are interested in how likely you think it is (in percentage terms) that the decision you made is actually your best decision, given your personal preferences and the available information.

Next

Figure 104: The instruction screen for the HEA task.

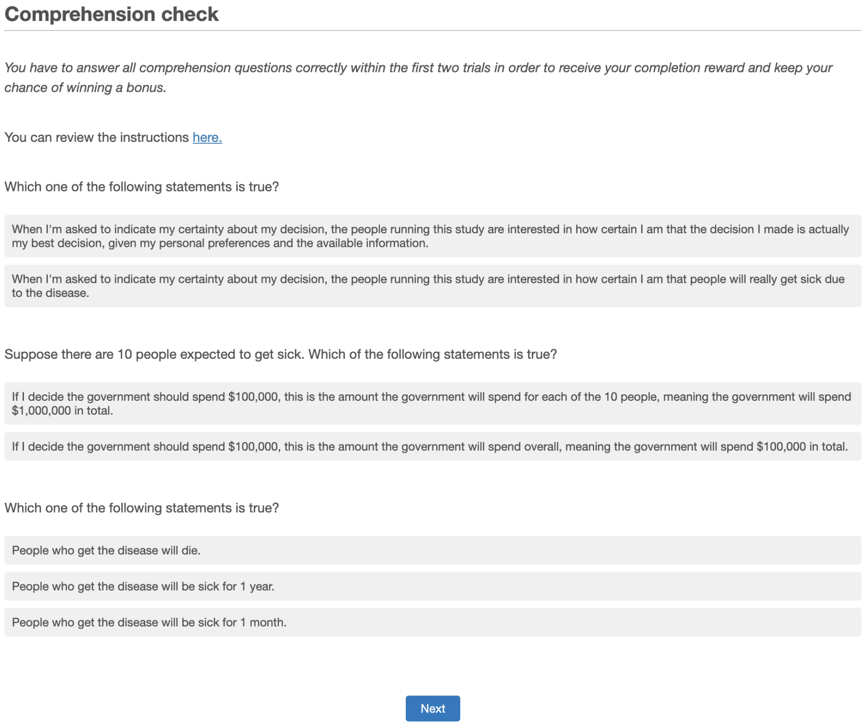


Figure 105: The comprehension screen for the HEA task.

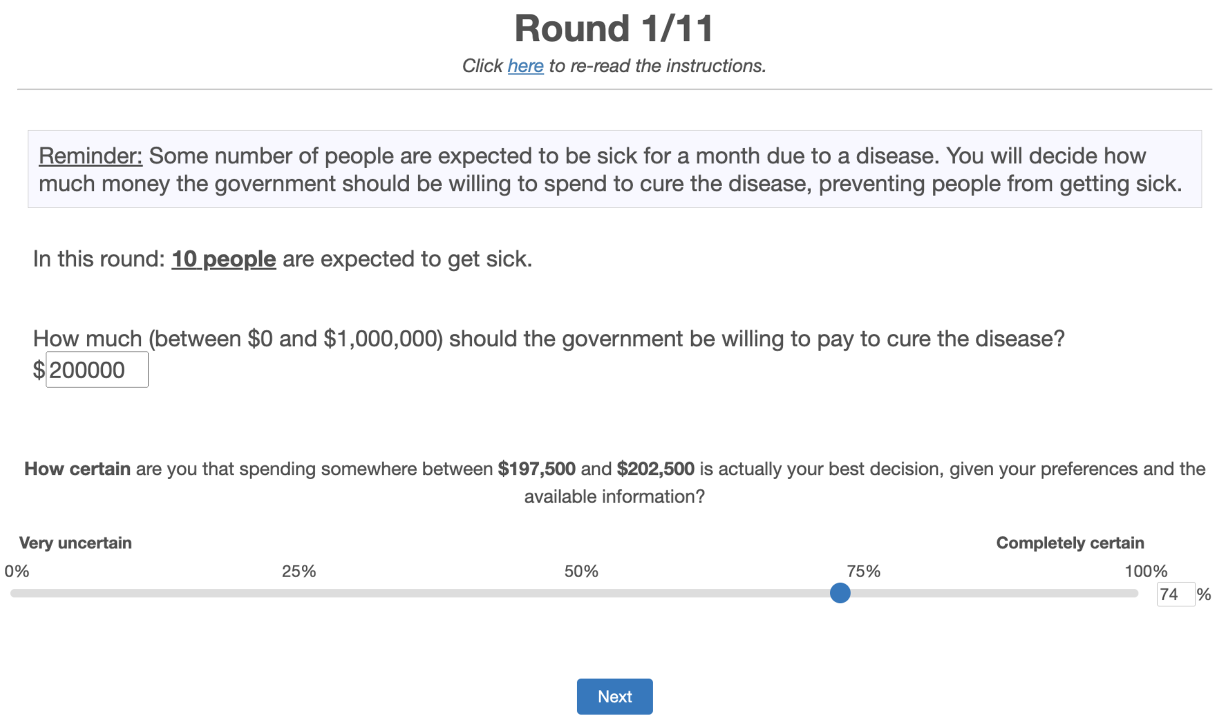


Figure 106: The decision screen for the HEA task.