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BEHAVIORAL ATTENUATION

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ABSTRACT

We report a large-scale examination of behavioral attenuation: due to information-processing constraints, the elasticity of people's decisions to fundamentals is generally too small. We implement 30 experiments on a broad range of economic decisions, including choice, valuation, belief formation, strategic games and generic optimization. In 93% of our experiments, the elasticity of decisions to fundamentals decreases in participants' cognitive uncertainty. Moreover, in decision problems with objective solutions, elasticities are universally smaller than is optimal. We show that the magnitude of attenuation is partly driven by the complexity of the decision problem. Many widely-studied anomalies represent special cases of behavioral attenuation.

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1 Introduction

In this paper we document the pervasiveness and economic importance of *behavioral attenuation*, a consequence of information-processing constraints that we hypothesize (i) is particularly widespread and (ii) can explain behavior across many different economic contexts and decision domains. The idea is that decision makers are often unsure how to map the fundamentals of economic decisions into utility-maximizing choices. Uncertainty about how exactly fundamentals should influence decisions leads people to treat 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 follow a recent literature on Bayesian imprecise cognition (e.g., Gabaix, 2019; Woodford, 2020; Ilut and Valchev, 2023; Enke and Graeber, 2023) to articulate how an imperfect understanding of the mapping between fundamentals and utility-maximizing choices produces behavioral attenuation: a reduced sensitivity of decisions to variation in parameters, relative to the benchmark that people optimize (whichever preferences or objective functions they have).

Our hypothesis is that because most economic 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 way, that product demand is attenuated with respect to price, that cooperation is attenuated to the incentives 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 principle of behavioral economics that both predicts new regularities and explains many choice anomalies that have been documented in the past (e.g., probability weighting; hyperbolic discounting over money; insensitivity of effort supply; conservatism; scope insensitivity in contingent valuation; insensitive information demand; fairness views that are insensitive to true merit; and insensitivities to interest rates, taxes and autocorrelations).

We make two main contributions. First, we document that behavioral attenuation is widespread, arising in nearly 30 distinct economic contexts. Second, we show that the degree of attenuation is partly predictable based on the complexity of the decision problem.

Study design. We designed a pre-registered series of online experiments in which we examine an unusually large number of distinct decision tasks from across economics (31 experiments in all). The selection of tasks was partly guided by a *crowdsourcing* approach. We contacted the authors of recent top publications in behavioral economics, 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 occurs. Based on this procedure, we collected ten tasks that were directly proposed by experts without influence from our side. The selection of another ten tasks was informed by expert suggestions but partly influenced by us, for example when an expert proposed several alternative tasks, requiring us to choose one. Finally, we designed an additional eleven tasks ourselves. 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. 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. 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). Our core hypothesis is that these slopes are flatter when people don't know how to optimize. Because we cannot directly observe an inability to optimize in many of our tasks, we resort to measuring cognitive uncertainty (*CU*): people's own uncertainty about whether they optimized (Enke and Graeber, 2023). After each decision, we elicit from subjects their subjective percentage chance that their decision was not optimal in the sense that either (i) it failed to maximize her own preferences (in subjective problems); or (ii) it failed to be payoff-maximizing (in objective problems).[1] To validate this measure, we show that, in each of our objective experiments, subjects' uncertainty that they optimized is strongly correlated with actual optimization failures.

In our main analyses, we link *CU* to the slope of decisions to identify behavioral attenuation in both subjective and objective tasks. In addition, in objective tasks we can

[1]Proximally, there are many ways that information-processing limitations can generate cognitive uncertainty, and we view all of them as potential drivers of attenuation. For instance, difficulty of optimization can arise due to difficulties in retrieving one's own preferences, the complexity of aggregating and trading off different problem components, or the difficulty of identifying normatively-optimal rules such as Bayes' rule (Oprea, 2024a).

also identify behavioral attenuation *directly* simply by comparing observed elasticities to theory-predicted, optimal ones.

Importantly, our experiment also allows us to study how processing failures are affected by both the "supply" and "demand" sides of information processing. On the supply side, people vary in their information-processing *capacity* (e.g., attention, time, cognitive control etc.). On the demand side, decision problems vary in their *complexity*, demanding varying degrees of information processing on the part of the subject. We decompose these two drivers of information-processing imperfections to some degree and test their relative role in generating attenuation, partly by exogenously varying the complexity of decision problems in pre-registered ways.

Evidence for behavioral attenuation. Our *CU* measures strongly suggest that people indeed struggle with mapping economic fundamentals into optimal decisions: in every one of our 31 experiments, the majority of subjects express doubt that they optimized.

This cognitive uncertainty is, in turn, strongly predictive of the elasticity of decisions to fundamentals. In 93% of our baseline experiments we find that higher *CU* is associated with a lower elasticity. These correlations are almost always statistically significant. By contrast, in no task do we find a signficant correlation in the opposite direction. These effects are economically large: 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 33% 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, seems to be that they all require significant information processing.

Because in objective tasks we know the 'ground truth' optimal elasticities, we can additionally directly compare them to the estimated elasticities. In *all objective tasks*, the observed elasticities are significantly smaller than the normative ones – direct evidence of behavioral attenuation that mirrors the results obtained using the *CU* data.

To study the relative importance of the supply and demand sides of information processing, we first investigate the role of subject-level differences. We find that while across-subject heterogeneity in *CU* is almost always a statistically significant predictor of overall attenuation, the quantitative magnitude of attenuation drops sharply by 3/4 in these analyses. This suggests that variation in subject-level characteristics (such as cognitive ability or global attentiveness to the experiment) has some influence, but is not the primary driver of attenuation in our data.

Problem complexity: Simple boundary points and diminishing sensitivity. We find that the degree of attenuation is strongly influenced by the demand side of information processing – i.e., problem complexity. To show this, we designed our experiments to include large variation in parameter values, including parameters at or near pre-registered "simple points." These are points at the boundaries of the parameter space that render a problem cognitively easier, for example because they involve dominant actions. For instance, determining optimal effort supply at wage θ may be cognitively difficult in general but it is trivial when $\theta = 0$. Similarly, determining one's optimal information demand for a binary signal with accuracy θ may be difficult in general, but it is trivial when $\theta = 50\%$, i.e. when the signal is uninformative.

Across our many experiments, the *CU* data strongly suggest that subjects indeed find problems easier to reason about when they involve parameters at or close to these simple boundary points. For most tasks the median subject exhibits full certainty they made optimal decisions at simple boundary points, and becomes progressively more uncertain as the parameter moves away from these simple points. Our interpretation of these patterns is that perceived problem complexity strongly depends on the degree to which a decision requires people to aggregate and trade off multiple problem components.

The insight that perceived problem complexity varies as a function of the distance to simple boundary points has immediate implications for understanding diminishing sensitivity: the well-known pattern in behavioral economics and other disciplines that decisions are often less sensitive to parameters further away from boundary points (e.g., Kahneman and Tversky, 1979; Weber, 1834). Behavioral attenuation sheds light on this pattern because if insensitivity is driven by the cognitive difficulty of optimizing, then there *should* be less attenuation in the neighborhood of boundary parameters at which identifying the optimal decision is easy. In fact, if perceived complexity increases rapidly enough away from simple points, our framework predicts regions of *excess sensitivity* in the neighborhood of simple points.

To provide evidence for this, we directly connect across-problem variation in perceived complexity (as measured by *CU*) to attenuation. To this effect, we estimate both "local" *CU* at a specific parameter value and the "local" elasticity of decisions around that parameter. For example, in our effort supply experiment, we connect average *CU* at a wage of zero to the local elasticity of decisions at a wage of \$0, and compare these quantities with average *CU* and the elasticity of decisions at a wage of \$0.50. We find that the local sensitivity of decisions is low at exactly those points at which average *CU* is locally high. Because this analysis only leverages variation across problem configurations, it nets out any across-subject differences in average *CU*.

This suggests two insights. First, the degree of insensitivity (attenuation) is partly driven by the complexity and information-processing demands imposed by specific problems, rather than subject-level differences in cognitive ability or effort. Second, an implication of this conclusion is that the classic pattern of diminishing sensitivity – one of the central regularities in behavioral economics – likely grows (at least in part) out of information-processing constraints.

Behavioral anomalies. Because we implement such an unusually large number of experiments, we also cover many domains in which prior research has identified insensitivity-related "anomalies" that led to the development of behavioral economic theories. These phenomena have appeared under many different labels in the literature, such as 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.

Part of the generality of behavioral attenuation stems from the fact that it is distinct from "underreaction" – attenuation is a shrinking of the *slope* of decisions, rather than a shrinking of the level. This is important because attenuation can produce and is consistent with both under- and overreaction, as has been documented for the case of under- and overreaction of beliefs (Augenblick et al., 2021; Ba et al., 2022).

Limits of attenuation. We hypothesized two 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 and (ii) is less likely to arise when decision-makers are forced to directly compare their decisions across multiple different realizations of the fundamentals. We find mixed evidence for both. We also show that a tenfold increase in incentives does not meaningfully affect either attenuation or *CU*.

Contribution and related literature. A growing literature studies the cognitive foundations of economic behavior. This work often studies information-processing constraints, and how those constraints 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 responses to information-processing constraints that allow economists to explain behavior (and unify prior anomalies) across many different, seemingly-unrelated domains.

Our main contribution to this literature is twofold. First, we document the pervasiveness and importance of one such domain-general response. We provide evidence that behavioral attenuation (and, with it, diminishing sensitivity) occurs across a large set of domains that were partly selected by independent experts. Second, we show that behavioral attenuation is driven by both a demand side (problem complexity) and a supply side, and that the former has predictable structure.

Our findings build 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, 2024b; Augenblick et al., 2021; Yang, 2023; Frydman and Jin, 2021, 2023; Shubatt and Yang, 2023; Charles et al., 2024; Oprea and Vieider, 2024). Most closely related, Enke and Graeber (2023) and Enke et al. (2023a) document that *CU* predicts the magnitude of probability weighting, belief updating and hyperbolic discounting over money. A key contribution of our paper is to show that attenuation appears considerably more generally than only in decision-making under uncertainty and over time, where it has been most intensively documented. This is a perhaps surprising, given that much of the cognitive literature emphasizes tendencies that seem to run contrary to insensitivity, such as overreaction effects or exaggerating differences (e.g., Afrouzi et al., 2023; Ba et al., 2022; 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; Vieider, 2022, 2021; Gabaix and Laibson, 2022; Gabaix and Graeber, 2023). Gabaix (2019) theorizes about a broader relevance of attenuation for behavioral economics phenomena.[2]

We interpret our results as suggesting that classic behavioral economics both applies more broadly than previously acknowledged and that parts of it are more unified than we might have thought. Parts of it are more unified because, as we have shown, various classic and newly-documented anomalies share a similar structure and seem rooted in a similar cognitive mechanism.[3] Yet our results also suggest that traditional models that fundamentally rest on the idea of diminishing sensitivity (such as prospect theory and hyperbolic discounting) have a much broader scope of application than previously thought, because their basic logic also applies far outside of their traditional domains of risk and time (see Prelec and Loewenstein, 1991, for an early discussion of this point).

Section 2 presents a formal framework that motivates the attenuation hypothesis.

[2]More broadly, our paper belongs to a nascent literature that studies and compares a 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).

[3]However, needless to say, we also emphasize that many other behavioral anomalies do not reflect an attenuation logic.

Sections 3 and 4 present the experimental design and results. Sections 5 studies the way behavioral attenuation relates to problem complexity and diminishing sensitivity, and Section 6 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 a utility-maximizing labor supply, then relative to a counterfactual scenario in which the wage is \$25, they will be prone to make decisions that are too much alike, relative to the utility-maximizing benchmark.

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 that describes decisions as constrained-Bayesian responses to 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 E, the DM has uncertainty about a set of decision 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 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 complexity 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, or before they have observed θ. 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 $N(a_d, \sigma_0^2)$.

The DM integrates her cognitive signal with her prior, and then takes a decision $a(\theta)$ equal to her Bayesian posterior mean over $a^*(\theta)$. In Appendix E, we show that the average $a(\theta)$ takes the form[4]

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

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:*

(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 in regions of the parameter space in which the level of cognitive noise does not vary too sharply in the parameter (i.e., in which the difficulty of accurately formulating the optimum is relatively similar across parameter values), the elasticity of decisions will be smaller than the elasticity of the optimal decision. The second part says that more uncertainty in the mental simulation 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

[4]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.

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.

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 (whatever objectives they in fact have).

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, the model is meant to be an as-if description of a more general intuition that may also apply to other heuristic behaviors.

Prediction 1 describes a setting in which the difficulty of inferring the optimum does not vary too sharply in the parameter. In many settings, however, there are some points in the parameter space at which the optimal action is transparent, 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 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 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 (e.g., because the complexity of the problem is increasing), 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. Unlike Prediction 1, this prediction is one that fundamentally concerns *across-problem-within-person* variation.

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:*

[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.

(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 $\overline{\theta}$.*

We do not offer a fully articulated theory of what causes a parameter to be a simple point. We pre-register simple boundary points in our experiments based on the principle of dominance in combination with other empirical considerations (see Section 5.1).[6]

Summarizing, while behavioral attenuation is the key implication of our model, the combination of an intermediate default and rapidly increasing cognitive noise away from simple points produces a secondary, testable hypothesis: in local regions near simple points people will instead display *excess sensitivity* (see Appendix E).

Empirical Implementation. To empirically test these predictions, we 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, 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 over the optimal action, 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. Thus, under our model, we can identify the presence of behavioral attenuation by examining the correlation between *CU* and measured parameter insensitivity.

By the same logic, we can also leverage *CU* to link cognitive noise 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.

[6]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).

3 Study Design

3.1 Overall Study Setup

Our experimental design is guided by three primary objectives. First, to effectively test the generality of the attenuation hypothesis, we select a broad range of tasks from across economics. Second, to incorporate what the profession deems to be relevant decision tasks, we partly consult experts in the selection of tasks. Third, to study how attenuation is influenced by problem complexity, we widely vary the decision-relevant parameters in our tasks in ways that we hypothesize vary the required information processing.

Expert Input for Task Selection: Design of Process. In order to satisfy the first objective, we implemented 31 separate experiments, allowing us to include a broad range of tasks. To satisfy the second, we partly 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 includes 29 researchers. These experts are very heterogeneous. Some are theorists, some experimentalists, and some applied researchers. They work in macro, finance, public, labor, environmental, and basic decision science. There is also great variety in the behavioral topics that our experts work on.

We had initially aimed for a total of 30 experiments, and deliberately invited fewer experts than needed to receive 30 proposals because we anticipated that some types of 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.

The expert consultation is described in detail in Appendix F. In a first step, we contacted the 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. The full email invitation is reproduced in Appendix F.2.

Based on these proposals, we designed and programmed experiments. We piloted each of the experiments with a small number of subjects (10–30) to validate 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. 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 one third of the experts sent detailed comments on the implementation and requested that changes be made. Finally, before making a draft of our paper available online, we re-contacted the experts to share a draft and asked them for any comments.

Expert Input for Task Selection: Results. 24 researchers replied to our invitation. 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 considered important by leading experts in different sub-fields. Second, we end up with tasks that are very heterogeneous, covering a broad range of research areas in economics.

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 asked us to implement.

While our expert consultation process provided substantial guidance, the degree of our own influence in the selection of tasks varied across expert interactions. The collection of expert interactions resulted in 20 tasks that we categorize into two sets. The first set of ten tasks reflects interactions in which we had no influence on the selection process because the expert's proposal was sufficiently detailed and corresponded to the requirements outlined in our email invitation that we could move to implementation. We refer to these tasks as *expert tasks* and associate them with the respective proposer's name in what follows (or "anonymous", if they chose to remain so).

A second set of ten tasks also benefited from our expert consultation process, yet the underlying interactions were more heterogeneous and provided us with varying degrees of influence over the task selection that we did not anticipate when sending our email invittaion. We provide a list of these issues in Appendix F.4. Almost all of these involve an initial expert proposal of multiple alternatives (from which we had to pick) or initially incomplete suggestions. Each of the resulting tasks was sent to the corresponding expert(s) for signoff prior to implementation. Still, we conservatively label them "EGOY+" tasks so as to not overstate the degree to which our hands were tied in the task selection process (EGOY refers to the authors of this paper).[7]

One of these "EGOY+" tasks is different from all other tasks in the sense that absent information-processing constraints, the elasticity of the decision to the parameter is zero. We, hence, additionally constructed 11 tasks ourselves, leaving us with 30 baseline tasks, plus one task designed to study the limits of attenuation.[8]

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.

[7]For their involvement in these "EGOY+" tasks, we thank Marta Serra-Garcia, Alex Imas, Sandro Ambuehl, Jonathan Zinman, Aakaash Rao, Heather Sarsons, Leonardo Bursztyn, Emmanuel Vespa, Jason Somerville, Judd Kessler, Ernesto Reuben and two researchers who wished to remain anonymous.

[8]Our main findings emerge across all three categories of tasks, see Section 4 and Appendix Figure 16.

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 rounds 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 that decision 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. The last two columns summarize the empirical results, which we return to in more detail below in Section 4.

Our tasks can be organized into eight broad topical 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 relationship of interest (for which we verified monotonicity in our pilots). Appendix A.1 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 G.

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. 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. 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 (the utility function is given).

Portfolio allocation. 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.

Effort supply. 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. 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. 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. 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. 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.

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	≈ 0%
Portfolio allocation – POA	Equity share	Return expectat.	Choice	EGOY+	n/a	28%
Forecast stock return – STO	Forecast asset value	Time horizon	Hypoth.	EGOY	n/a	11%
Estimate tax burden – TAX	Tax estimate	HH income	Accuracy	EGOY	9 %	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	44%	24%
Search – SEA	Search effort (IV)	Search cost	Choice	EGOY+	49%	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	42%	7%
Avoid externalities – EXT	WTP to reduce emissions	Size of reduction	Choice	v.d. Weele / Schwardm.	n/a	43%
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	EGOY+	n/a	35%
Dictator game – DIG	Giving	P [donation lost]	Choice	Roth	n/a	29%
Contingent valuation – HEA	Societal WTP for vaccine	People saved	Hypoth.	EGOY+	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	n/a	-5%
Beauty contest – GUE	Guess number	Multiplier	Accuracy	EGOY	n/a	31%
Disclosure game – CHT	Reveal / withhold info	True state	Choice	EGOY+	n/a	30%
Political decisions						
Voting – VOT	Vote or not (IV)	Number of voters	Choice	EGOY+	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	EGOY+	n/a	34%
Belief updating – BEU	Posterior belief	Info accuracy	Prox. Bayes	Anonymous	20%	26%
Forecasting – FOR	Forecast asset value	Info accuracy	Prox. Bayes	EGOY+	47%	32%
Recall – REC	Recall company value	Company value	Accuracy	Kwon	62%	46%
Signal aggregation – SIA	Aggregate signals	Number of sources	Accuracy	EGOY+	16%	22%
Rational inattention – RIA	Lottery / safe paym.	Expected value diff.	Choice	EGOY+	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 ($1-\hat{\omega}^e/\omega^e_R$, see eq. (4)). Last column shows % decrease in sensitivity b/w $CU = 0\%$ and $CU = 50\%$ ($\hat{\phi}^e$, see eq. (2)).

Fairness views. 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. 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. Participants state a hypothetical societal WTP for a vaccine as a function of the number of sick people prevented. Average WTP increases in the number of sick people.

Prisoner's dilemma. 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. 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. 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. 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. 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. Participants forecast a deterministic process whose innovation is given by a weighted average of the previous innovation and a fixed positive trend. 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 correct forecast.[9]

Recall. 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. 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. 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 by a constant. 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. 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. 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.

[9]When we initially ran the FOR experiment, the innovation of the process was given by a weighted average of the previous innovation and a mean-zero shock. However, after we ran the experiment, we discovered an error in the comprehension checks that suggested using a particular incorrect heuristic (to simply ignore the mean-zero shock). We were thus forced to drop the data and re-run the task. When re-running, we replaced the mean-zero shock with a deterministic non-zero trend to avoid the incorrect heuristic our initial faulty comprehension check suggested.

Newsvendor game. 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. 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. 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. Standard three-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. 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. 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. 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. 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. 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.

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 these data.

3.3 Variation in Parameters and Pre-Registered Simple Points

In each of our experiments, we varied the main decision-relevant parameter over a wide range. One reason for this is that we hypothesize that the information processing required to optimize (i.e., the *complexity* of the problem) varies with parameters. Varying problem complexity allows us to study the "demand side" of information processing in a manner that nets out the "supply side" of subject-level differences in cognitive capacity (attentiveness, cognitive effort, etc.).

Much of what makes it hard to make optimal economic decisions is the need to intensively trade off and aggregate information to identify an optimal decision. Because of this we should expect the complexity 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 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). Importantly, these kinds of "simple points" typically occur at the logical boundaries of the parameter space, i.e., at a payout probability of zero or one, a marginal cost of zero, and so on.

Because of this, in almost all experiments, we deliberately included (and pre-registered) such "potential simple points" at natural boundaries, as well as points close to those simple points. For example, in the valuation of lotteries, the payout probabilities included (among others) 0%, 1%, 99% and 100%. In the effort supply task, the piece rates included (among others) $0 and $0.01.

In our pre-registration, we listed 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.1 contains the details for each task. We pre-registered that, in our analyses, we would conclude that a *potential* simple point is an *actual* simple point if cognitive uncertainty is significantly lower at the point, compared to the five nearest neighboring parameter values.

3.4 Cognitive Uncertainty Elicitation

After each decision, we elicited cognitive uncertainty (*CU*). Loosely speaking, our general approach is to ask participants how certain they are that they optimized. 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 own 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 dragged 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).[10] Appendix A.1 contains the precise *CU* questions used for each task.

Uncertainty about optimization (*CU*) can arise from multiple potential channels. First, it may be difficult or costly for people to *retrieve* information on their own preferences (their utility function), producing preference uncertainty. Second, people may struggle when attempting to computationally *combine* their utility function with problem fundamentals. Third, people may find it difficult to negotiate *tradeoffs* across different problem components when assessing the optimum. Fourth, in objective problems, people may have trouble formulating the *formal rules* they need to correctly solve a problem. All of

[10]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 presumably at least 50%. 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.

these proximal sources of *CU* are consistent with the information-processing constraints we hypothesize are responsible for behavioral attenuation.[11]

CU is fundamentally a measure of the severity of information-processing constraints. As such, as cognitive scientists emphasize,[12] it is affected both by a supply side (the information-processing capacity a decision maker brings into a problem) and by a demand side (the information-processing demands imposed by the complexity of a problem). One of our key interests is to study the relative importance of the two for behavioral attenuation.

3.5 Logistics, Sample Size, Incentives and Pre-Registration

All experiments were conduced on *Prolific*, which Gupta et al. (2021) identify as the 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 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 6 below), we pool the data in what follows.

All experiments are pre-registered 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

[11] To avoid misinterpretation of the *CU* elicitation as an elicitation of beliefs about uncertainty in the external environment (for example, uncertainty about whether the subject will actually get paid), we include a comprehension check in each of our experiments. The comprehension check verified that subjects' understand that the *CU* question elicits uncertainty about the ability to identify an optimum, see Appendix G. Moreover, many of our analyses rely on within-subject variation that hold a subject's understanding of the *CU* question fixed, removing this concern.

[12] As Herbert Simon famously wrote "Human rational behavior is shaped by a scissors whose two blades are the structure of task environments and the computational capabilities of the actor" (Simon, 1990)

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, our pre-registered sample sizes were based on intuition about which tasks might be less noisy, and in which we might therefore recruit fewer than 250 subjects without being underpowered (an effort on our part 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 in the initial data-collection. For full transparency, Appendix C 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 the 88,829 decisions in the dataset, all in the TAX experiment. The reason extreme outliers occur in this experiment but not in others is that it is a free number-entry task and therefore subject to accidental inclusion of extra digits.

4 Results

The attenuation hypothesis rests on the premise that information-processing constraints are widespread across economic domains. Our *CU* data strongly suggest that information-processing constrains are indeed pervasive. For each of our 30 main experiments, Appendix Figure 11 shows the fraction of decisions that are associated with strictly positive *CU*. In *every single* task, the majority of decisions is associated with strictly positive *CU*. This fraction varies between 59% (in TID) and 95% (in PRS). We find similarly high rates of *CU* in both subjective and objective tasks.

Importantly, our data also allow us to verify that subjects' beliefs about the optimality of their decisions is highly predictive of actual optimization failures, reinforcing our interpretation of *CU* as a measure of information-processing constraints. In the subset of our tasks in which there is an objectively correct answer, we calculate the correlation between elicited *CU* and the magnitude of mistakes (measured using the log absolute deviation between the subject's decision and the true optimal choice). At the level of individual decisions, *CU* is significantly correlated with objective mistakes in every one of our eight objective tasks, with an average correlation coefficient of $r = 0.31$ ($p < 0.01$).

We also study the link between *CU* and mistakes across different problem configurations (i.e., across different parameters), netting out subject-level variation. Here, we also find that in those problems in which median *CU* is low, objective mistake rates are low too (the average correlation across experiments is $r = 0.68$, $p < 0.01$).

In summary, uncertainty about the ability to optimize is widespread and is highly predictive of actual optimization failures, both at the level of individual decisions, and at the level of problems that potentially differ in their complexity.

4.1 Attenuation: A Look at the Raw Data

Figure 1 plots raw data from six of our 30 main 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 these data down based on subjects' decision-level *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 4.2, this attenuation is a universal phenomenon in our objective tasks.

Second, in all three of these 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 4.2, this linkage between *CU* and objective attenuation is 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 (and pre-registered) "simple points," giving rise to *diminishing sensitivity*.[13] As we discuss in more depth in Section 5.1 below, this pattern is also

[13]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). 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

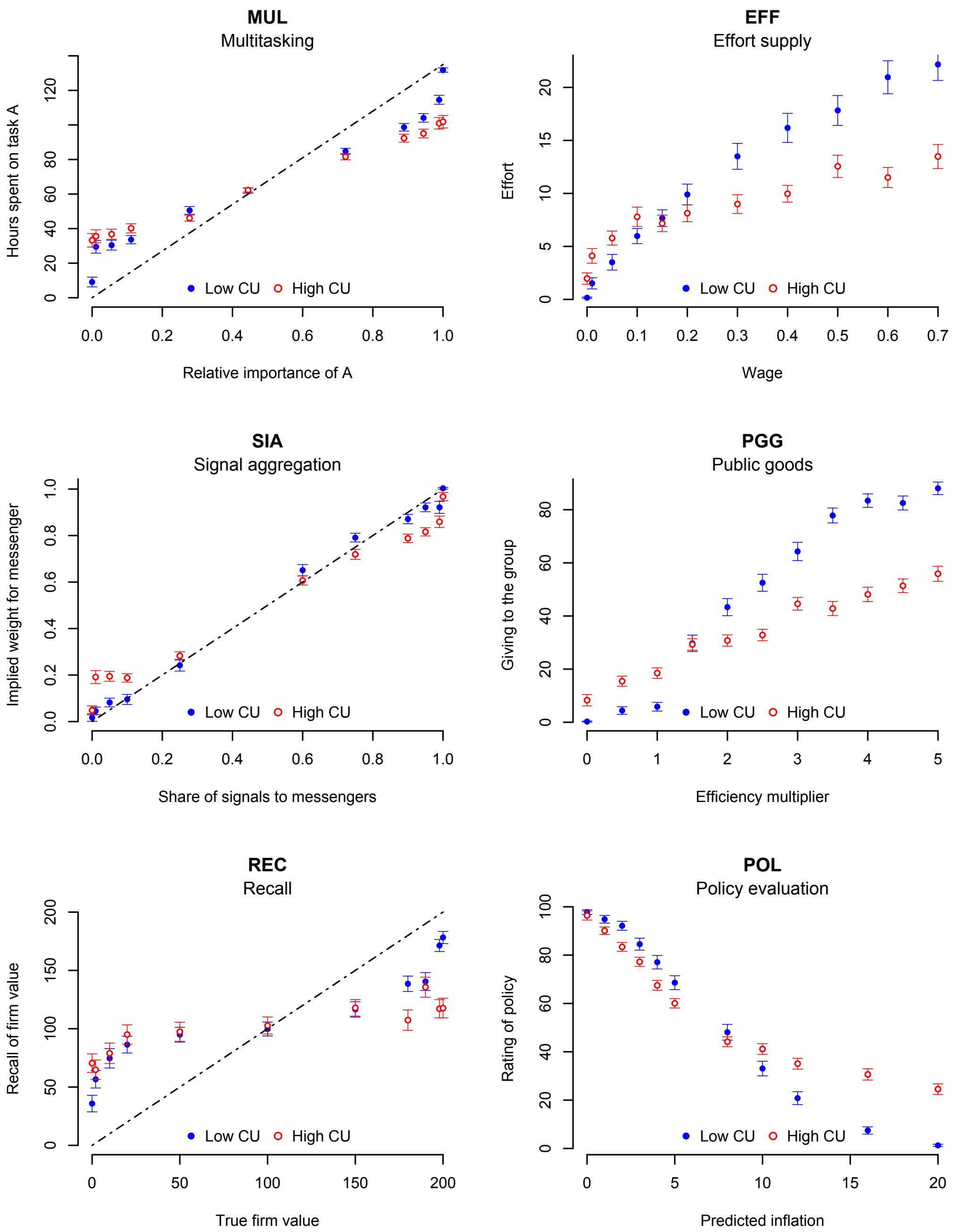


Figure 1: Decisions as a function of parameters, with sample split at median *CU* at a given parameter. Top left: Effort allocation to one of two tasks as a function of task's relative importance (MUL). Middle left: Weight placed on message as a function of number of signals observed by messenger (SIA). 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.

near-universal in our data, and serves as a key piece of evidence for understanding how attenuation is shaped by the complexity of problems.

no signals or all of them).

4.2 Econometric Analysis

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* concerning her decision. Our hypothesis is that the sign of this interaction is negative (after normalizing the main effect of the parameter to be positive).

Importantly, per our pre-analysis plan, we drop from this baseline analysis of attenuation those tasks that involve 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. When decision problems are very simple, there is less reason to expect attenuation. We analyze these potential simple points separately in Section 5.2 when we discuss diminishing sensitivity.

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, $CU^e_{i,j}$. 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.[14] We always cluster the standard errors at the subject level. 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 linear regressions.[15] Appendix A.1 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 estimated β^e, which we do in Appendix Tables 3-5. 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.

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

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

[15]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.

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). Formally:

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

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

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.

For 28 out of 30 tasks the t-statistics are negative, indicating that, in almost all tasks, behavior becomes *more inelastic* as subjects become less certain in their ability to identify the optimum. 22 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 (PRS and PRD) and these exceptions are small and statistically insignificant (t-statistics of 0.016 and 0.35, respectively).[16]

In Appendix B.2 we report t-statistics adjusted using standard meta-analytic techniques which yield similar conclusions (see the red distribution in the margin of the top panel of Figure 2.

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

[16]The attenuation hypothesis is *weakest* in the prisoner's dilemma (PRD). By contrast, one of the *strongest* instances of attenuation is the Public goods game (PGG). Interestingly, the PGG is often interpreted as a *more complex* version of the prisoner's dilemma (i.e., a multi-player, continuous action version of the same social dilemma). One interpretation is that PRD is too simple to produce attenuation, and that PGG provides a counterfactual assessment of how attenuation would emerge if the problem were to be made more complex.

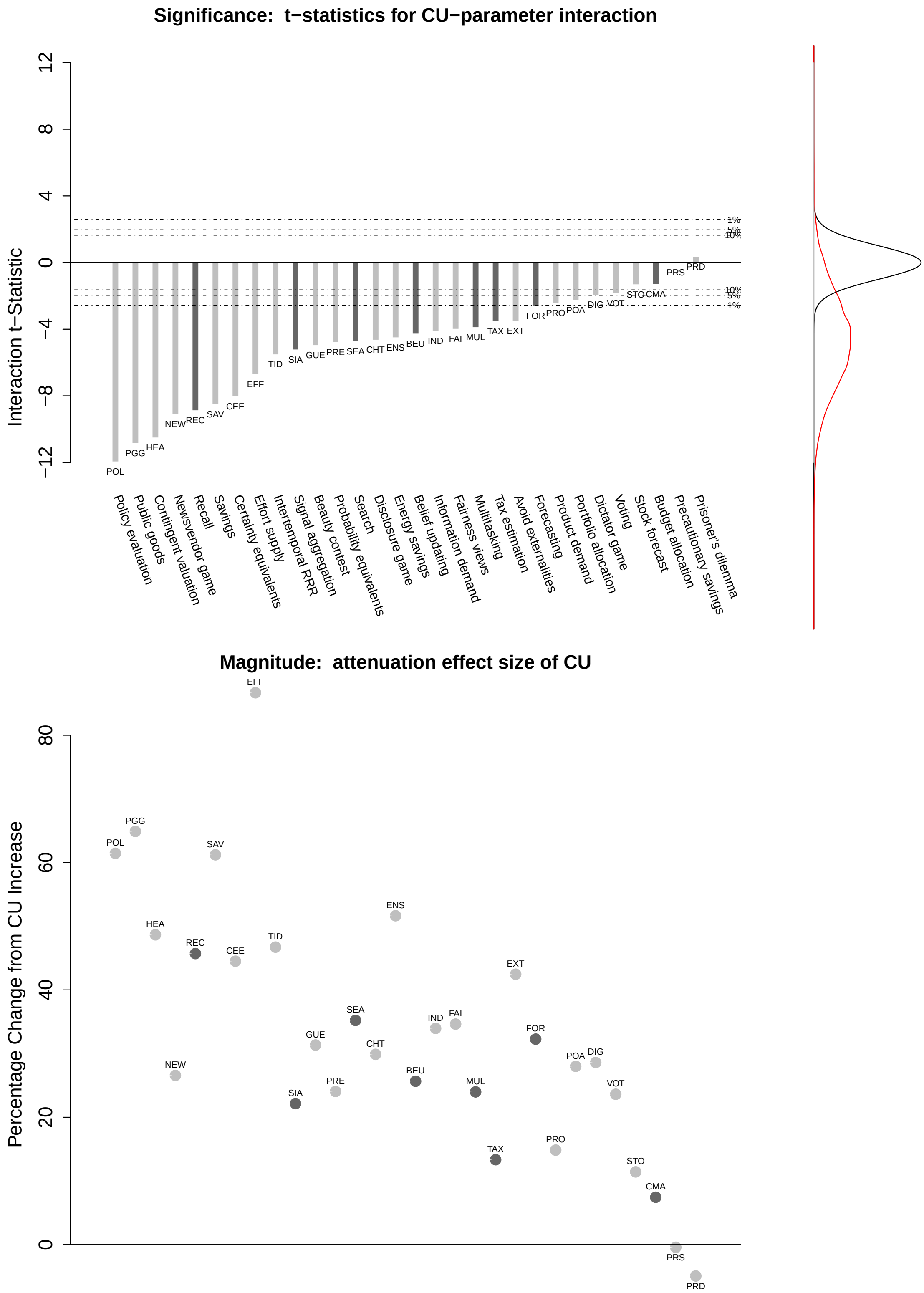


Figure 2: Behavioral attenuation and cognitive uncertainty. The top panel plots the t-statistic associated with $\hat{\beta}^e$ in (1). For comparison, we plot a standard normal distribution in black. The red distribution shows the distribution of adjusted t-statistics from a meta analysis (Bayesian hierarchical regression), see Appendix B.2. 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.

of decisions. On average, the reduction in sensitivity is equal to 33%, 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 economic decision tasks. The same 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 and dots in Figure 2 indicates that the results are very similar across the subjective and objective tasks. In both categories, most experiments show *CU*-linked insensitivity, with similar cross-experiment variation in quantitative magnitudes and statistical significance. We take this similarity in results across our tasks as initial evidence that our results in even the subjective tasks reflect information-processing imperfections rather than (for example) insensitivity-generating preferences that happen to be correlated with *CU*. Attenuation emerges across all categories of tasks, with a mean (median) magnitude of 34.4% (35.5%) in expert tasks, 32.0% (32.3%) in EGOY+ tasks, and 33% (26.6%) in EGOY tasks (see also Appendix Figure 16).

Intensive margin of cognitive uncertainty. A potential concern is that expressions of positive *CU* might be due to subjects inattentively or randomly clicking on their screen, in which case variation in *CU* contains little information about variation in information-processing frictions. In Appendix Figure 15 we replicate the top panel of Figure 2 by restricting attention to observations with $CU_{i,j} > 0$. The results are very similar. What's more, as we will show below, the vast majority of subjects express systematically higher *CU* in tasks we pre-registered as more complex, further indicating that *CU* measures information-processing constraints rather than mere random behavior.

Compression or uncertainty aversion? The framework presented in Section 2 posits that attenuation arises as a result of a compression effect, according to which people's decisions regress towards a common intermediate decision. An alternative possibility is that attenuation is driven by "cognitive uncertainty aversion", by which we mean a type of risk aversion over one's own *CU* (as in, for example, models of caution; Cerreia-Vioglio et al., 2015, 2022; Chakraborty, 2021). The key behavioral signature that separates a compression effect from *CU* aversion is the "flipping" pattern emphasized earlier in the discussion of Figure 1: if the optimal decision is an increasing function of the parameter, then compression predicts that high-*CU* decisions are higher than low-*CU* decisions at low parameter values, but lower at high parameter values. In contrast, for those of our tasks for which models of caution are currently available, *CU* aversion predicts that high-*CU* decisions are always lower than low-*CU* decisions.[17]

In Figure 1, we reported pronounced flipping patterns in six of our tasks. Formally testing for the same pattern in each of our 30 tasks,[18] we find that 26 tasks exhibit the flipping pattern, including *all* of the tasks in which attenuation is statistically significant at least at the 5% level. In only one task (VOT) do we find a pattern consistent with *CU*-aversion; the remaining three tasks are inconclusive.

To be clear, in reporting these results we do not mean to suggest that *CU* aversion is not a plausibly important economic phenomenon – we think it likely is. However, this kind of aversion and the compression effect we formalize in Section 2 are distinct phenomena, and our analyses strongly suggest that attenuation in our data is driven by compression effects.[19]

4.3 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 to the rationak benchmark – and to verify that objective attenuation is associated as hypothesized with *CU*. As described in our pre-analysis plan, we estimate the following equation:[20]

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

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 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 *all* of our 8 objective tasks we find that *CU* is strongly associated with the degree of

[17]To the extent that greater *CU* captures greater preference uncertainty, models of caution assert that it produces lower valuation of actions that yield risky/delayed payoffs or non-pecuniary outcomes relative to actions that yield certain/immediate payoffs or monetary outcomes.

[18]Formally, we define a flipping pattern as being present if above-median-*CU* decisions are higher than below-median-*CU* decisions at the two lowest parameters, but lower at the two highest parameters.

[19]One potential way to reconcile caution and compression effects is to observe that tending towards intermediate options itself represents cautious behavior, perhaps reflecting a desire to avoid large mistakes.

[20]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).

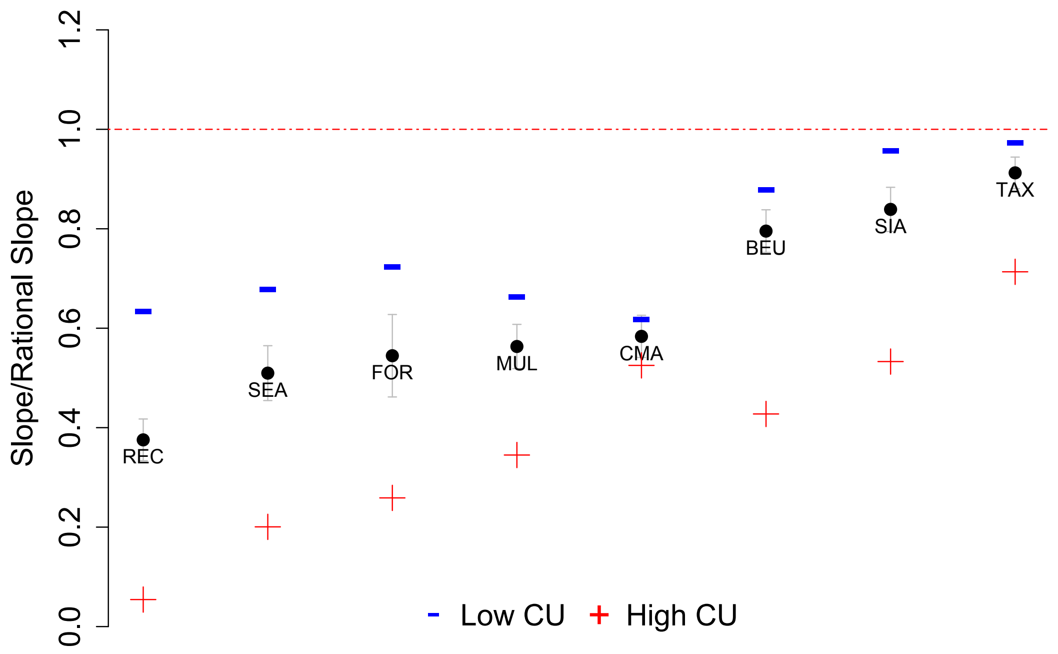


Figure 3: Behavioral attenuation relative to normative benchmarks in objective tasks. For each task, the black dot plots $\hat{\omega}^e/\omega^e_R$ and 95% CIs, see equation (4). The red and blue dots correspond to the fitted values of equation (1) for $CU = 0\%$ (blue) and $CU = 100\%$ (red).

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, we find not only direct (and universal) evidence of behavioral attenuation, we also find evidence that it is reliably predicted by *CU*.

4.4 Robustness and Bounds

In Online Appendix D, we discuss the robustness and bounds of behavioral attenuation. On the *robustness* side, we show that attenuation is unaffected by an order of magnitude increase in incentives (implemented in variations of experiments BEU, CMA, REC, SIA and VOT). We also document some of the demographic (e.g., gender and age) and choice process (e.g., response time) predictors of CU and attenuation.

On the *bounds* side, we report results from two additional experiments meant to test some hypotheses on the limitations of behavioral attenuation. First, as suggested by one of our experts (Sandro Ambuehl), we use the RIA task to study the hypothesis that *CU*-linked attenuation should disappear or even reverse when the parameter of interest has a very small or even no effect on optimal behavior (in a rational model). Recall that in the RIA experiment, under a fully rational model, decision makers should not respond at all to variation in the key varied parameter. We find that, as predicted, higher *CU* subjects respond slightly *more* strongly to the normatively irrelevant parameter, though this difference is statistically insignificant, see Online Appendix D.

Second, we hypothesized that attenuation might be weakened or even eliminated by forcing subjects to directly compare decisions under multiple parameters simultaneously (as in "joint evaluation" designs in the literature). We tested this using new, pre-registered "Joint" experiments in which we asked subjects in SAV (one of our subjective tasks) and MUL (an objective test) to make initial hypothetical decisions about how to respond to very small or large parameters. As detailed in Online Appendix D, we find some evidence (though mixed) that this kind of intervention can reduce behavioral attenuation – a finding with potential policy implications for addressing the bias.

4.5 Within- and Across-Subject Variation

Averaging across all experiments, subject fixed effects explain 44% of the variation in *CU*. This suggests that subject-level differences in cognitive effort or ability (the supply side of information processing) may be one important contributor to attenuation. To study this directly, we re-estimate eq. (1) using each subject's average *CU* rather than the uncertainty associated with a given decision. We then re-compute the implied attenuation effect size $\hat{\phi}^e$. Appendix Figure 12 compares the original estimates with those obtained using the subject-level average *CU* measure. Appendix Figure 13 reports the same exercise for the t-statistics.

The results show that the magnitude of attenuation is always lower (and usually substantially so) when we restrict attention to across-subject variation in average *CU*. The average attenuation effect size $\hat{\phi}^e$ drops from 33.0 to 8.8, and the average t-statistic from -4.8 to -1.39.

This suggests that a large part of the overall attenuation effect that we document in our pre-registered analysis does not reflect across-subject variation in cognitive effort or cognitive ability, but rather within-subject variation.[21] Moreover, these results also show that the *CU*-attenuation link is not driven by heterogeneous interpretations of the *CU* question across subjects.

What drives within-subject variation in *CU* and decision elasticities? Some part of this variation is likely idiosyncratic and caused by subject-specific variation in the timing of distracting events, attention allocation, or the order of rounds within the experiment. However, another part is highly systematic: as we analyze in the next section, *CU* strongly increases as the main decision-relevant parameter departs from simple boundary points. This within-subject variation will allow us to link attenuation to the demand side of information processing: the *complexity* of the decision problem.

[21]Indeed, when we re-estimate eq. (1) controlling for subject fixed effects, we continue to find a significant link between *CU* and decision elasticities. Appendix Figure 14 shows the results. 29 out of 30 tasks exhibit a negative t-statistic in this analysis, with 22 of those statistically significant at the 5% level.

5 Problem Complexity and Diminishing Sensitivity

We leverage the simple insight that even within a given task, some decisions require more information-processing than others, so that we should expect to observe a link between *CU* and insensitivity not only across subjects, but also *across different configurations* of the same task. As suggested by our model in Section 2, this will also allow us to demonstrate a linkage between behavioral attenuation and the classic regularity of *diminishing sensitivity*.

5.1 Simple Points

Figure 5 plots median *CU* in each of our 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. As we pre-registered, throughout this section, we restrict the sample to those tasks that have a potential simple point.

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.[22]

5.2 Diminishing Sensitivity

The insight that decisions become more difficult as parameters depart from simple boundary points has potential implications for understanding diminishing sensitivity. As spelled out in Section 2, the same psychological forces driving behavioral attenuation should also produce locally *lower* sensitivity at parameters that induce *greater* cognitive uncertainty. Because, as we've just shown, *CU* is generally lowest at simple boundary points, our model therefore *predicts* that information-processing constraints should produce *diminishing sensitivity*, a classic pattern previously documented in many decision contexts.

Diminishing sensitivity is indeed pervasive in our data.[23] 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.

[22]The one exception is FOR, for which we pre-registered potential simple points of 0% (future growth equals a fixed trend of +5) and 100% (future growth exactly equals past growth). The *CU* data suggest that 100% is actually a simple point, while 0% is not.

[23]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.

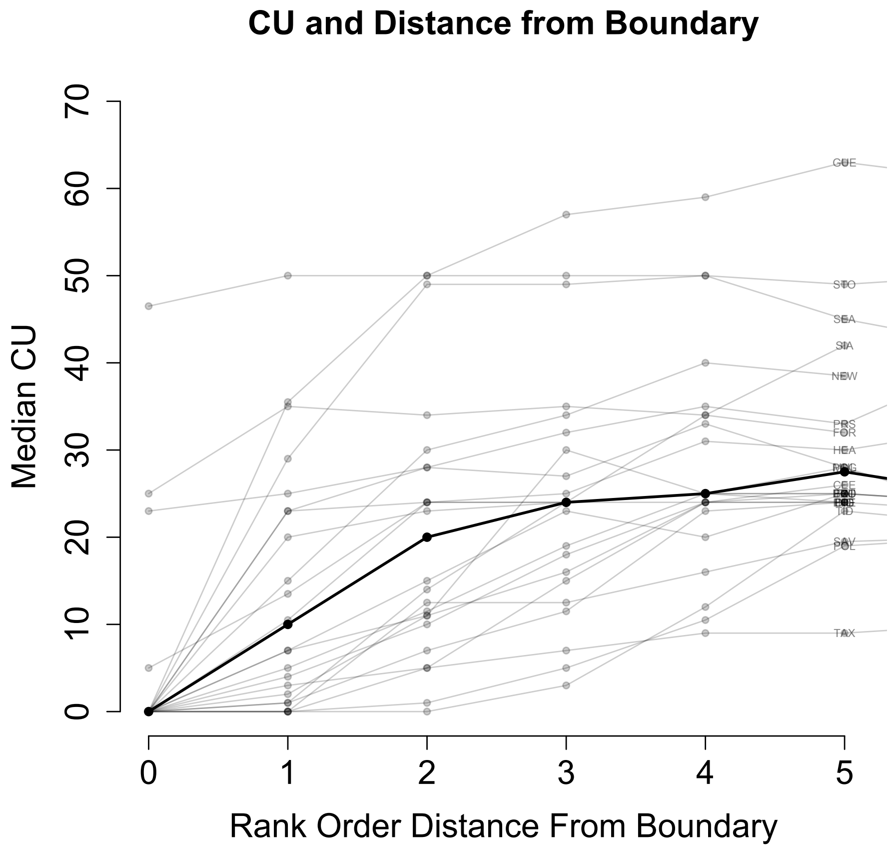


Figure 4: Median cognitive uncertainty as a function of distance to the nearest simple boundary point (measured in ordinal ranks), separately for each experiment. Solid line shows overall median across all experiments. Sample includes those 25 experiments for which we pre-registered at least one potential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

We then test for diminishing sensitivity by estimating, for each experiment e,

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

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 – clear evidence that diminishing sensitivity can arise purely as a consequence of information-processing constraints. Moreover, as with attenuation, diminishing sensitivity is very 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 may also reflect information-processing imperfections.

5.3 Across-Problem Variation in Complexity and Elasticity

Next, we show that the variation in task complexity (as measured by *CU*) 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 average *CU* at that parameter. For instance, we link the local slope of decisions at a wage of $\theta = 0$ to average *CU* at $\theta = 0$. 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* 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.[24] Similarly, for each parameter, we calculate average *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.

Importantly, this analysis only leverages variation in *CU* across different problem configurations and, hence, nets out subject-level differences in overall information-processing capacity (cognitive ability, effort, attentiveness etc.).

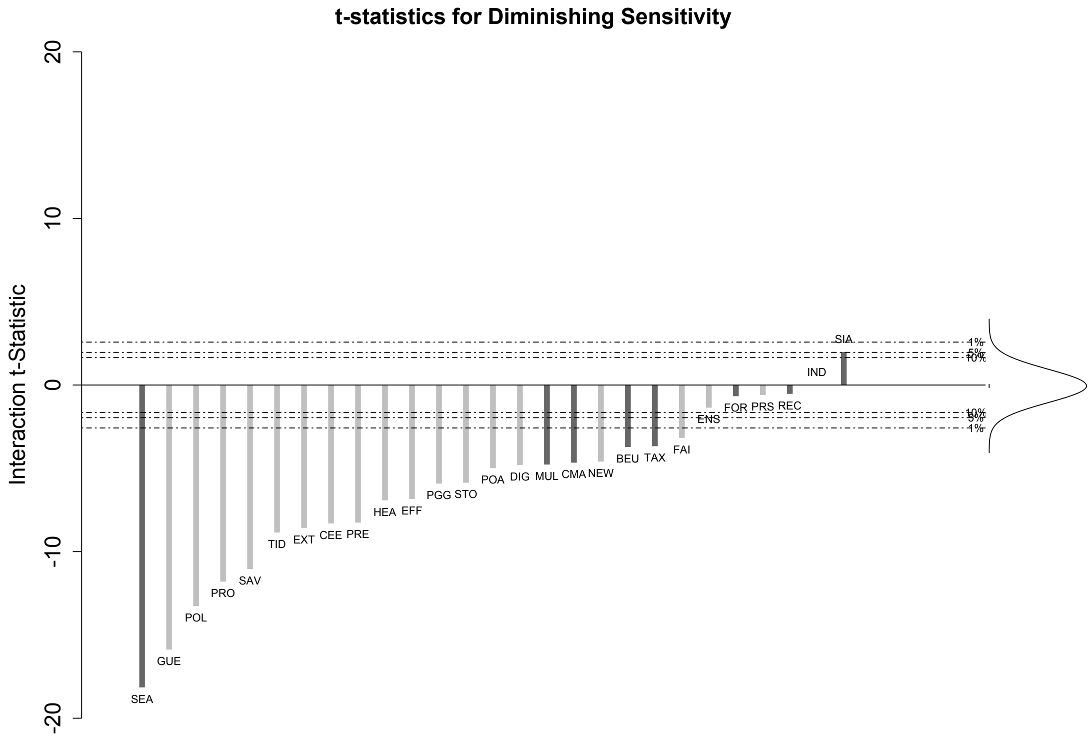
The bottom panel of Figure 5 shows the results by providing a binned scatter plot of the relative local decision sensitivities against relative local *CU*. The figure pools observations from all experiments, but controls for experiment fixed effects, such that it only reflects within-experiment across-parameter 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

[24] More formally, for each experiment e and parameter value θ_j^e, we estimate the OLS regression

$$a_{i,j}^e = \alpha_j^e + \xi_j^e \theta_j^e + \sum_x \chi^e d_x^e + \epsilon_{i,j}^e$$

in two different samples. First, we estimate it locally around parameter θ_j^e, i.e., only including $\{\theta_{j-1}^e, \theta_j^e, \theta_{j+1}^e\}$ (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 $\hat{\xi}_j^e$ 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.



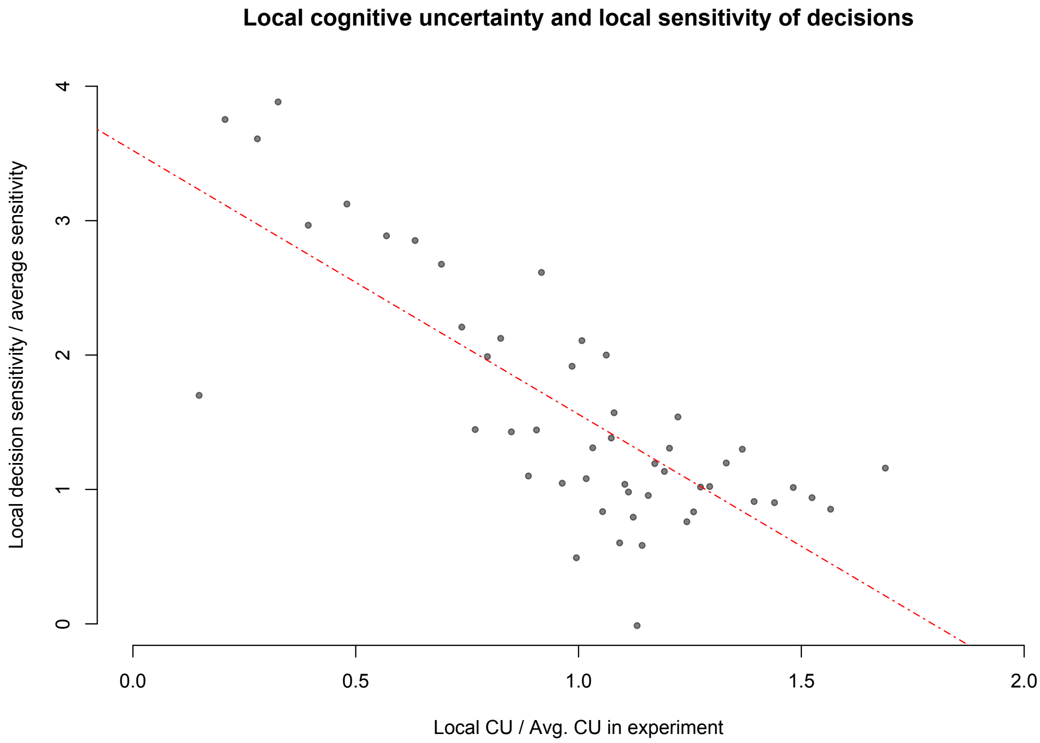


Figure 5: Top panel: Distribution of t-statistics for diminishing sensitivity ($\hat{\beta}_d^e$ in eq. (5)). Bottom panel: Binned scatter plot of the correlation between local CU at θ_j (normalized by average CU in the experiment) and the local sensitivity of decisions at parameters $\{\theta_{j-1}, \theta_j, \theta_{j+1}\}$ (normalized by the average sensitivity in the experiment). 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.

predicted by the model (partial $r = -0.48$, $p < 0.01$). As local *CU* rises, the relative local sensitivity of decisions to the parameter drops sharply. We interpret this evidence as strongly suggesting that a higher difficulty of information processing produces greater insensitivity of decisions, in a manner that is orthogonal to across-subject differences in information-processing capacity.

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). This suggests an interpretation of diminishing sensitivity: it is to a great extent a description of the way the intensity of behavioral attenuation changes as parameters move away from simple boundary points.

6 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, requiring intensive information processing. Both the supply side of information processing (each decision maker's overall cognitive capacity for a task) and the demand side (problem complexity) contribute to attenuation.

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 2 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. Indeed, various researchers, going back at least to Prelec and Loewenstein (1991), Hilbert (2012) and Hsee et al. (2019), have noted that many behavioral economics anomalies appear to reflect a form of insensitivity to relevant parameters.

For example, prior work has puzzled over why effort supply in experiments is often 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 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 pa-

Table 2: 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)
SAV	Insensitivity of investment to interest rate	Sharpe and Suarez (2015)
FOR	Insensitivity to autocorrelation parameter	Afrouzi et al. (2023)
FAI	Insensitivity of rewards to luck	Cappelen et al. (2022)

rameter (see Shubatt and Yang (2023) for a formal derivation of this point). Likewise, widespread evidence of hyperbolic discounting of monetary rewards in the intertemporal choice literature can be described as insensitivity of the value of delayed payments relative to standard exponential benchmarks (see Ebert and Prelec (2007), Enke et al. (2023a) and Shubatt and Yang (2023)).

Our results suggest that the insensitivities that characterize these 16 anomalies may partly be rooted in a shared cognitive mechanism, and therefore might be predicted, interpreted and explained on the same basis.

Behavioral attenuation vs. insensitivity-generating preferences. A perennial alternative explanation for insensitities like the ones we document, is domain-specific preferences (for e.g., risk, time etc.). Given our results, we think this is less plausible and far less parsimonious than the explanation we offer. First, in order to accept a preferences-based explantion, one would have to believe that insensitivity-generating preferences happen to coincide with cognitive uncertainty both (i) across subjects and (ii) across parameters. Given that no theory of preferences that we are aware of predicts any sort of relationship between self-doubt and elasticities, this can only be described as a dual pattern of coincidences. Second, one would have to believe that this pattern of coincidence is for some reason universal, arising in similar ways across the many decision domains we study: social decisions, intertemporal decisions, decisions under risk, strategic decisions, labor-related decisions, and so on. Finally, these correlations between cognitive uncertainty and insensitivity (both across subjects and parameters) would have to occur on completely different bases in objective and subjective tasks since information-processing mistakes are the *only* explanation available in objective tasks where preferences are not available as an explanation.

Summarizing, to us, an explanation of information-processing constraints and resulting behavioral attenuation seems a far more internally coherent and parsimonious way of organizing our findings.

Extending the reach of a classical pattern. The identification of (i) relatively high insensitivity and (ii) 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 a generic inability to optimize (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 more broadly, highly influential ideas from behavioral economics that have been useful for understanding and predicting risky and intertemporal behavior, may prove equally useful for predicting and explaining behavior in many other economic settings as well.

Expert crowd-sourcing. We implemented a process for crowd-sourcing the selection of some experimental tasks to a panel of independent experts. We believe that this research strategy effectively 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 would have arrived at ourselves. This methodology is connected to and extends the growing body of work using expert panels in research, e.g., the 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 generic response to information-processing constraints that is 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 widespread 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.

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ONLINE APPENDIX

A Study Details

A.1 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) – these points are always classified as "simple".
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. Specifically, a potential simple point is an ex-post simple point if cognitive uncertainty at that parameter is significantly lower than at the five nearest parameters (at the 5% level).
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) an earnings drift of +5 annually. Participants observe past earnings and the persistence parameter (the weight of (1)) and then forecast 2024 earnings. The persistence of the earnings trend 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 - 5) / (earnings 2023 - earnings 2022 - 5). Independent variable: predictability.

6. Rational regression coefficient: 1

7. “*How certain are you that the 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 correct 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 for Main Experiments

B.1 Taskwise Raw Data

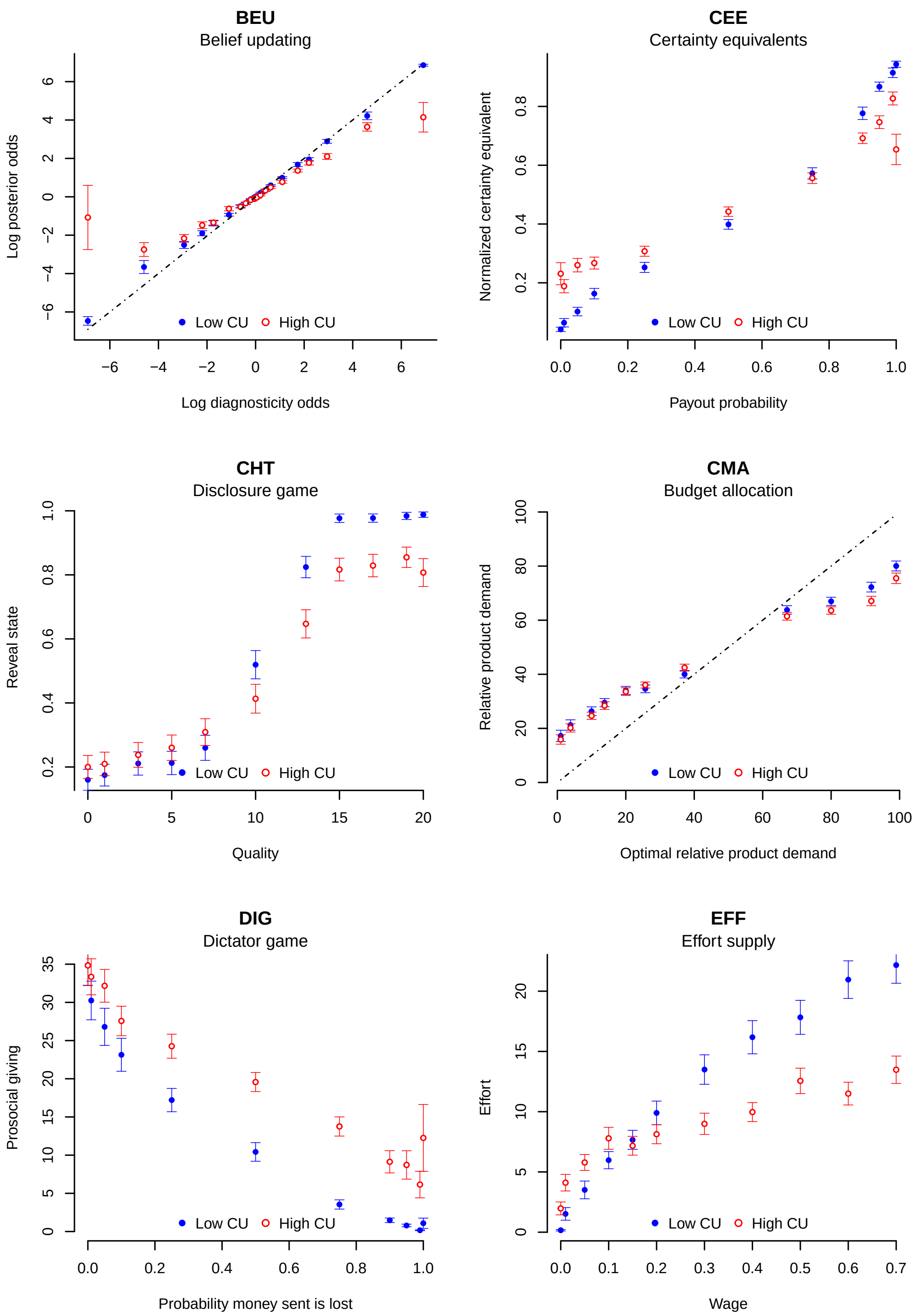


Figure 6: Decisions as a function of parameters.

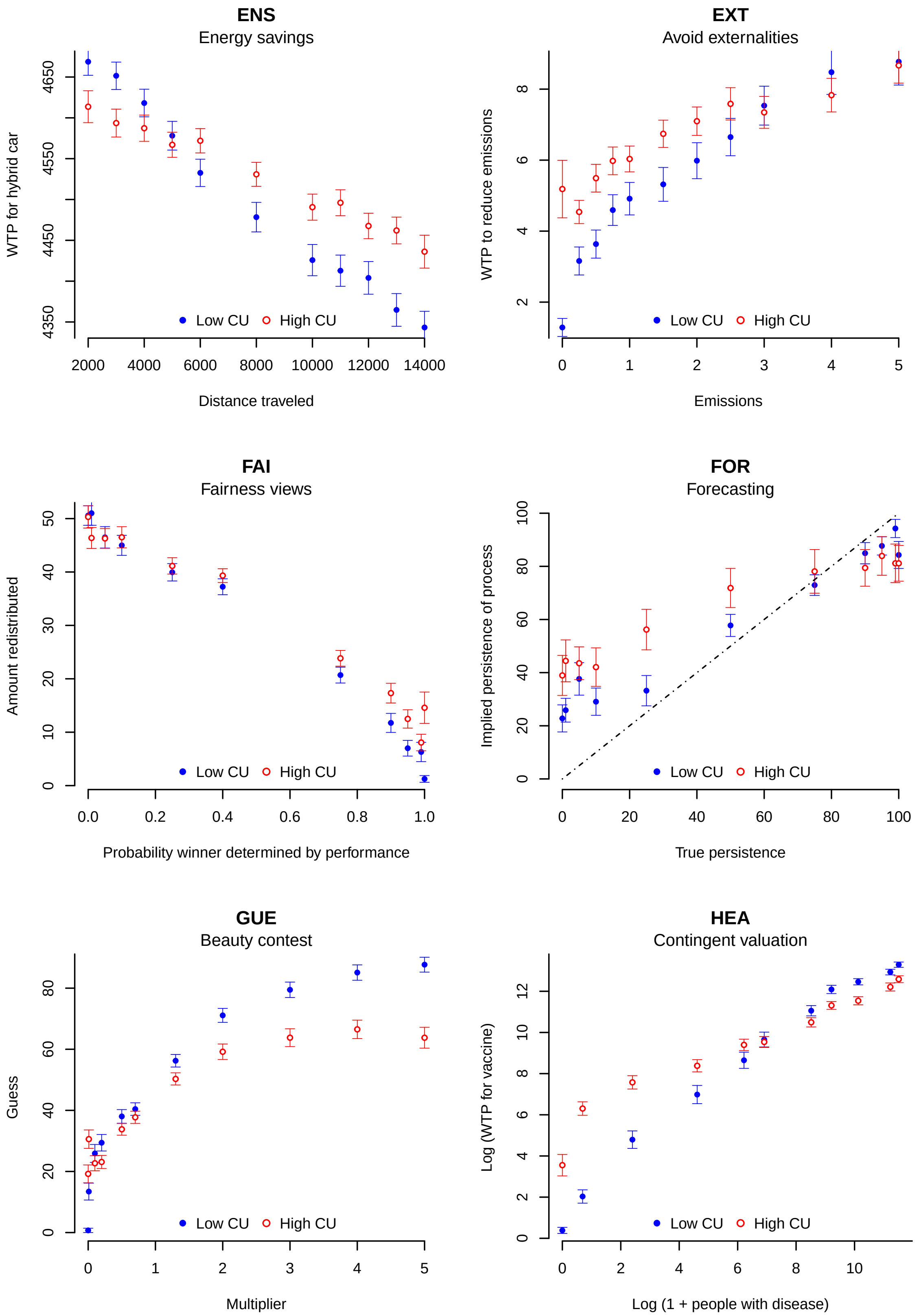


Figure 7: Decisions as a function of parameters.

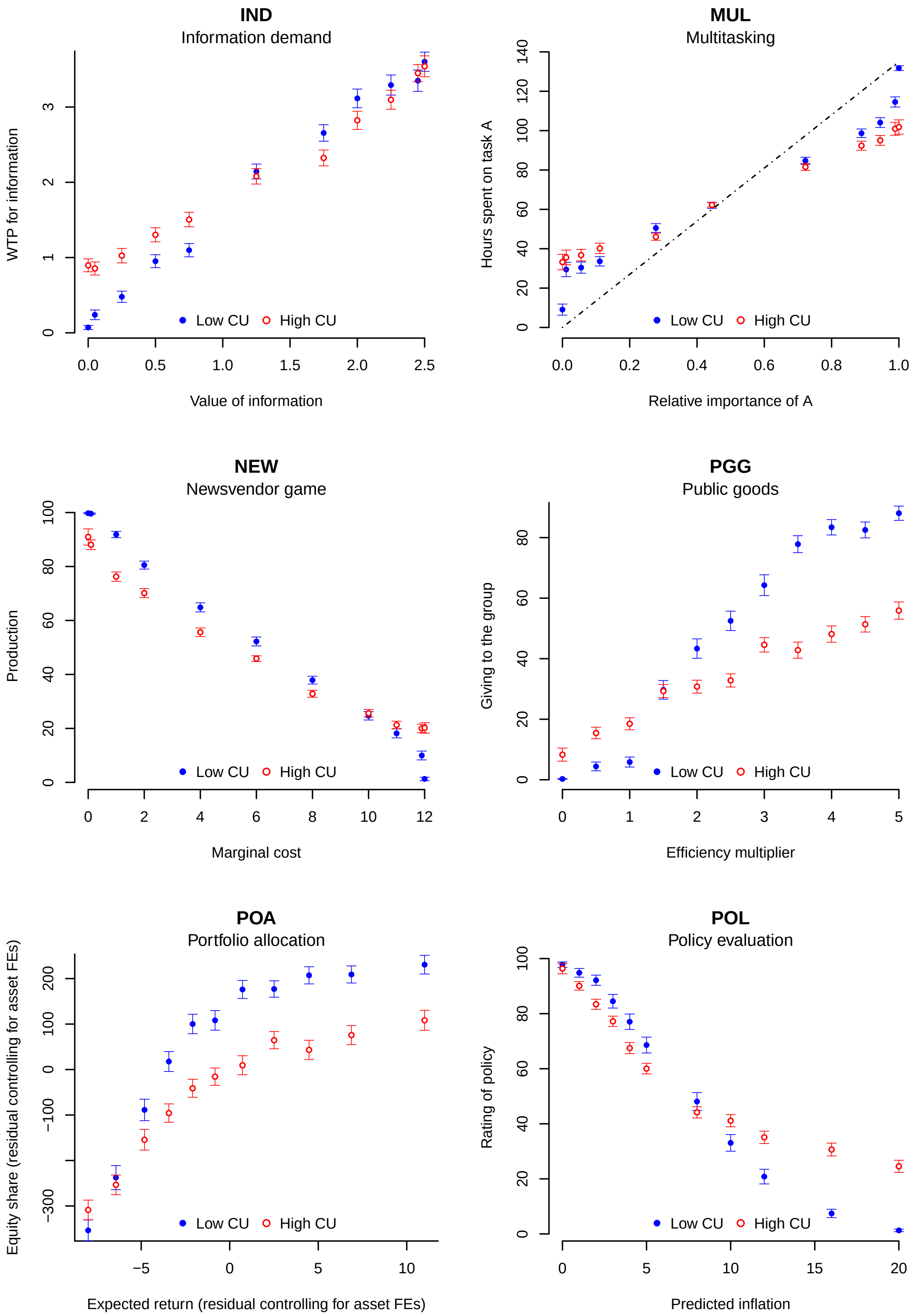


Figure 8: Decisions as a function of parameters.

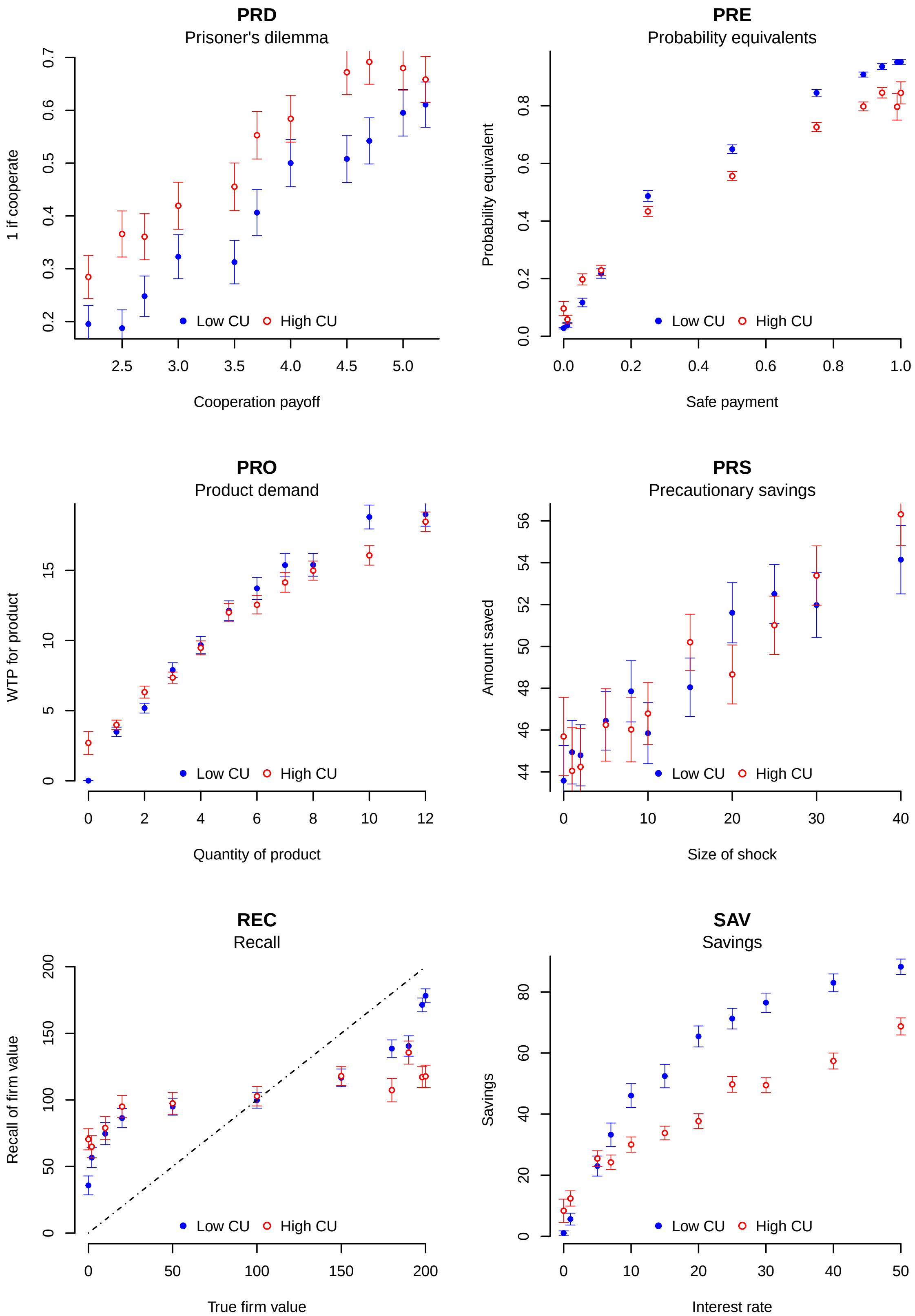


Figure 9: Decisions as a function of parameters.

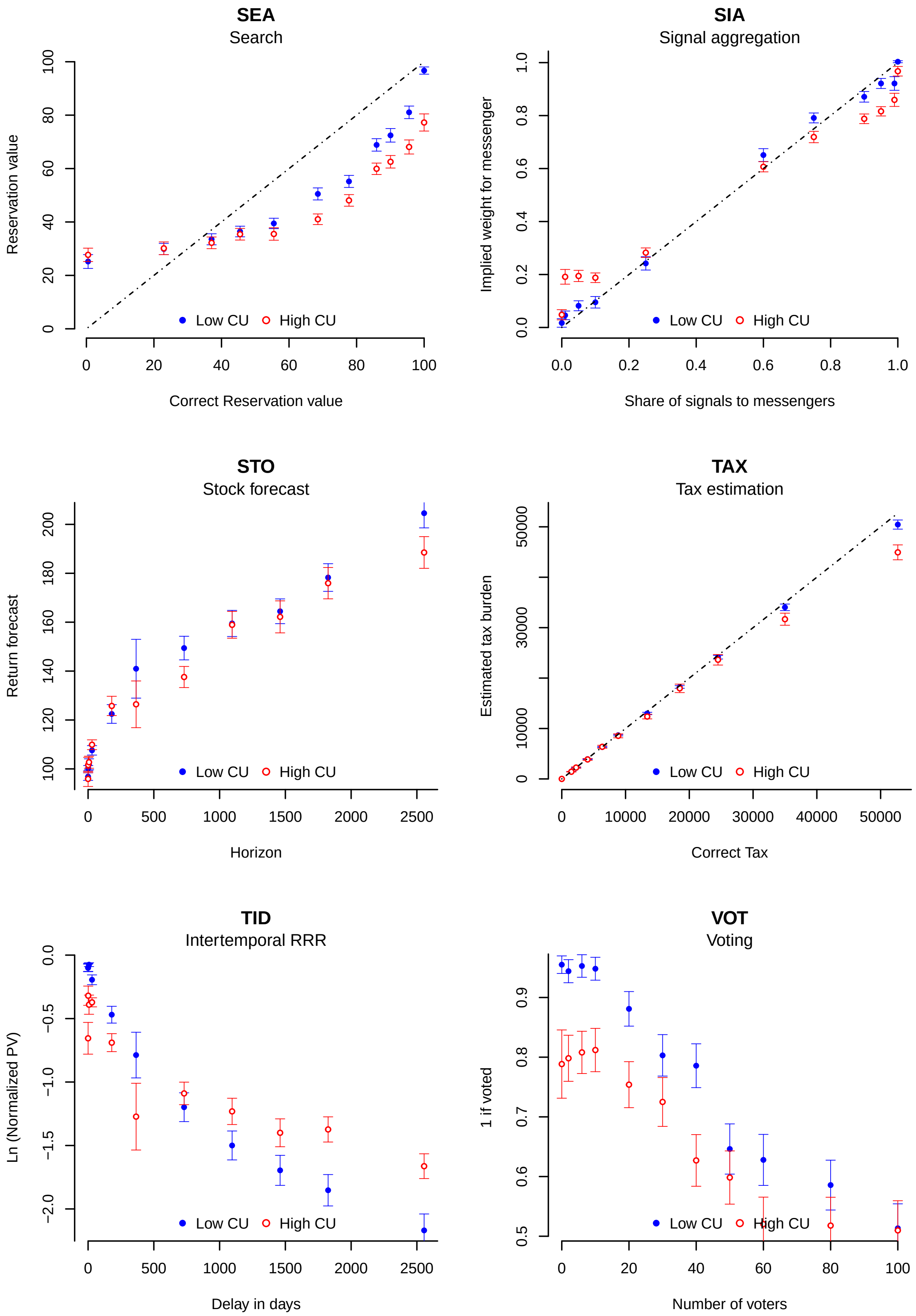


Figure 10: Decisions as a function of parameters.

B.2 Bayesian Meta-Analysis

The main hypothesis behind our paper is that there is an overarching structure behind the many experiments we run, which is a lower sensitivity to parameters when people are less sure they understand what is optimal. We, hence, additionally report t-statistics adjusted using standard meta-analytic techniques, i.e., using Bayesian hierarchical regressions. 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.

Our 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 $x_1, x_2, ...$ across tasks $e = 1, 2, ...$ 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:

$$\hat{x}_e | x_e, \sigma_e \sim \mathcal{N}(x_e, \sigma_e^2) \tag{6}$$

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:

$$x_e | x_0, \tau \sim \mathcal{N}(x_0, \tau^2) \tag{7}$$

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:

$$\hat{x}_e \mid x_0, \sigma_e, \tau \sim \mathcal{N}(x_0, \sigma_e^2 + \tau^2) \tag{8}$$

Estimating this model requires empirical 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).

The red distribution in the margin of the top panel of Figure 2 shows the results. The meta-analytic distribution of t-statistics is very different from the null hypothesis $N(0,1)$ distribution, with a mean adjusted t-statistic of -4.7. This corroborates our main finding of widespread and quantitatively meaningful attenuation.

B.3 Additional Figures

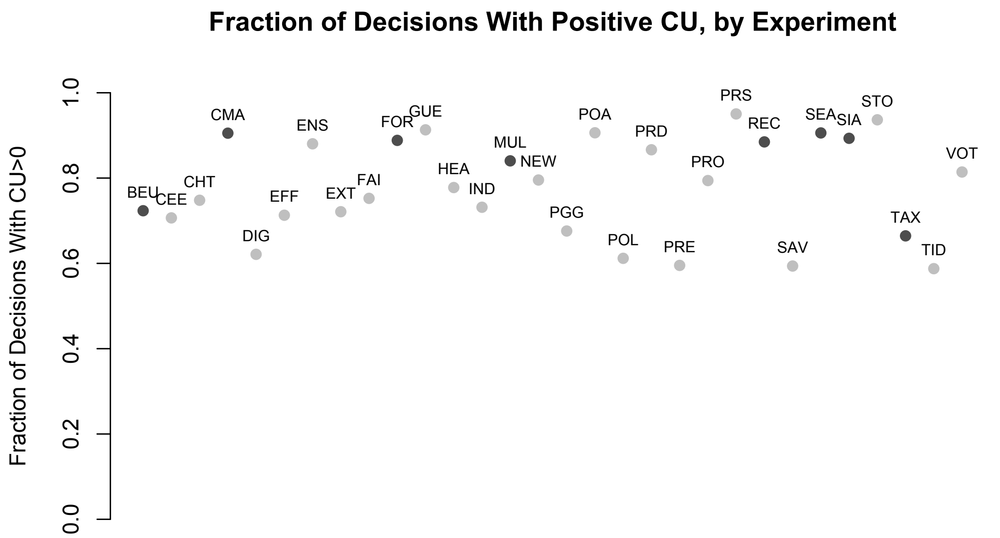


Figure 11: Fraction of decisions associated with strictly positive CU, by experiment. Tasks displayed in black have objectively correct solutions, while those displayed in grey are subjective decision problems that involve unknown (to us as researchers) preferences or information sets.

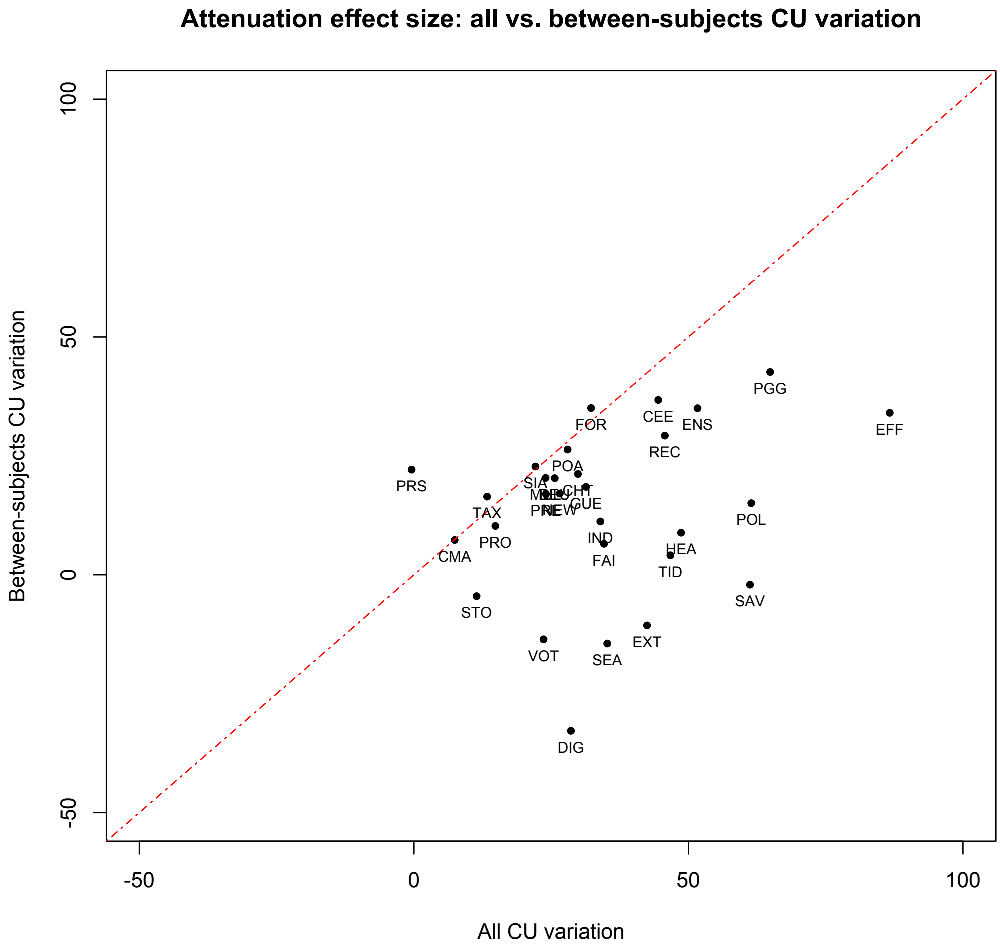


Figure 12: Behavioral attenuation with decision-level and subject-level *CU*. The x-axis shows $\hat{\phi}^e$, calculated by estimating eq. (1) using decision-level cognitive uncertainty, and the y-axis shows $\hat{\phi}^e$, calculated by estimating eq. (1) using subject-level average cognitive uncertainty.

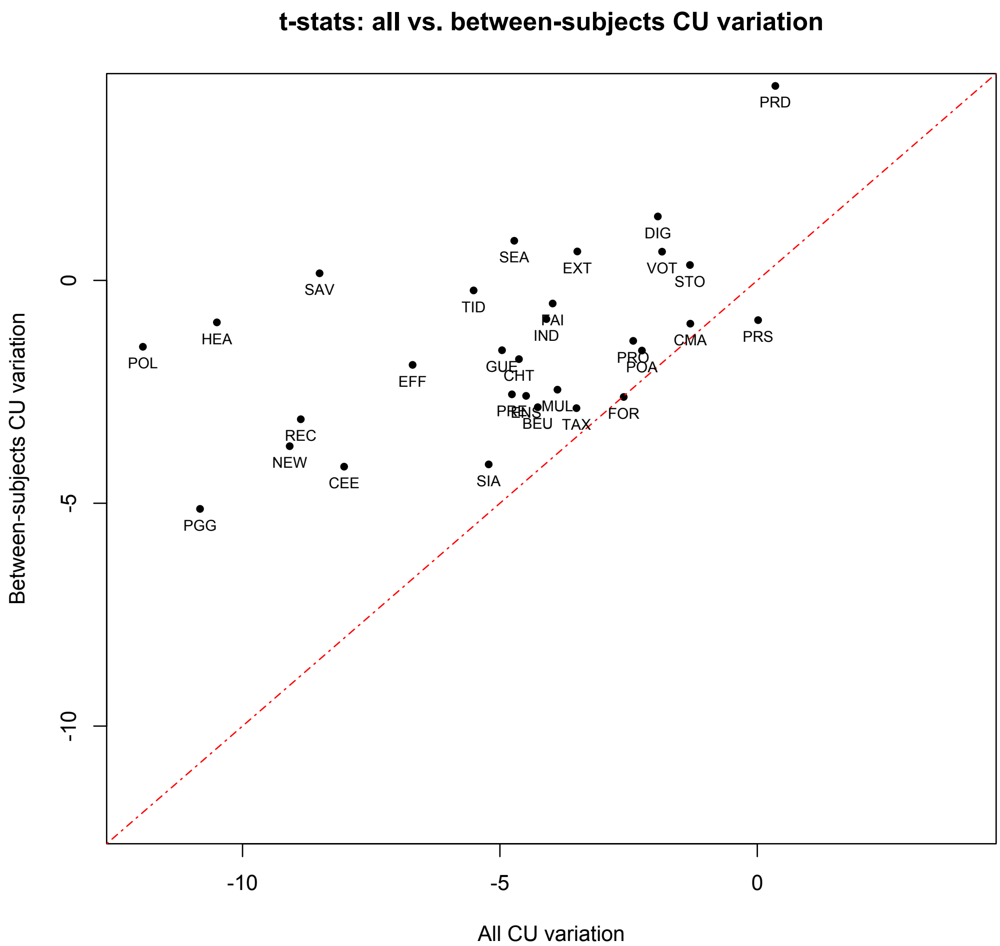


Figure 13: Behavioral attenuation with decision-level and subject-level *CU*. The x-axis shows the t-statistic associated with $\hat{\beta}^e$ in (1) when using decision-level cognitive uncertainty, and the y-axis shows the same object when using subject-level average cognitive uncertainty.

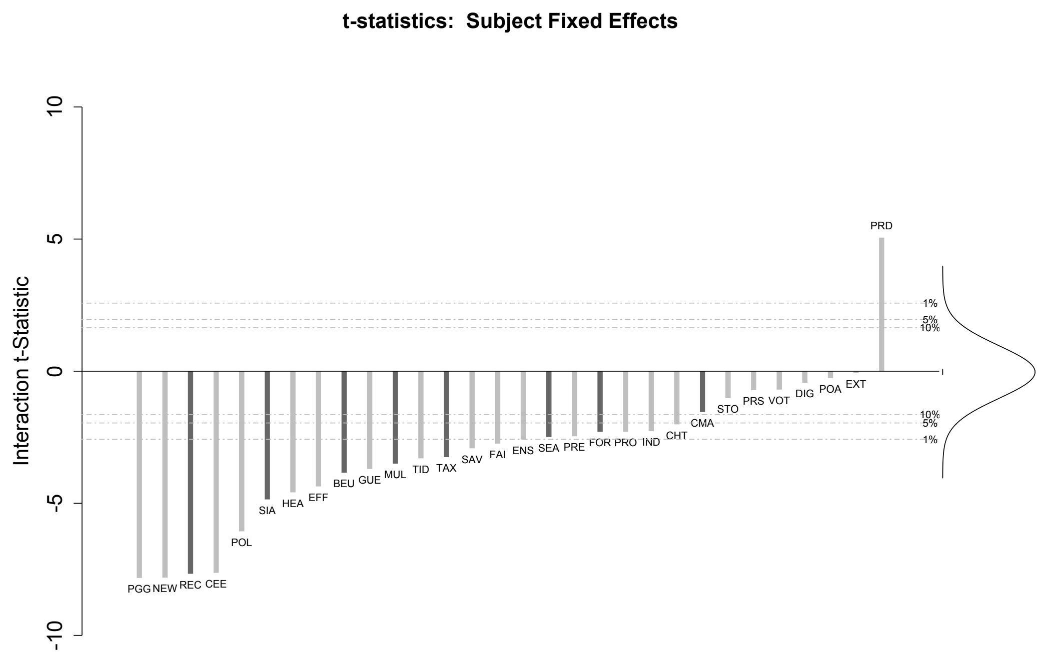


Figure 14: Sensitivity to parameters and cognitive uncertainty within subjects. The figure plots the t-statistic associated with $\hat{\beta}^e$, when estimating (1) controlling for subject fixed effects.

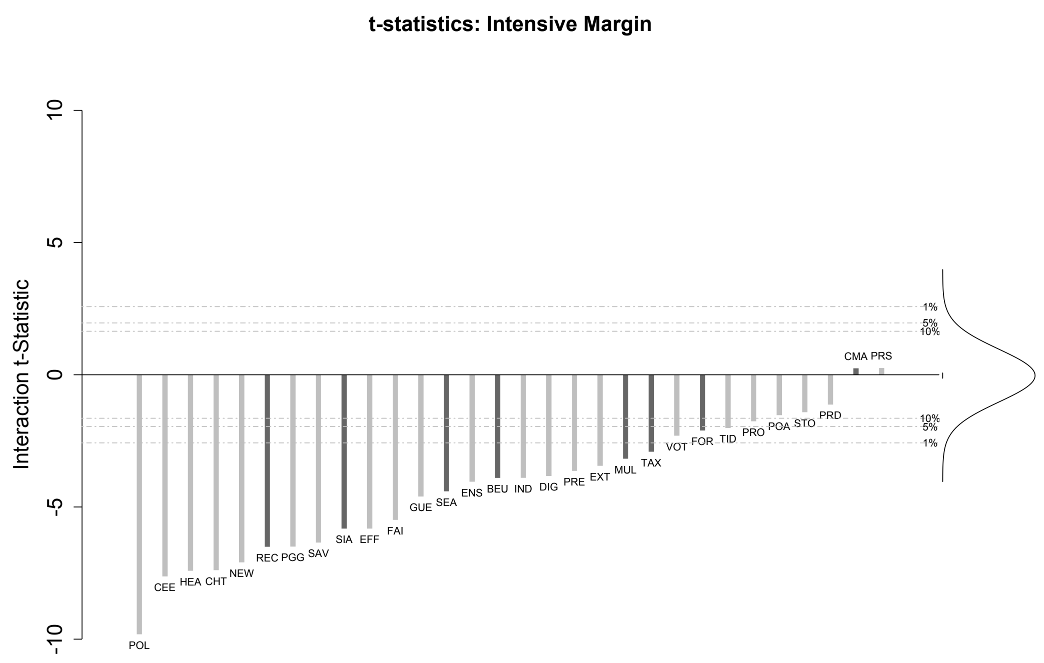


Figure 15: Sensitivity to parameters and cognitive uncertainty within subjects. The figure plots the t-statistic associated with $\hat{\beta}^e$, when estimating (1), restricting only to subjects with $CU > 0$.

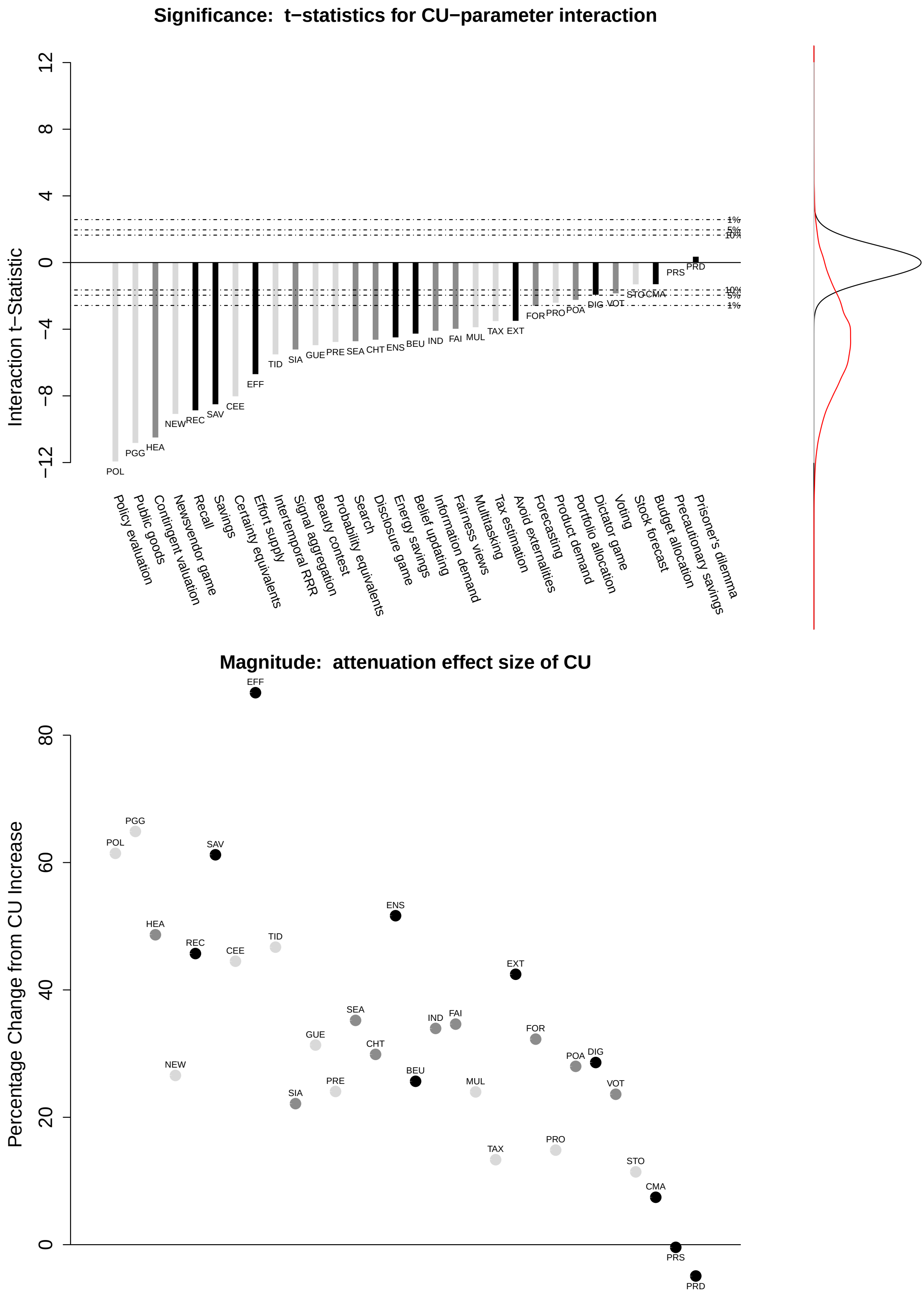


Figure 16: Behavioral attenuation and cognitive uncertainty for different categories of tasks. The top panel plots the t-statistic associated with $\hat{\beta}^e$ in (1). For comparison, we plot a standard normal distribution in black. The red distribution shows the distribution of adjusted t-statistics from a meta analysis (Bayesian hierarchical regression), see Appendix B.2. The bottom panel plots $\hat{\phi}^e$. Tasks displayed in black are "expert tasks," those in dark gray are "EGOY+" tasks and the light gray ones are "EGOY" tasks (see also Table 1).

B.4 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^{***}	23.15^{***}
	(0.08)	(0.01)	(0.04)	(2.11)	(2.04)	(0.70)	(23.63)	(0.43)	(1.92)	(5.45)
Par.	0.88^{***}	0.83^{***}	0.06^{***}	0.62^{***}	28.52^{***}	29.97^{***}	0.03^{***}	1.26^{***}	46.73^{***}	0.72^{***}
	(0.03)	(0.02)	(0.00)	(0.04)	(2.24)	(2.28)	(0.00)	(0.12)	(2.42)	(0.06)
CU	-0.24^{*}	0.27^{***}	0.30	2.05	-7.23	7.24^{***}	150.86^{**}	2.21^{**}	8.46^{*}	27.94^{*}
	(0.14)	(0.05)	(0.20)	(3.61)	(5.96)	(1.96)	(64.46)	(1.08)	(5.03)	(15.79)
Par. × CU	-0.45^{***}	-0.74^{***}	-0.07^{***}	-0.09	-16.32^{*}	-51.95^{***}	-0.03^{***}	-1.07^{***}	-32.37^{***}	-0.46^{***}
	(0.11)	(0.09)	(0.01)	(0.07)	(8.44)	(7.76)	(0.01)	(0.31)	(8.14)	(0.17)
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	0.09
Num. obs.	2340	2259	2250	2871	2268	2530	2783	2500	2277	2250

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

Table 3: Separate estimates of equation (1) from the body of the paper for each of ten experiments. The dependent variable is the decision subjects take, while "'Par." is the main decision-relevant parameter in the experiment. See A.1 for the details for each task.

	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 4: Separate estimates of equation (1) from the body of the paper for each of ten experiments. The dependent variable is the decision subjects take, while "Par." is the main decision-relevant parameter in the experiment. See A.1 for the details for each task.

	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 5: Separate estimates of equation (1) from the body of the paper for each of ten experiments. The dependent variable is the decision subjects take, while "'Par." is the main decision-relevant parameter in the experiment. See A.1 for the details for each task.

C Replication of Results with Pre-Registered Sample

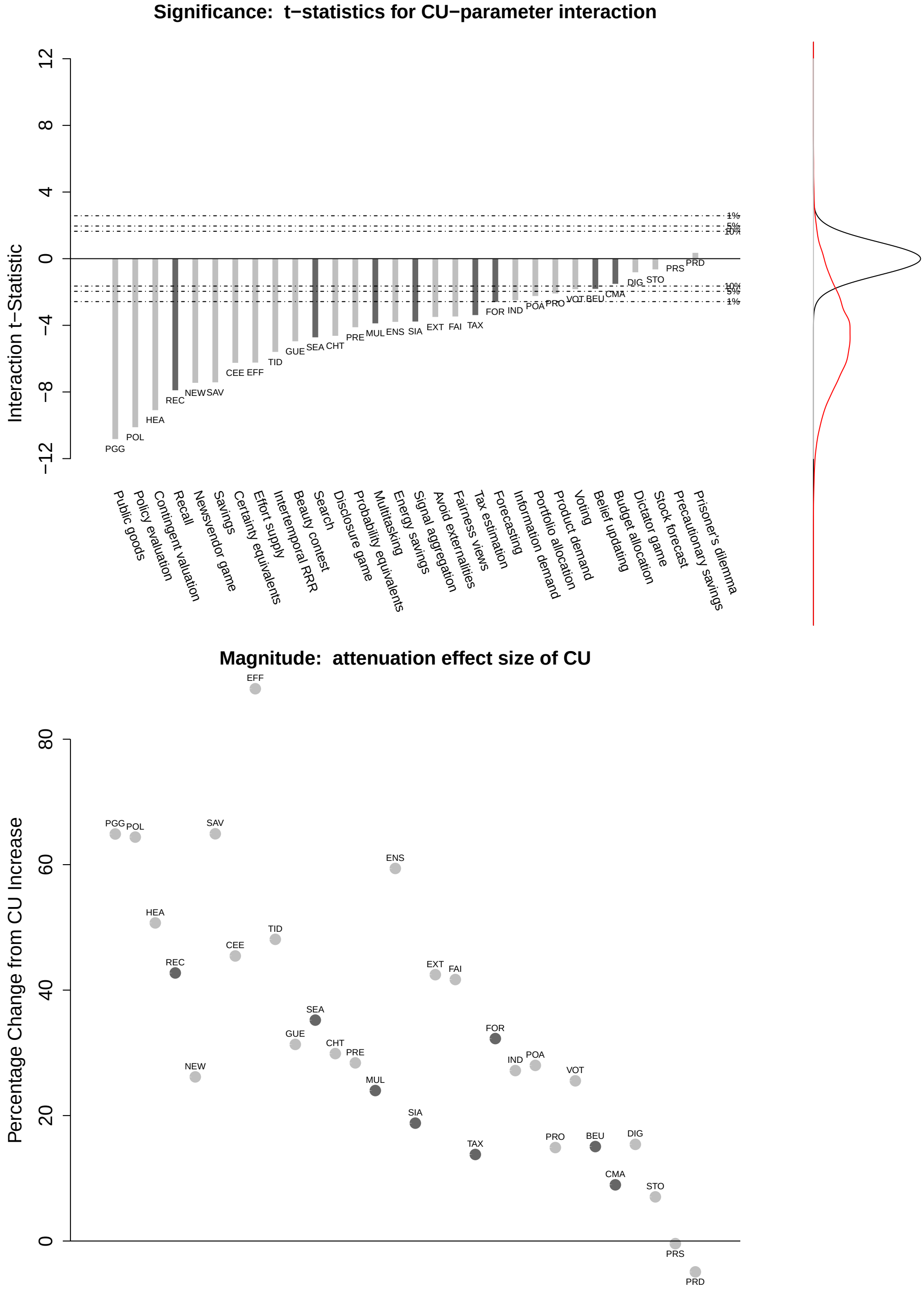


Figure 17: Replication with pre-registered sample. Behavioral attenuation and cognitive uncertainty. The top panel plots the t-statistic associated with $\hat{\beta}^e$ in (1). For comparison, we plot a standard normal distribution in black. The red distribution shows the distribution of adjusted t-statistics 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.

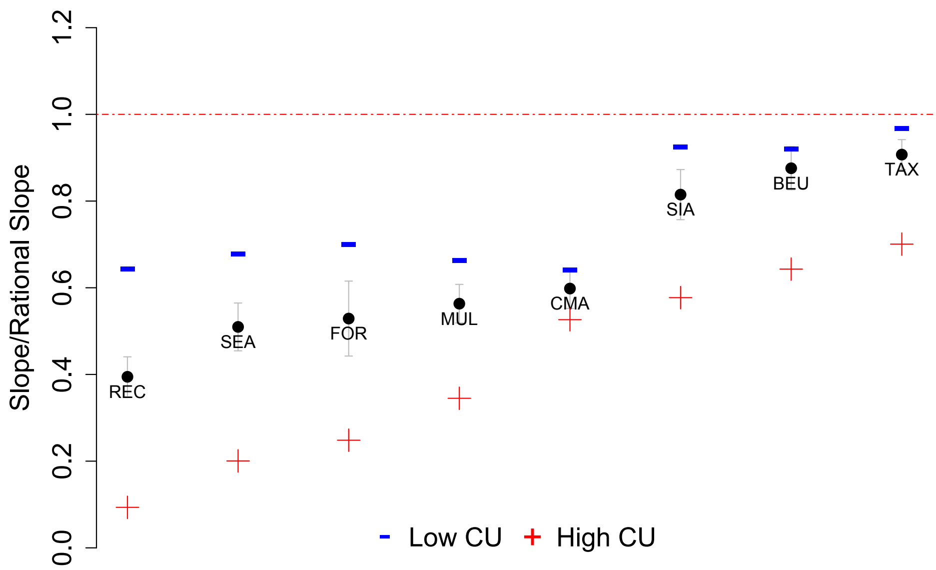


Figure 18: Replication with pre-registered sample. Behavioral attenuation relative to normative benchmarks in objective tasks. For each task, the black dot plots $\hat{\omega}^e/\omega_R^e$ and 95% CIs, see equation (4). The red and blue dots correspond to the fitted values of equation (1) for $CU = 0\%$ (blue) and $CU = 100\%$ (red).

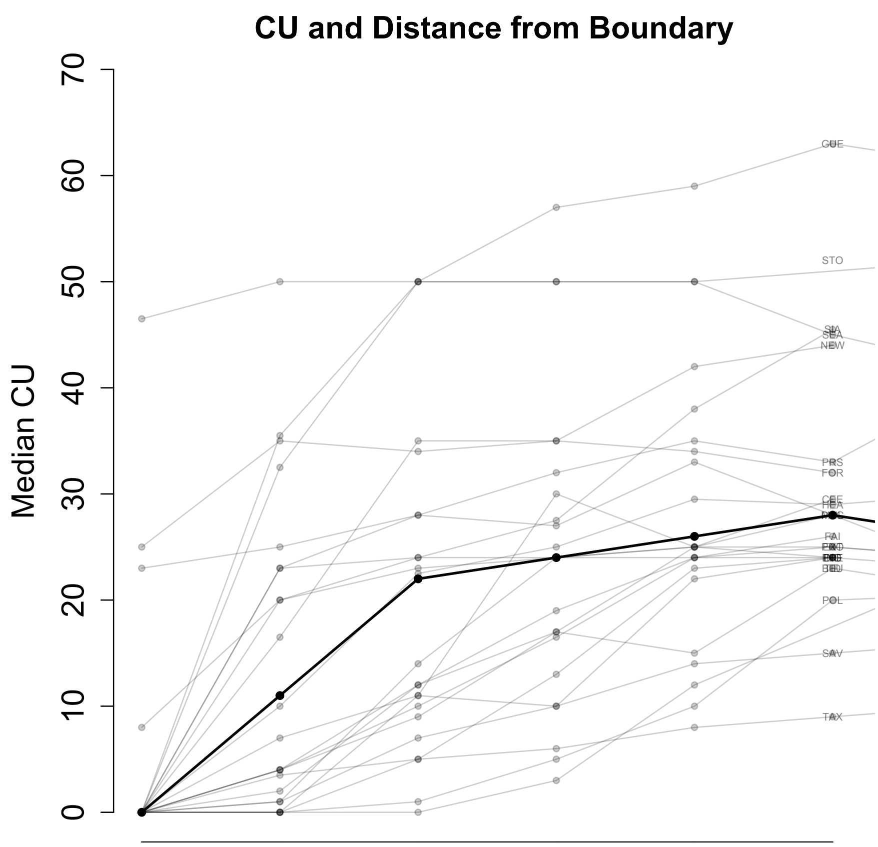


Figure 19: Replication with pre-registered sample. Median cognitive uncertainty as a function of distance to the nearest boundary point (measured in ordinal ranks), separately for each experiment. Solid line shows overall median across all experiments. Sample includes those 25 experiments for which we pre-registered at least one potential simple point at the boundary of the parameter space.

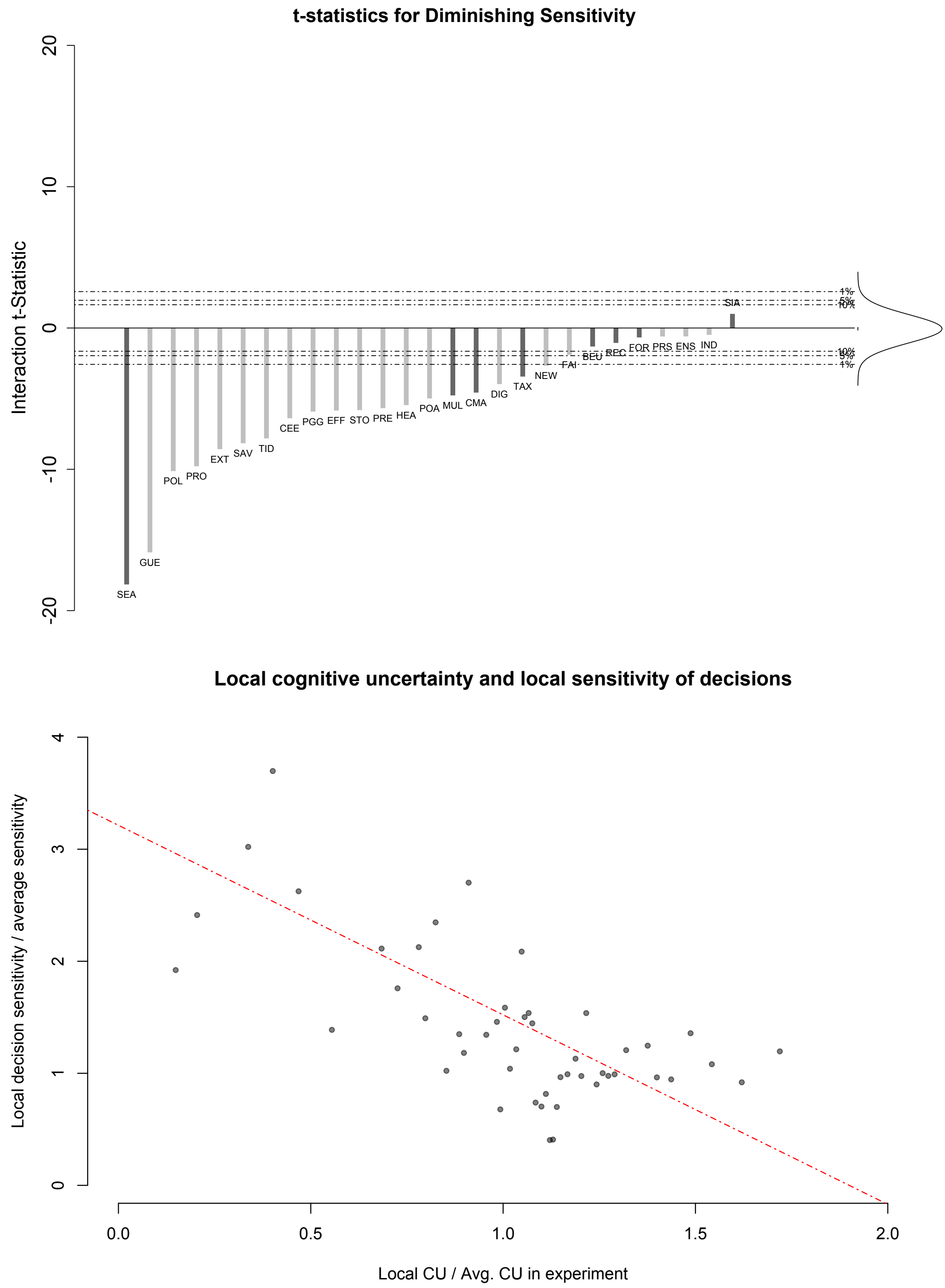


Figure 20: Replication with pre-registered sample. Top panel: Distribution of t-statistics for diminishing sensitivity ($\hat{\beta}_d^e$ in eq. (5)). Bottom panel: Binned scatter plot of the correlation between local *CU* at θ_j (normalized by average *CU* in the experiment) and the local sensitivity of decisions at parameters $\{\theta_{j-1}, \theta_j, \theta_{j+1}\}$ (normalized by the average sensitivity in the experiment). 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.

D The Bounds of Attenuation

In this Section we discuss several findings and diagnostic treatments that point to the robustness and limits of behavioral attenuation.

Stake size, cognitive effort and demographics. To what degree does attenuation reflect low stakes, low cognitive effort or demographics – three common sources of explanation for deviations from standard predictions? To study this, Table 6 presents OLS regressions in which the dependent variable is the subject-level slope (sensitivity) of decisions, computed in a standardized way across experiments.[25] Recall that a lower slope means more attenuation.

Column (1) shows that a tenfold increase in incentives – implemented in experiments BEU, CMA, REC, SIA and VOT – does not significantly affect attenuation. We take this as tentative evidence for the robustness of the attenuation phenomenon, but we do not wish to suggest that we believe attenuation will always be independent of the stake size.

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 6 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 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 ex-

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

$$a^e_{i,j} = \nu^e_i + \omega^e_i\, \theta^e_j + \sum_x \chi^e d^e_x + u^e_{i,j}\,, \tag{9}$$

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 6: 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	0.061	0.059	−0.028	−0.019	−0.003	0.016
	(0.041)	(0.041)	(0.041)	(0.037)	(0.038)	(0.038)	(0.048)
Log [Completion time experiment] (std.)		-0.030^{***}	-0.026^{***}		-0.067^{***}	-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			-0.052^{***}			0.133^{***}	0.134^{***}
			(0.016)			(0.016)	(0.018)
Log [Response time decision] (std.)					0.117^{***}	0.116^{***}	0.112^{***}
					(0.006)	(0.006)	(0.006)
Distance from boundary (rank, 0-11)							0.064^{***}
							(0.002)
Experiment fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.005	0.007	0.009	0.000	0.013	0.019	0.047
Num. obs.	7604	7604	7572	82281	80903	80567	69152

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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

ample, 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 determine whether the lottery upside or downside will realize by verifying a few mathematical equations. Because of the illustrative potential of this task we included it in our design even though it is structurally different from all other tasks; we did this with the explicit intention (shared with Ambuehl ahead of time) to include it as a test of the limits of the phenomenon, rather than as a baseline task.

In this experiment, we find, as expected, that decisions that are associated with higher *CU* are slightly more sensitive to variation in the problem parameter, though this relationship is not statistically significant.[26] Note that we used a smaller sample size than the

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

experiment that motivated our study setup (Ambuehl et al., 2022). It is thus conceivable that we would have found a statistically significant positive interaction coefficient had we opted for a larger sample.

Bound #2: 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 not only 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 ran a pre-registered variant ("*Joint*") of two of our experiments: savings as a function of the interest rate (SAV, a subjective task) and allocation between two tasks in a multitasking environment (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. Later, 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.

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.[27] Figure 21 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 behavioral attenuation can be corrected by external parties via framing, at least in some circumstances. Alternative implementations of this intervention might lead to more consistent results, but our findings suggest that behavioral attenuation may be more robust than we originally hypothesized.

[27]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.

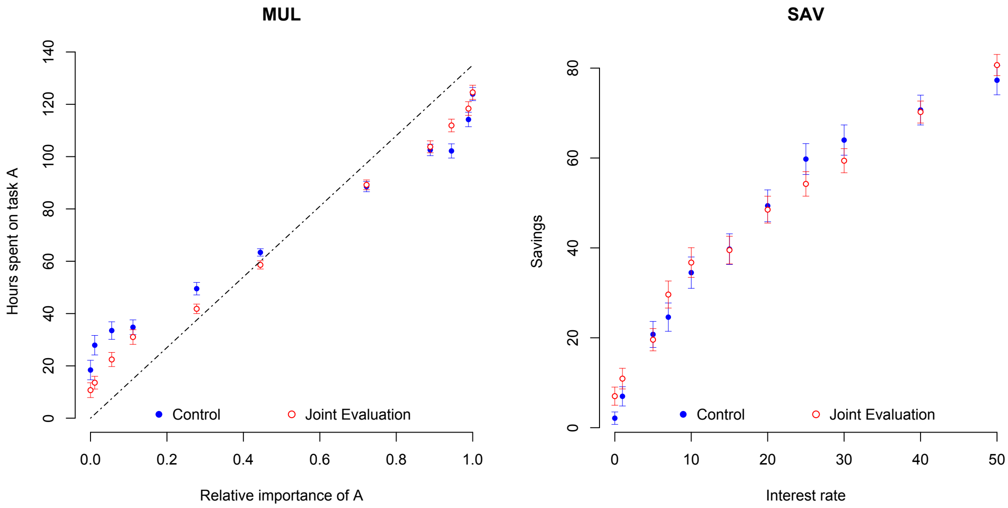


Figure 21: Raw data for the *Joint* treatment in tasks MUL and SAV.

E 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

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

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

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

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 $\underline{\theta}$ □

The following result formalizes how our model can generate excess sensitivity local to simply boundary points if cognitive noise is sufficiently sharply increasing away from the simoly points.

Proposition 3. *(Excess Sensitivity Near Simple Points) Suppose that $a_d(\theta)$ is interior. If $\underline{\theta}$ exists and $\frac{\partial}{\partial \underline{\delta}}\sigma_a^2(\underline{\theta})$ is positive and sufficiently large, then $\frac{\partial}{\partial \theta}a(\theta) > \frac{\partial}{\partial \theta}a^*(\theta)$ in a neigh-*

borhood around $\underline{\theta}$. Likewise, if $\overline{\theta}$ exists and $\frac{\partial}{\partial \overline{\delta}}\sigma_a^2(\overline{\theta})$ is positive and sufficiently large, then $\frac{\partial}{\partial \theta}a(\theta) > \frac{\partial}{\partial \theta}a^*(\theta)$ in a neighborhood around $\overline{\theta}$.

Proof. First prove the statement regarding $\underline{\theta}$. Note that

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

Since $a_d(\theta)$ is interior, we have $a^*(\underline{\theta})-a_d(\underline{\theta})<0$. We have

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

and so if $\frac{\partial}{\partial \underline{\delta}}\sigma_a^2(\underline{\theta}) = \frac{\partial}{\partial \theta}\sigma_a^2(\underline{\theta})$ is positive and sufficiently large, then $\frac{\partial}{\partial \theta}\lambda\cdot(a^*(\underline{\theta}) - a_d(\underline{\theta})) > -(1-\lambda)\cdot\frac{\partial}{\partial \theta}(a_d(\underline{\theta})-a^*(\underline{\theta}))$, and so $\frac{\partial}{\partial \theta}[a(\underline{\theta})-a^*(\underline{\theta})] > 0$. By continuity, this implies that $\frac{\partial}{\partial \theta}[a(\theta)-a^*(\theta)] > 0$ for θ in a neighborhood of $\underline{\theta}$. The proof of the statement regarding $\overline{\theta}$ is analogous. □

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 4. *(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 $\sigma_a(\theta)$. □

F Additional Information on Expert Consultation for Task Selection

This Appendix provides additional information on the expert consultation. We first outline the sequence of events in the consultation process we designed. Second, we reproduce the email that was sent to the experts. Third, we list task proposals that failed the monotonicity requirement in the pilots. Fourth, we list issues in the consultation process that lead us to conservatively classify a task as "EGOY+" task rather than "expert task".

F.1 Steps in Expert Consultation Process

1. Send email invitation to contribute a task based on a template (see below). The template specifies the common deadline for submitting a contribution.
2. Experts who reply to invitation:
   (a) If expert proposes a single, qualifying task: Ask for additional clarification whenever necessary.
   (b) If expert does not propose a single qualifying application (see list of reasons in Appendix F.4): Further interactions to arrive at a qualifying proposal.
3. Design and implementation of the experimental task using a shared template for instructions and coding.
4. Pilot with small sample of $N = 10-30$ subjects to confirm monotonicity. Return to experts if monotonicity requirement fails (see also Appendix F.3).
5. Send link of final online experiment to corresponding expert, invite feedback with a deadline of one week.
6. Send paper draft to all contributing experts with invitation to check for accuracy before posting the first draft of the paper.

F.2 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

F.3 Proposals that Failed Pilot Test for Monotonicity

We piloted each qualifying proposal with a small sample of between $N = 10-30$ subjects. Our condition for an application to be excluded due to a violation of the monotonicity requirement was the following: We ran OLS regressions of the decision on the experimental parameter in two samples: (i) the full sample and (ii) restricting attention to parameters that were not "simple boundary points" (e.g. a wage of zero). A task was counted as satisfying monotonicity when the OLS coefficients was significantly different from zero at the 10% level in both samples.

The following task proposals failed monotonicity:

- Sender-receiver disclosure game, where the proposal was to study the receiver's choice as a function of the degree of conflict between sender and receiver incentives. Because this did not produce monotonicity, after consultation with the expert we instead studied sender behavior in the disclosure game (task CHT).

- An extended dictator game inspired by Schumacher et al. (2017). The dictator can send money to receivers, where for each Dollar the dictator gives up, a Dollar is sent to each receiver. The proposal was to study the sensitivity of giving behavior to the number of receivers (because a higher number of receivers increases the efficiency of giving). We did not find monotonicity, leading the expert to drop the task and propose a new one (HEA).

F.4 Issues in Expert Consultation Process that Lead to "EGOY+" Classification

When we designed our expert consultation process, there was no template available in the literature for us to use. As a result, we encountered several issues that we did not anticipate and which lead us to conservatively classify a task as "EGOY+" (where EGOY refers to the authors of this paper) rather than as an expert task so as to not overstate the degree to which our hands were tied in the task selection process. With hindsight, our invitation email and procedures could have been clearer. We describe the issues we encountered below. Moreover, we also provide a suggestion for how – in our experience – other researchers who wish to follow a similar design strategy could pre-empt such issues going forward.

Each of the below issues was encountered in the interactions with at least one expert. Because these issue provided varying degrees of influence from our side on the selection of the task, in the interest of conservatism we consider each individual issue sufficient to classify a task as "EGOY+" task. We note in how many expert interactions we encountered each issue, yet to preserve privacy we refrain from associating the issues with specific experts (multiple issues can apply to a single expert interaction).

1. Six experts sent more than one qualifying proposal, requiring us to choose one of the alternative (our email did not emphasize enough that only one proposal should be sent).

   → Suggestion: Expert invitation should highlight that not more than one proposal can be sent, and that if more than one is sent, only the first one will be considered.

2. Five experts sent slightly ambiguous proposals (no concrete choice context) or incomplete proposals (no experimental decision or no exogenous parameter was specified). This triggered a back-and-forth with us, which means we had some degree of influence over the task selection.

   → Suggestion: If incomplete or ambiguous proposals are submitted, reply using a pre-specified template response that does not involve any suggestive language.

3. Three experts made their proposals on the phone or other mediums without available record.

→ Suggestion: Only rely on email and retain internal copies.

4. Two experts made very similar proposals, leading us to propose merging these tasks with minimal adjustment, which the respective experts agreed to. However, these minimal adjustments mean that we had some influence over the selection of the task.

   → Suggestion: If proposal is close but not identical to an existing proposal, accept both versions or discard second one and ask for alternative. In general, coordinate timeline such that all proposals are considered jointly at a specific date (rather than sequentially based on order of arrival).

5. Three experts sent applications that feature a theoretically predicted sensitivity of zero. We discarded these proposals / asked for new ones, meaning we had some influence over task selection.

   → Suggestion: Specify task qualifications in an exhaustive way.

6. One expert sent a novel research hypothesis without an existing experimental paradigm. We discarded this proposal / asked for a new one, meaning we had some influence over task selection.

   → Suggestion: Specify task qualifications in an exhaustive way.

7. One expert selected a task from a set of example applications that we provided.

   → Suggestion: Avoid provision of examples or list to choose from.

In all, eleven experts sent proposals that lead to ten expert tasks, and 13 experts sent proposals that led to ten "EGOY+" tasks.

We emphasize again that the "issues" encountered in the expert interactions noted above are the result of our own imprecise invitation email and procedures. We are very grateful to all experts for volunteering their time and expertise for our study.

G Experimental Instructions and Decision Screens

G.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 22: The instruction screen for CHT task.

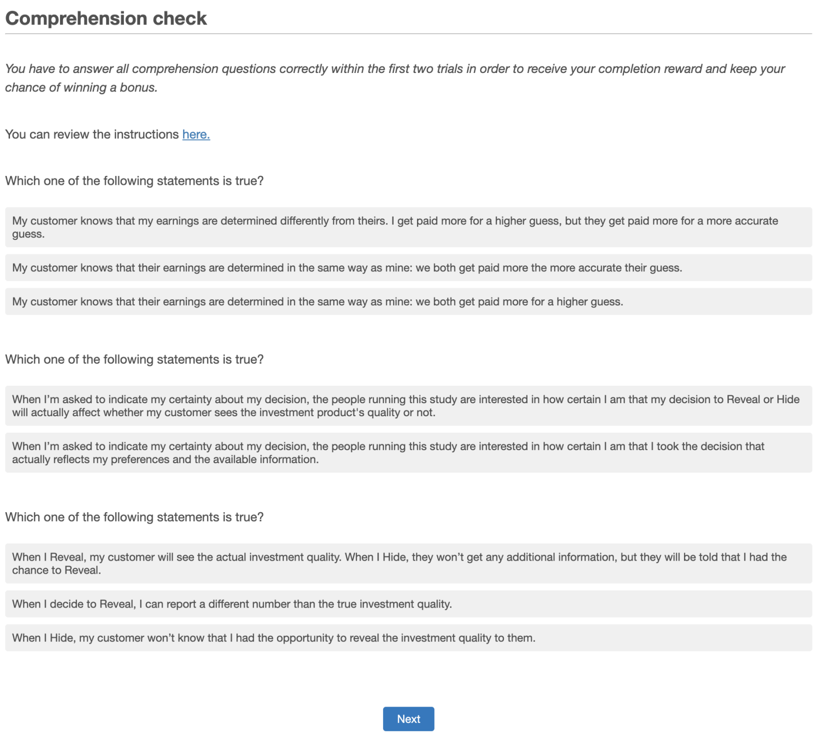


Figure 23: Comprehension check for CHT task.

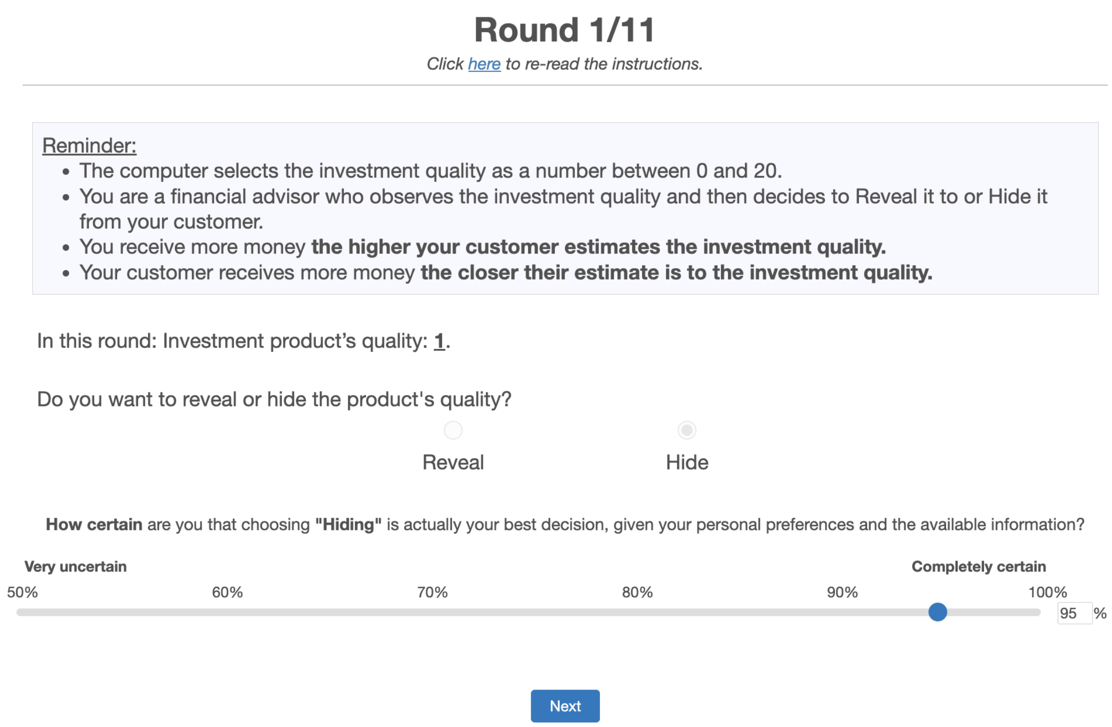


Figure 24: Decision screen for CHT task.

G.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.

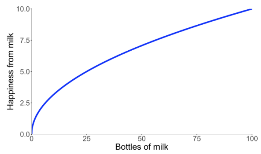
Your task:

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**.

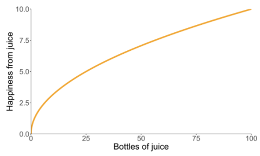
- The consumer's overall happiness is given by the square root of the amount of milk consumed plus the square root of the amount of juice consumed, where amounts are measured in bottles:

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

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



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



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:
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 25: The instruction screen for CMA task.

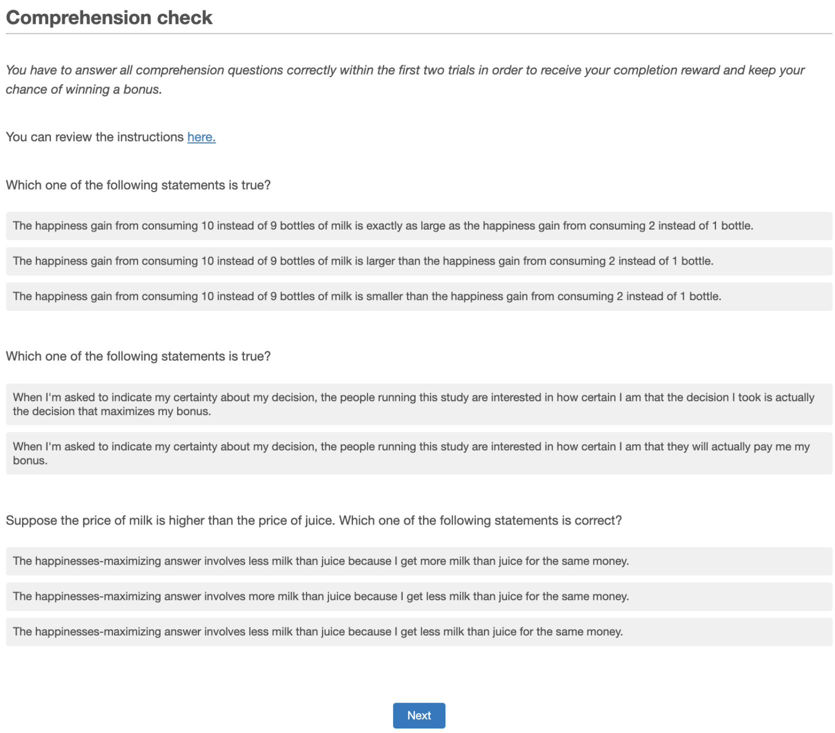


Figure 26: Comprehension check for CMA task.

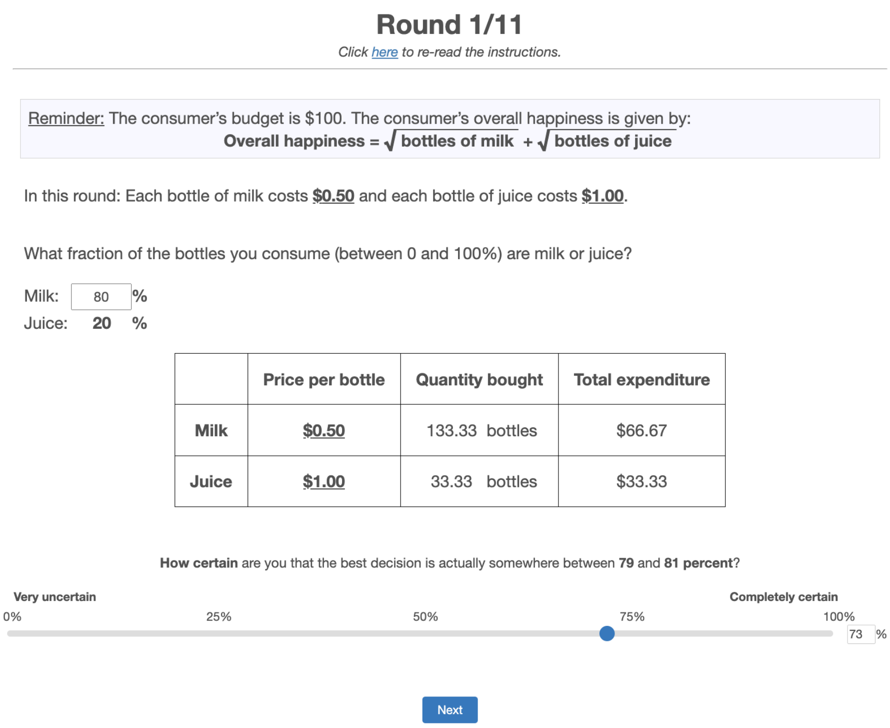
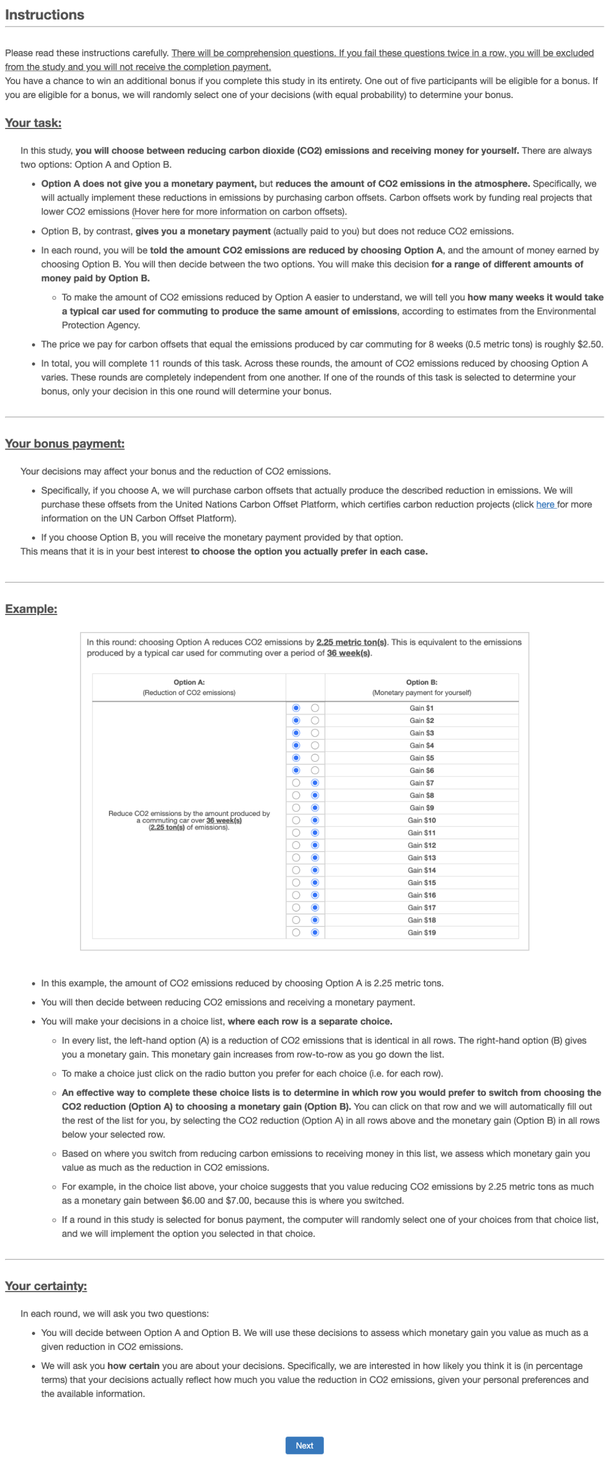


Figure 27: Decision screen for CMA task.

G.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 28: The instruction screen for EXT task.

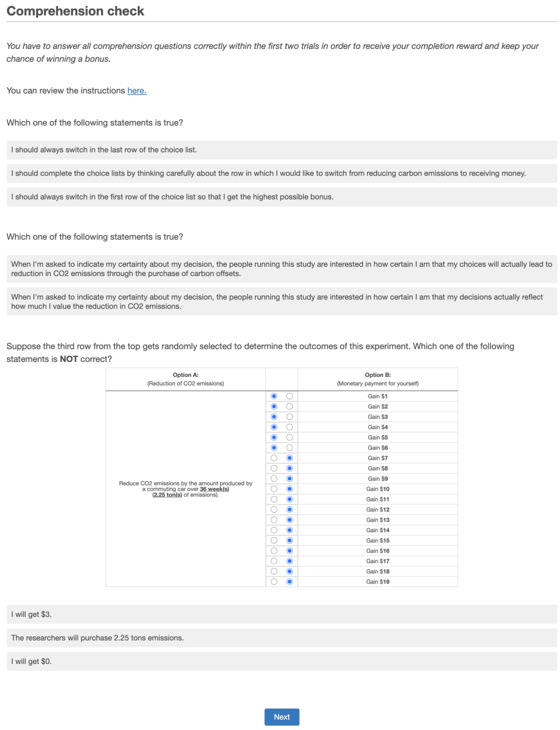


Figure 29: Comprehension check for EXT task.

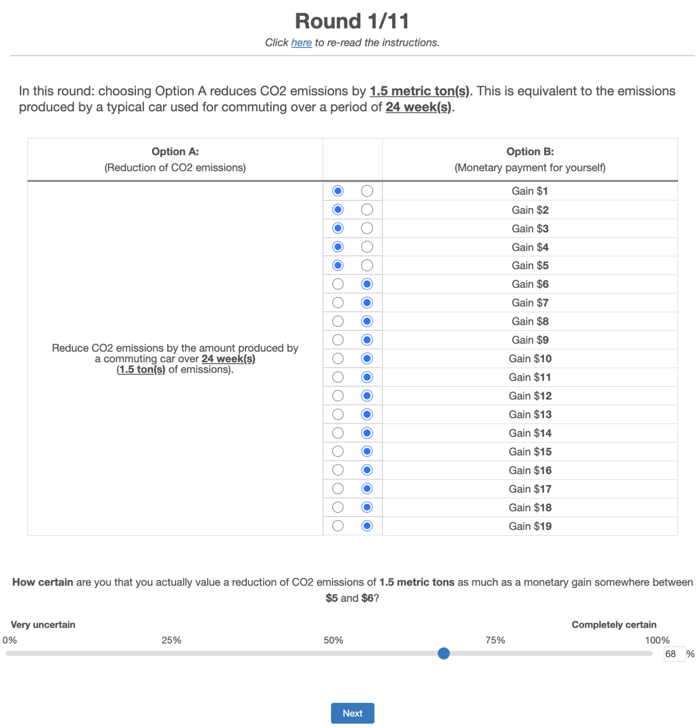
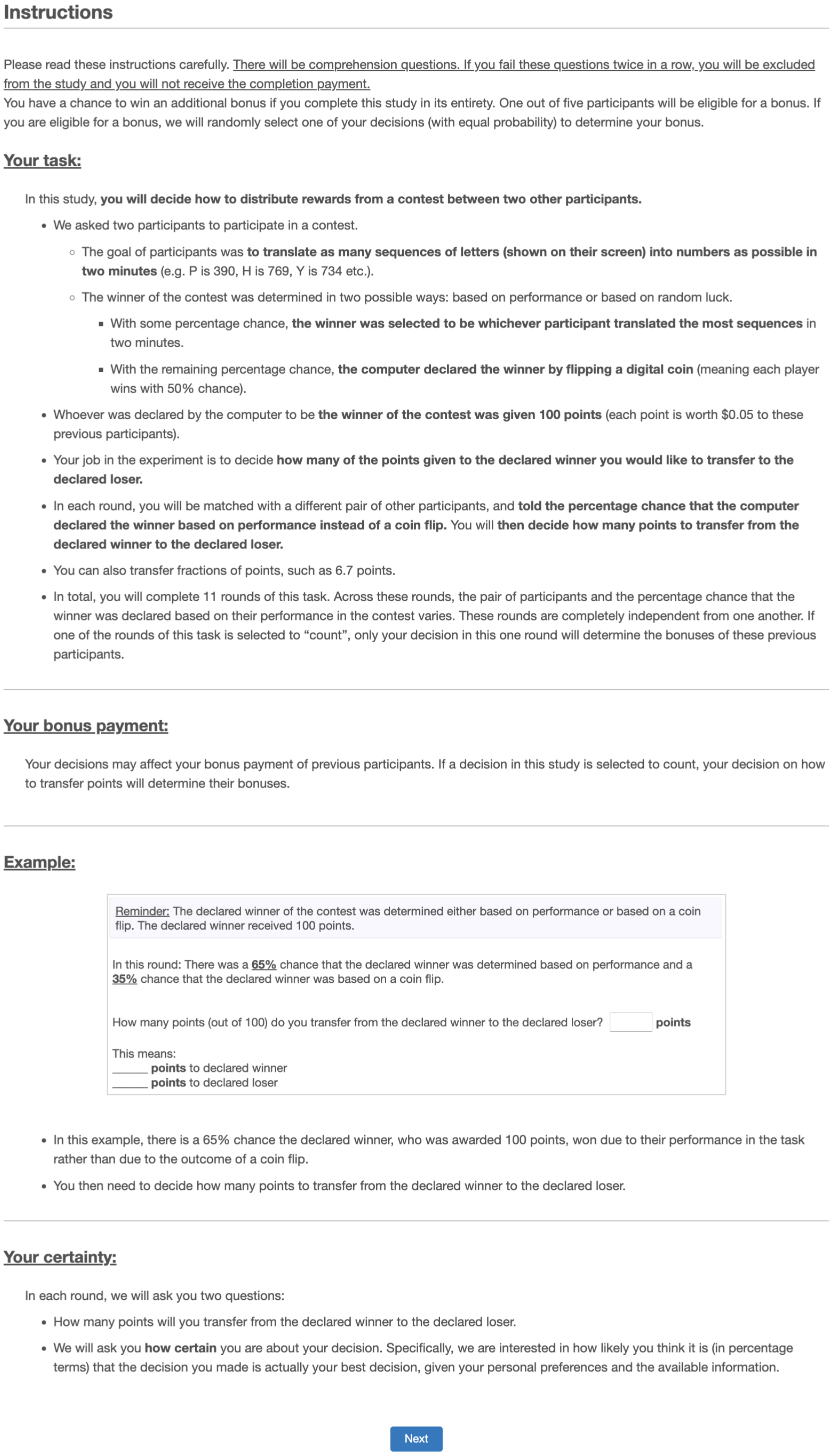


Figure 30: Decision screen for EXT task.

G.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 31: The instruction screen for 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 32: Comprehension check for 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 33: Decision screen for FAI task.

G.5 IND

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, **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.

Your bonus payment:

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.**

Example:

Reminder: 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 **70%**.
→ This means that if you follow the hint, your guess will have a **70%** chance of being correct, and a **30%** 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.

Your certainty:

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 34: The instruction screen for IND task.

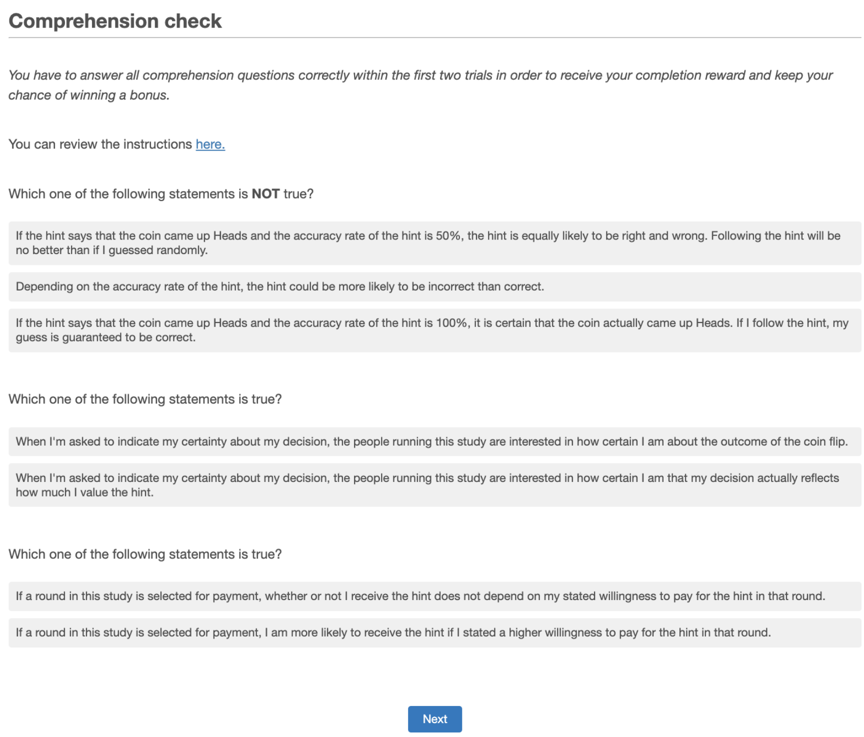


Figure 35: Comprehension check for IND task.

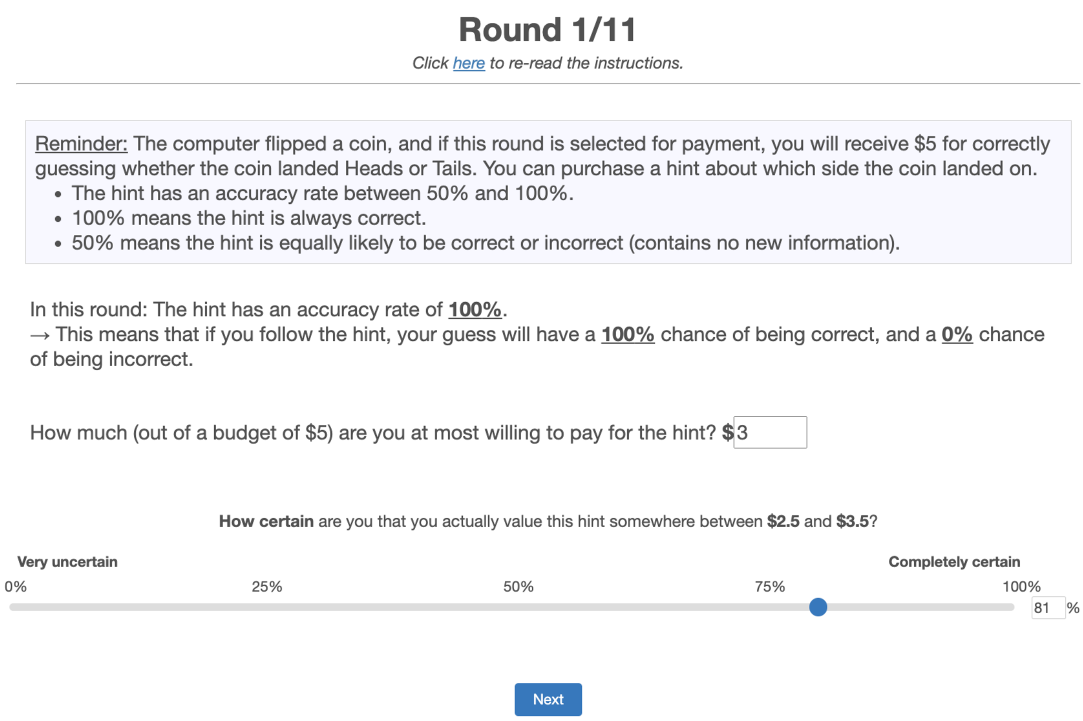


Figure 36: Decision screen for IND task.

G.6 SAV

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 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.

Your bonus payment:

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.**

Example:

Reminder: 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 **22%**.

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.

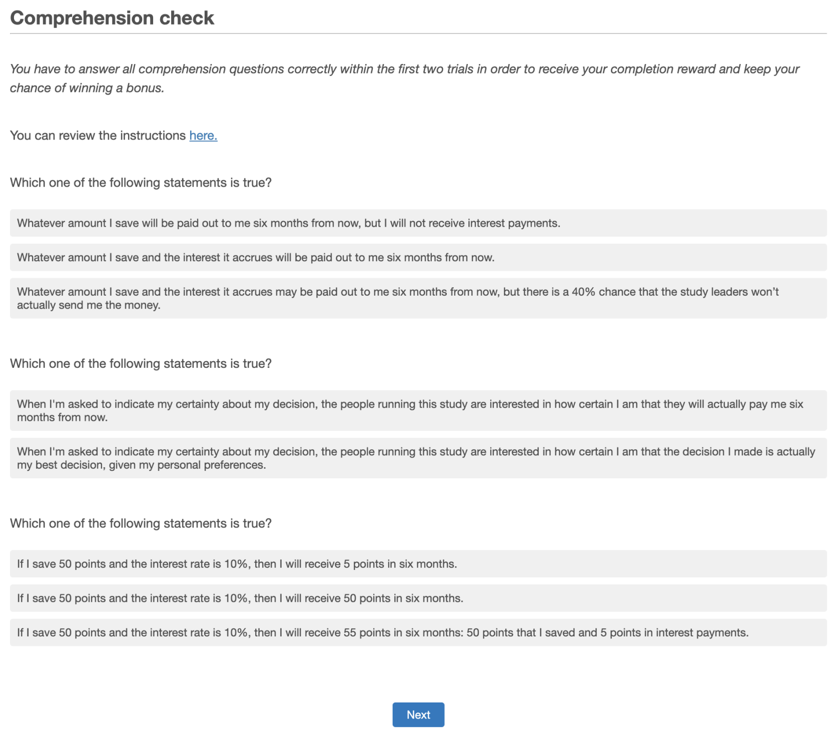
Your certainty:

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 37: The instruction screen for SAV 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?

Whatever amount I save will be paid out to me six months from now, but I will not receive interest payments.

Whatever amount I save and the interest it accrues will be paid out to me six months from now.

Whatever amount I save and the interest it accrues may be paid out to me six months from now, but there is a 40% chance that the study leaders won't actually send me the money.

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 they will actually pay me six months from now.

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.

Which one of the following statements is true?

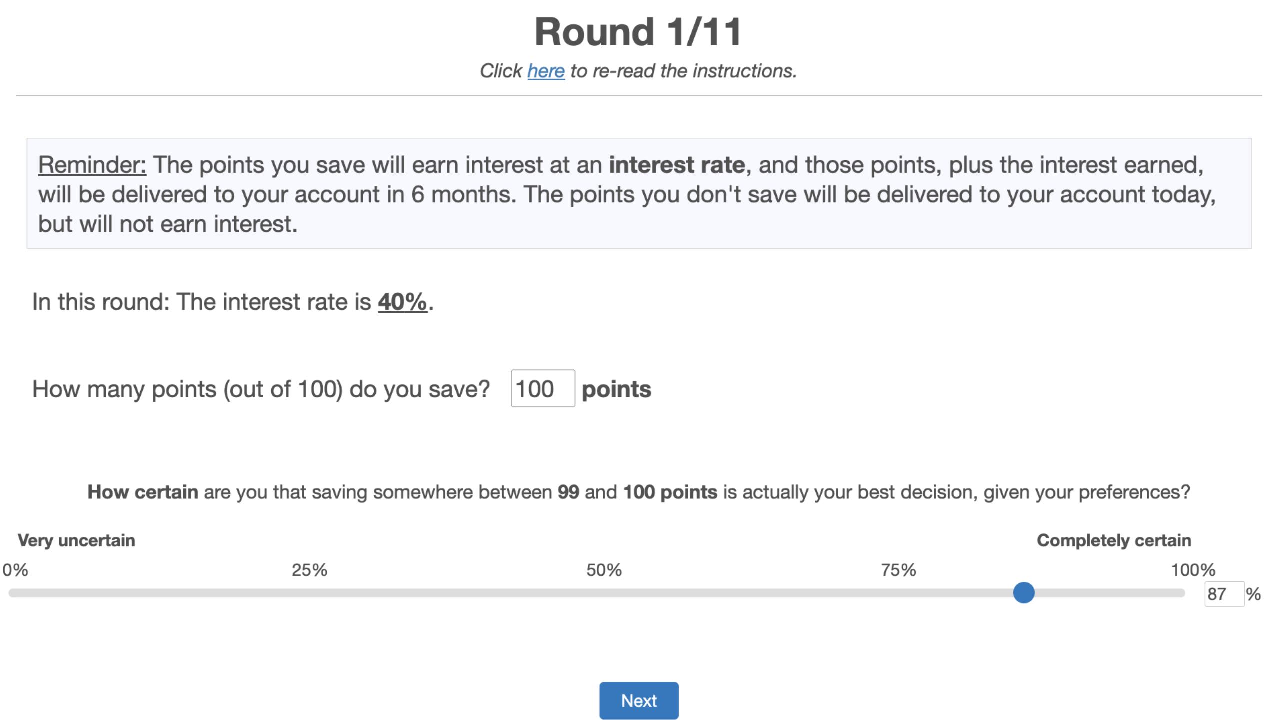
If I save 50 points and the interest rate is 10%, then I will receive 5 points in six months.

If I save 50 points and the interest rate is 10%, then I will receive 50 points in six months.

If I save 50 points and the interest rate is 10%, then I will receive 55 points in six months: 50 points that I saved and 5 points in interest payments.

Next

Figure 38: Comprehension check for SAV task.



Round 1/11

Click here to re-read the instructions.

Reminder: 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 **40%**.

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

How certain are you that saving somewhere between **99** and **100 points** is actually your best decision, given your preferences?

Very uncertain **Completely certain**

0% 25% 50% 75% 100%

87 %

Next

Figure 39: Decision screen for SAV task.

G.7 SEA

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, 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.

Your bonus payment:

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.

Example:

Reminder: 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 **3 points** 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.

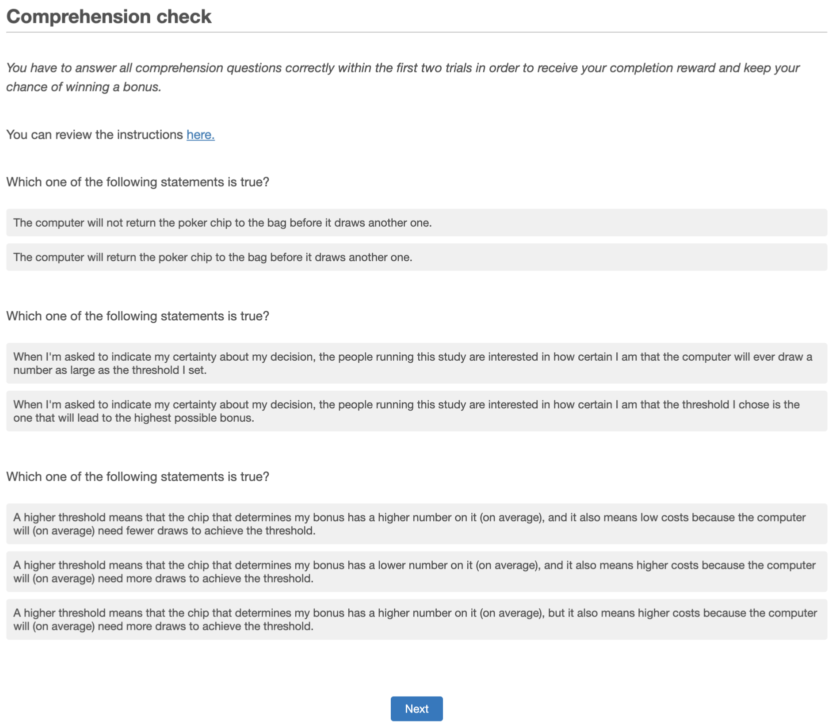
Your certainty:

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 40: The instruction screen for SEA 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 computer will not return the poker chip to the bag before it draws another one.

The computer will return the poker chip to the bag before it draws another one.

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 computer will ever draw a number as large as the threshold I set.

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 threshold I chose is the one that will lead to the highest possible bonus.

Which one of the following statements is true?

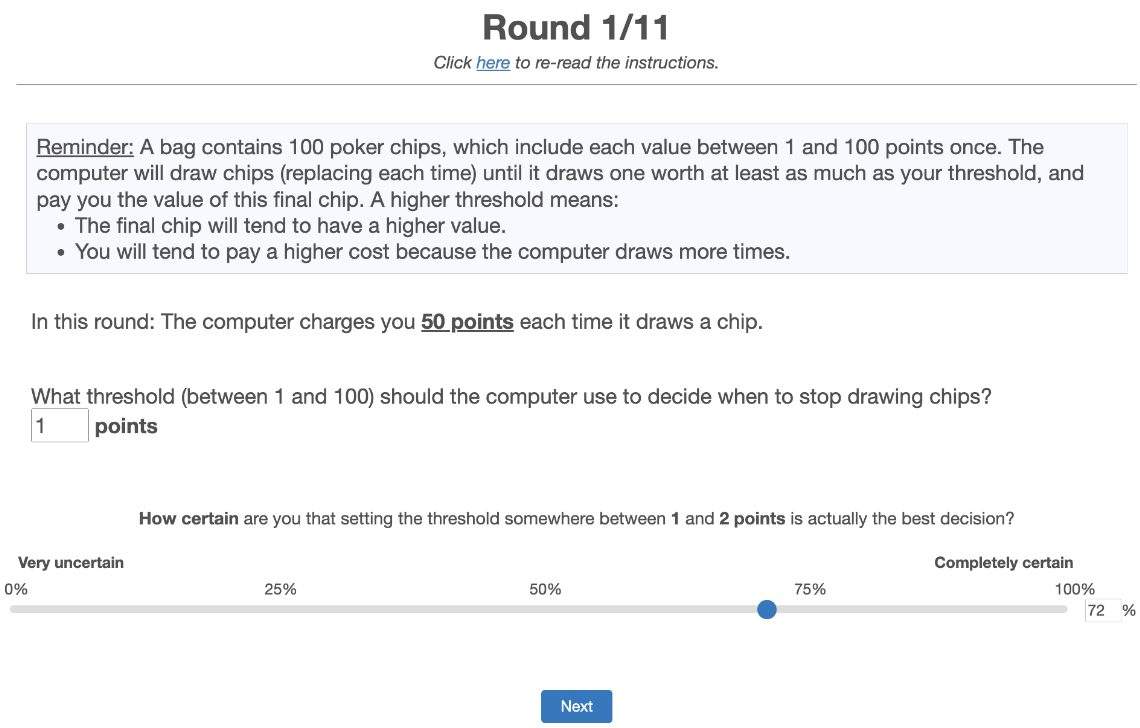
A higher threshold means that the chip that determines my bonus has a higher number on it (on average), and it also means low costs because the computer will (on average) need fewer draws to achieve the threshold.

A higher threshold means that the chip that determines my bonus has a lower number on it (on average), and it also means higher costs because the computer will (on average) need more draws to achieve the threshold.

A higher threshold means that the chip that determines my bonus has a higher number on it (on average), but it also means higher costs because the computer will (on average) need more draws to achieve the threshold.

Next

Figure 41: Comprehension check for SEA task.



Round 1/11

Click here to re-read the instructions.

Reminder: 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 **50 points** each time it draws a chip.

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

1 **points**

How certain are you that setting the threshold somewhere between **1** and **2 points** is actually the best decision?

Very uncertain **Completely certain**

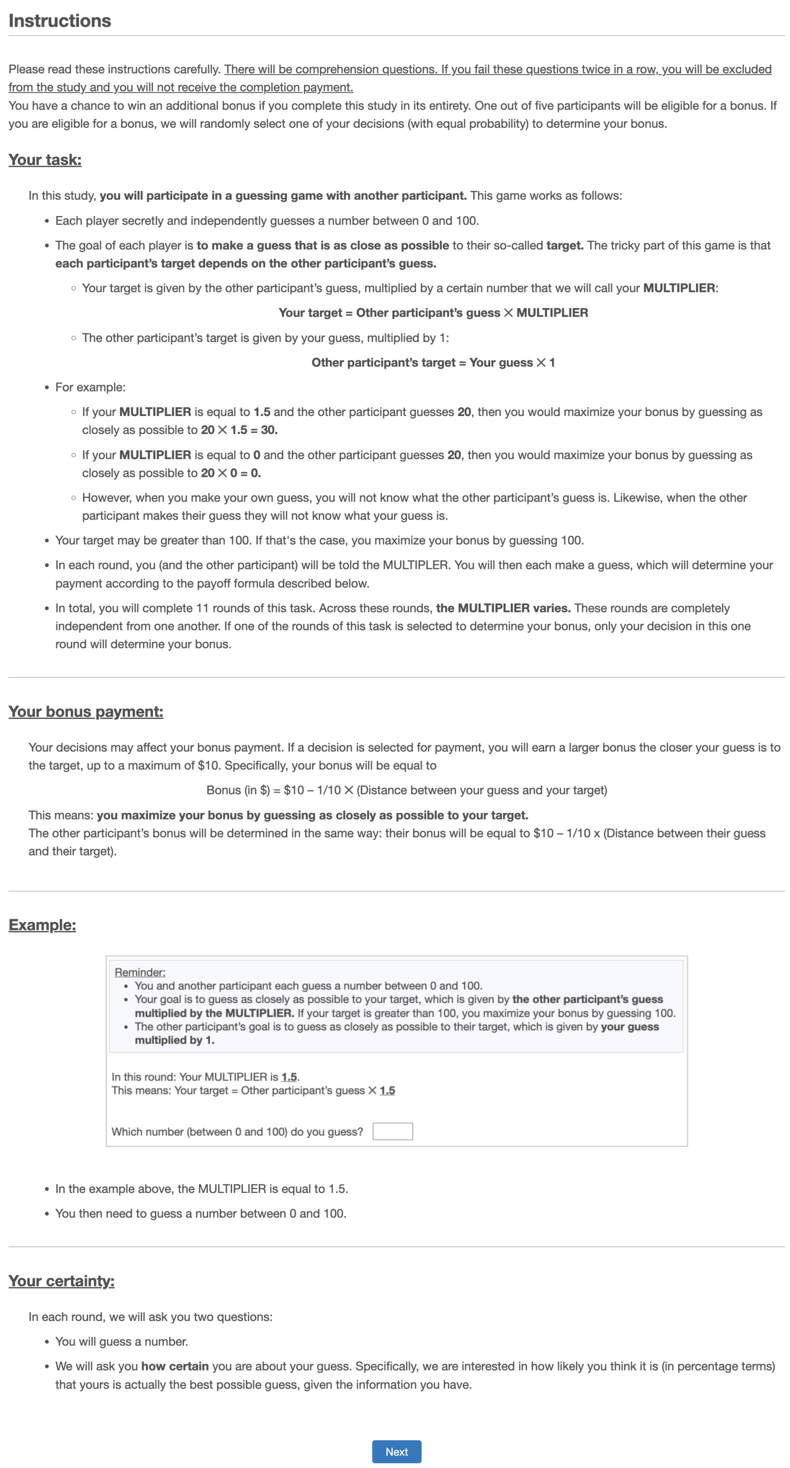
0% 25% 50% 75% 100%

72 %

Next

Figure 42: Decision screen for SEA task.

G.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 43: The instruction screen for GUE task.

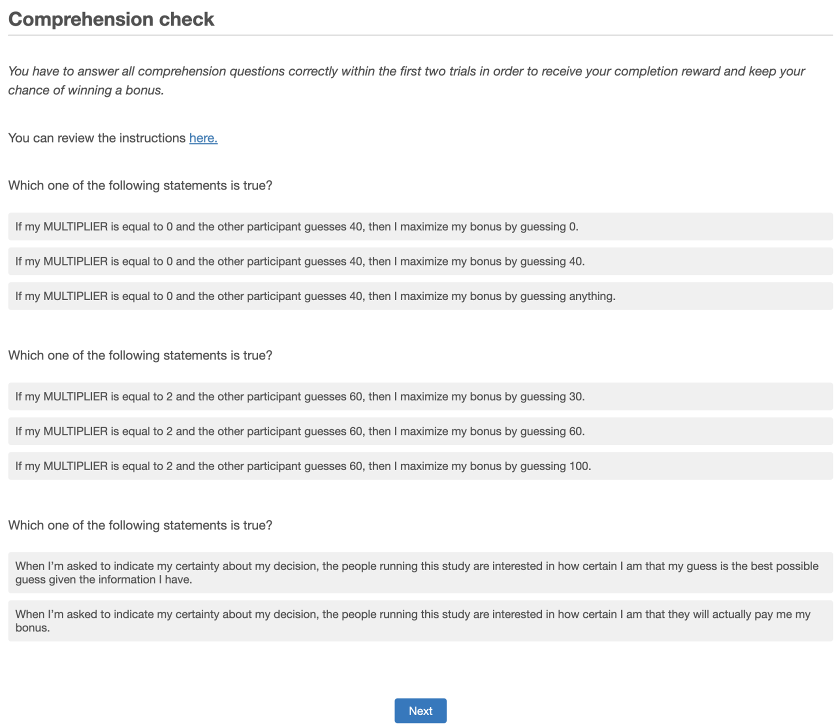


Figure 44: Comprehension check for GUE task.

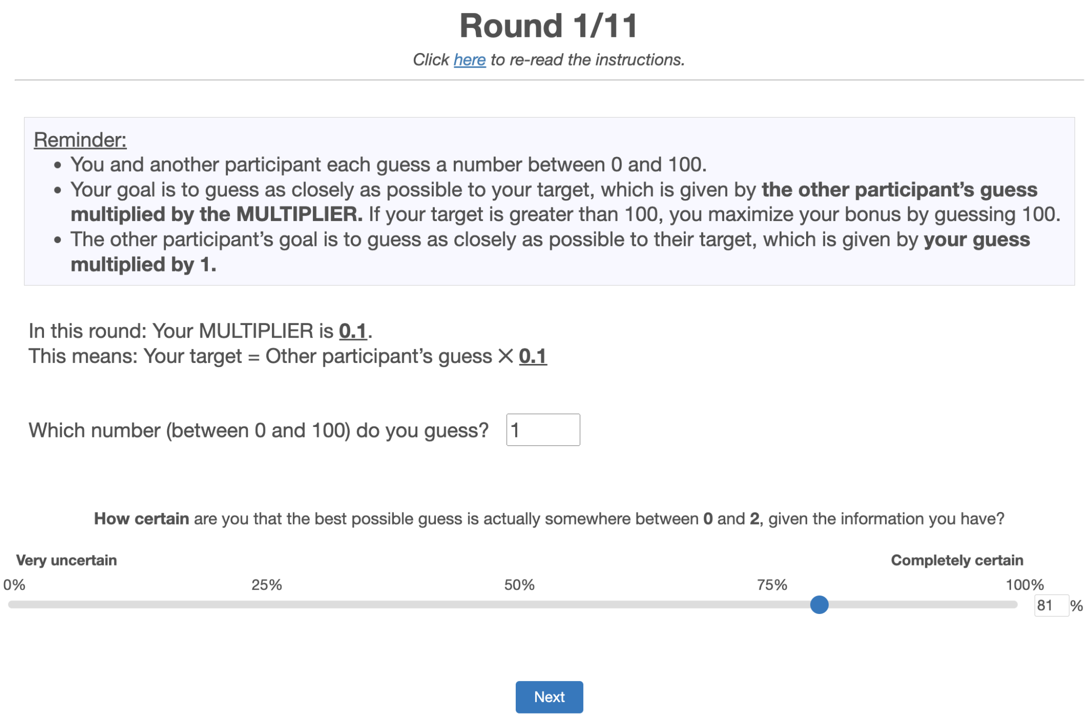


Figure 45: Decision screen for GUE task.

G.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.

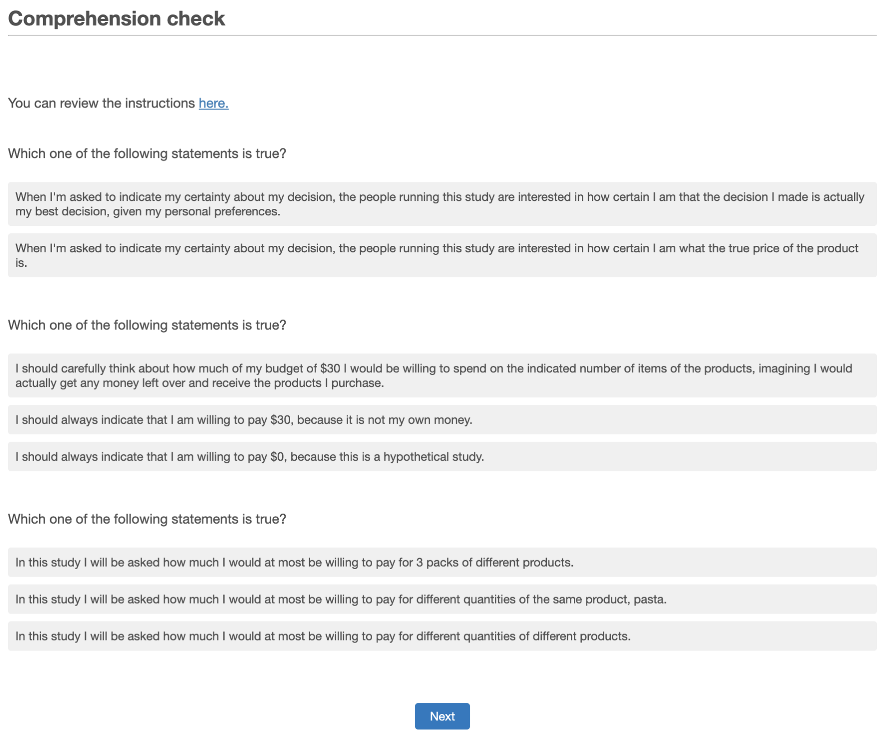
Your certainty:

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 46: The instruction screen for GPT task.



Comprehension check

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 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 what the true price of the product is.

Which one of the following statements is true?

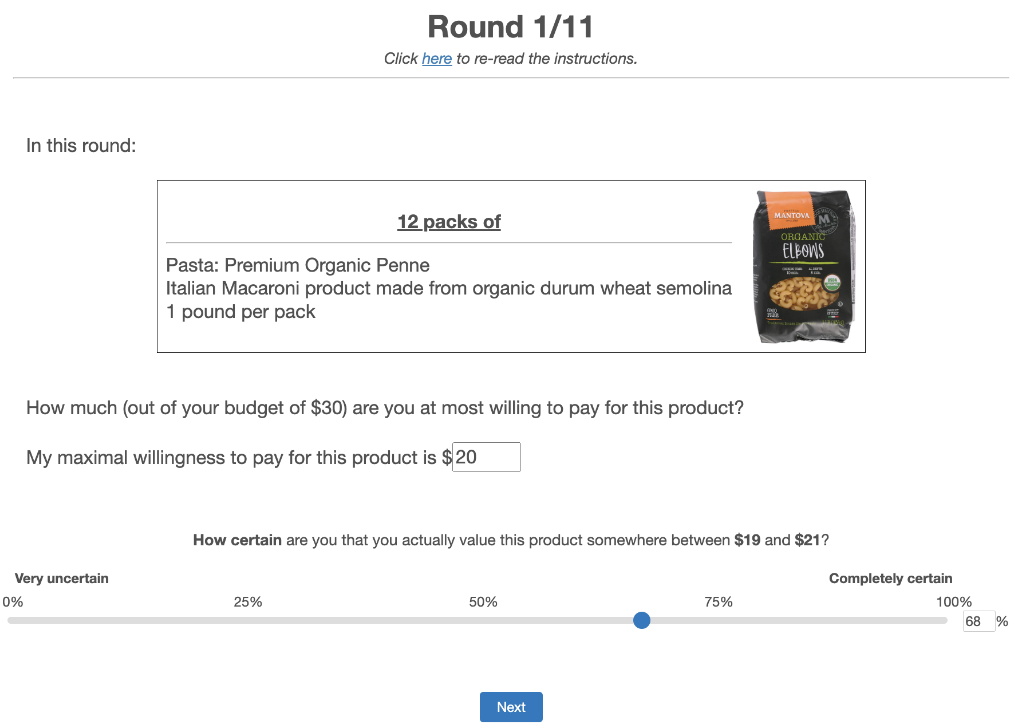
- I should carefully think about how much of my budget of $30 I would be willing to spend on the indicated number of items of the products, imagining I would actually get any money left over and receive the products I purchase.
- I should always indicate that I am willing to pay $30, because it is not my own money.
- I should always indicate that I am willing to pay $0, because this is a hypothetical study.

Which one of the following statements is true?

- In this study I will be asked how much I would at most be willing to pay for 3 packs of different products.
- In this study I will be asked how much I would at most be willing to pay for different quantities of the same product, pasta.
- In this study I will be asked how much I would at most be willing to pay for different quantities of different products.

Next

Figure 47: Comprehension check for GPT task.



Round 1/11

Click here to re-read the instructions.

In this round:

12 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 $ 20

How certain are you that you actually value this product somewhere between **$19** and **$21**?

Very uncertain **Completely certain**

0% 25% 50% 75% 100% 68 %

Next

Figure 48: Decision screen for GPT task.

G.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 49: The instruction screen for PAC task.

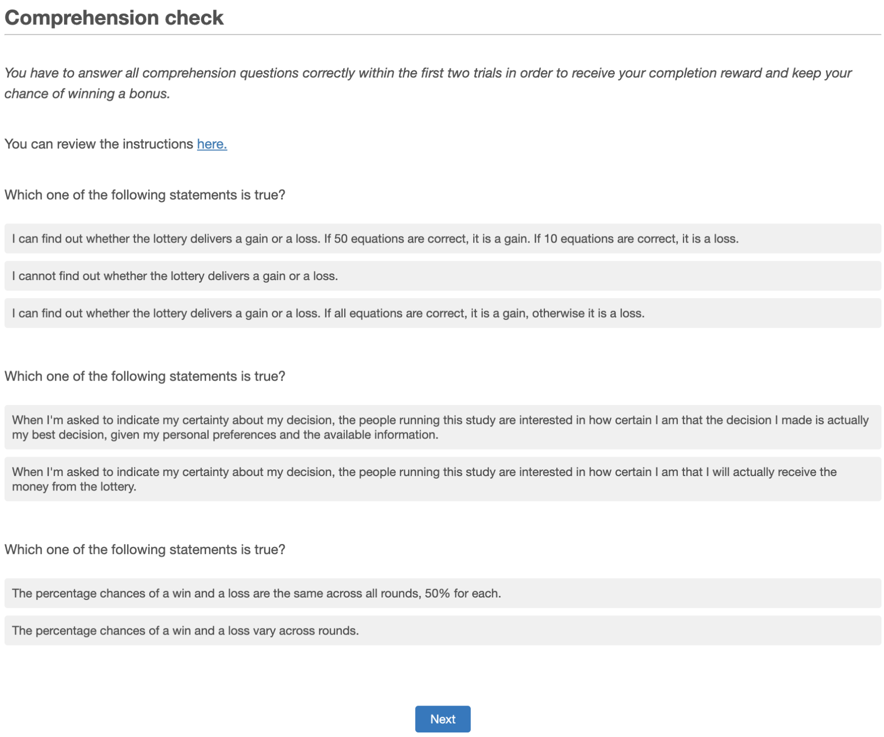


Figure 50: Comprehension check for PAC task.

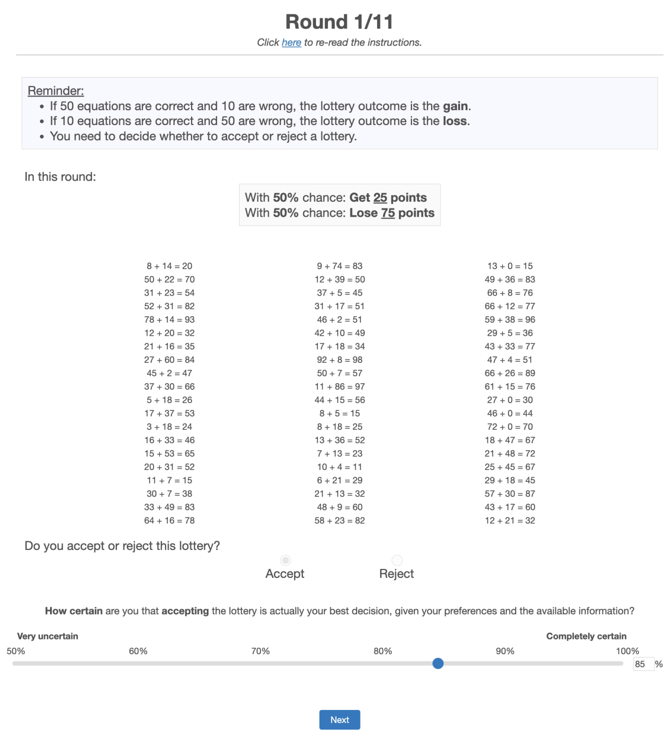


Figure 51: Decision screen for PAC task.

G.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 52: The instruction screen for POA task.

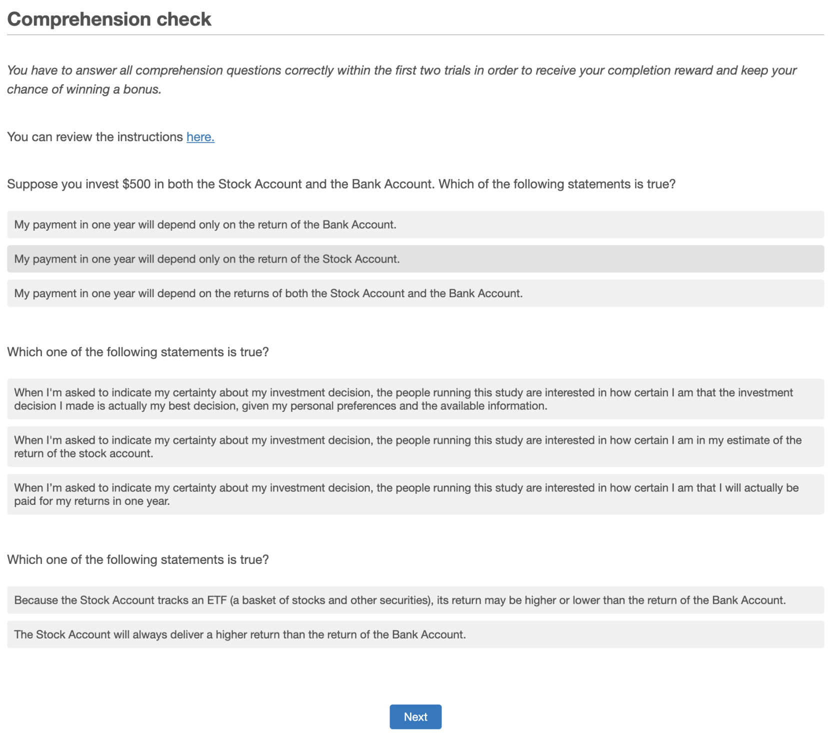


Figure 53: Comprehension check for POA task.

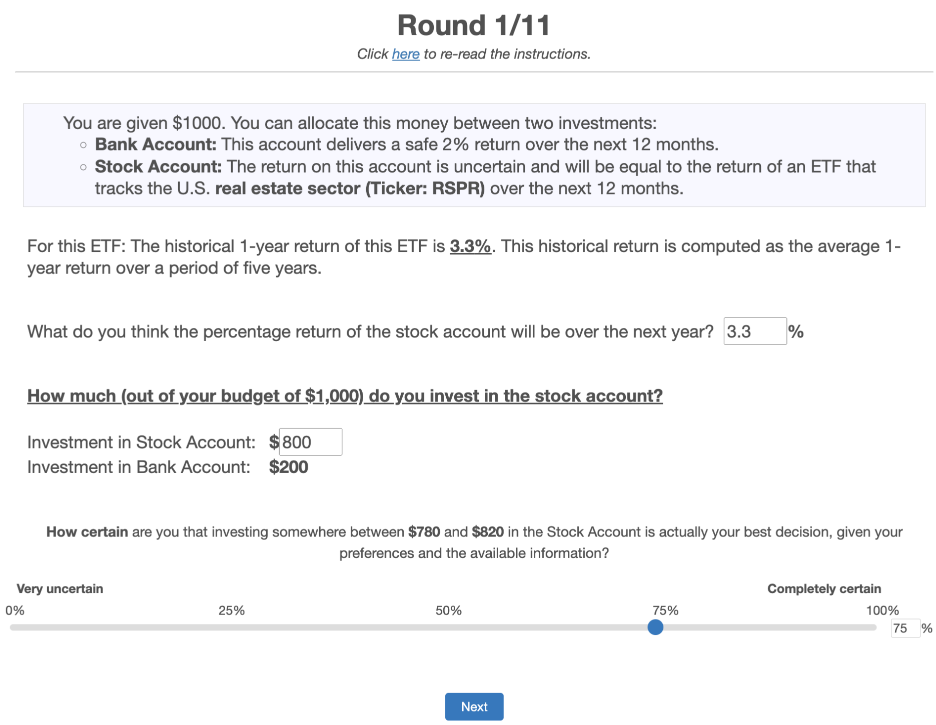


Figure 54: Decision screen for POA task.

G.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.

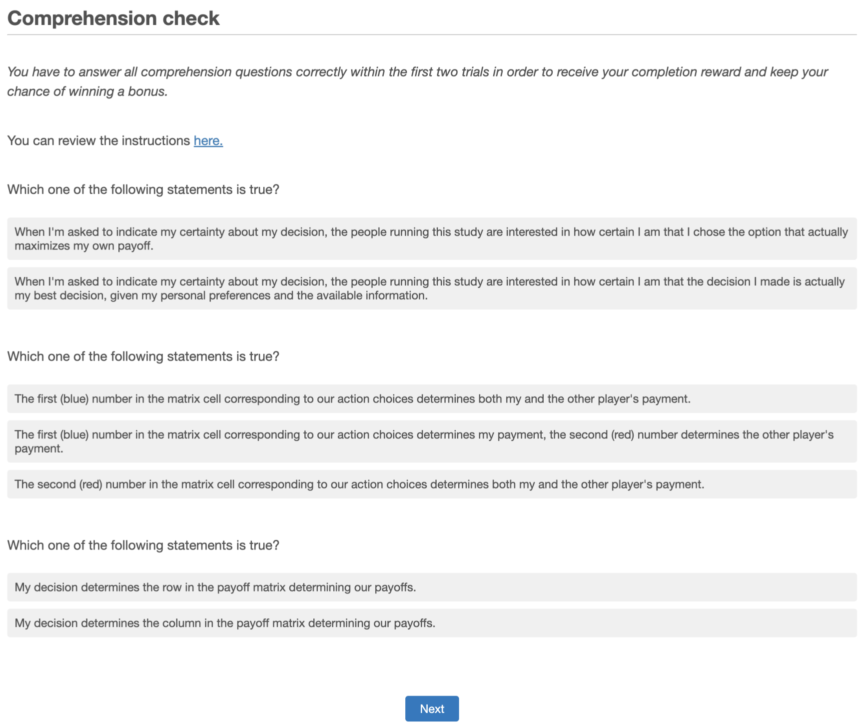
Your certainty:

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 55: The instruction screen for PRD 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 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.

Which one of the following statements is true?

The first (blue) number in the matrix cell corresponding to our action choices determines both my and the other player's payment.

The first (blue) number in the matrix cell corresponding to our action choices determines my payment, the second (red) number determines the other player's payment.

The second (red) number in the matrix cell corresponding to our action choices determines both my and the other player's payment.

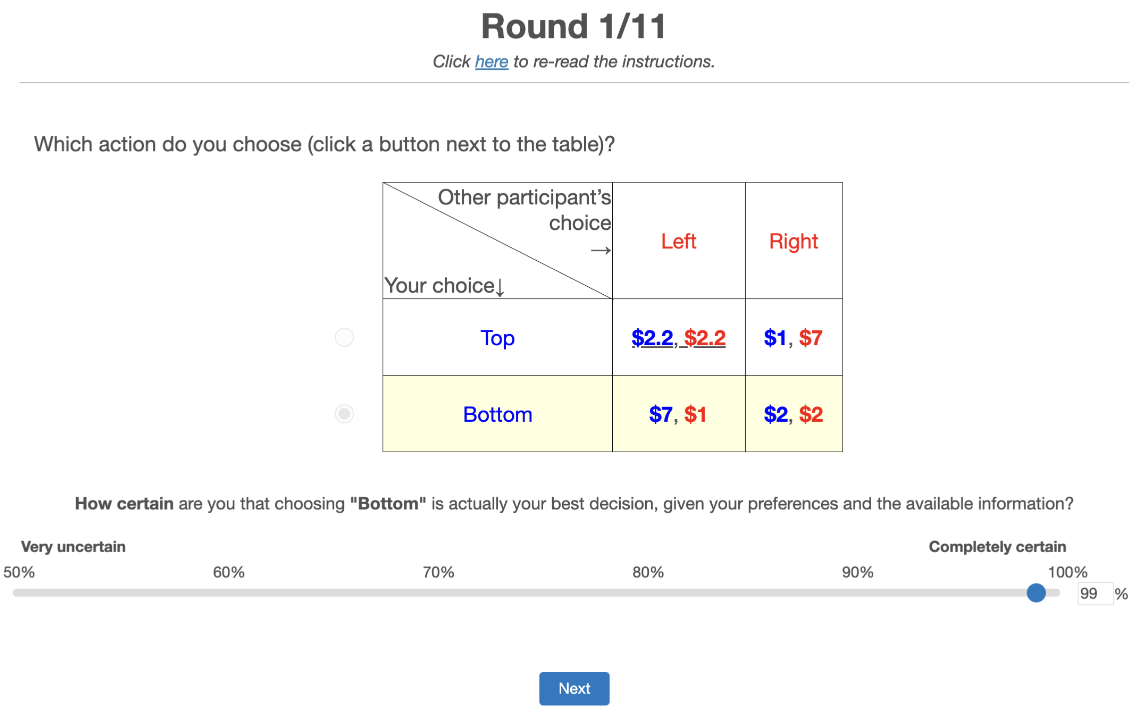
Which one of the following statements is true?

My decision determines the row in the payoff matrix determining our payoffs.

My decision determines the column in the payoff matrix determining our payoffs.

Next

Figure 56: Comprehension check for PRD task.



Round 1/11

Click here to re-read the instructions.

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

Other participant's choice → / Your choice ↓	Left	Right
Top	$2.2, $2.2	$1, $7
Bottom	$7, $1	$2, $2

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

Very uncertain **Completely certain**

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

99 %

Next

Figure 57: Decision screen for PRD task.

G.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 58: The instruction screen for PRE task.

Figure 59: Comprehension check for PRE task.

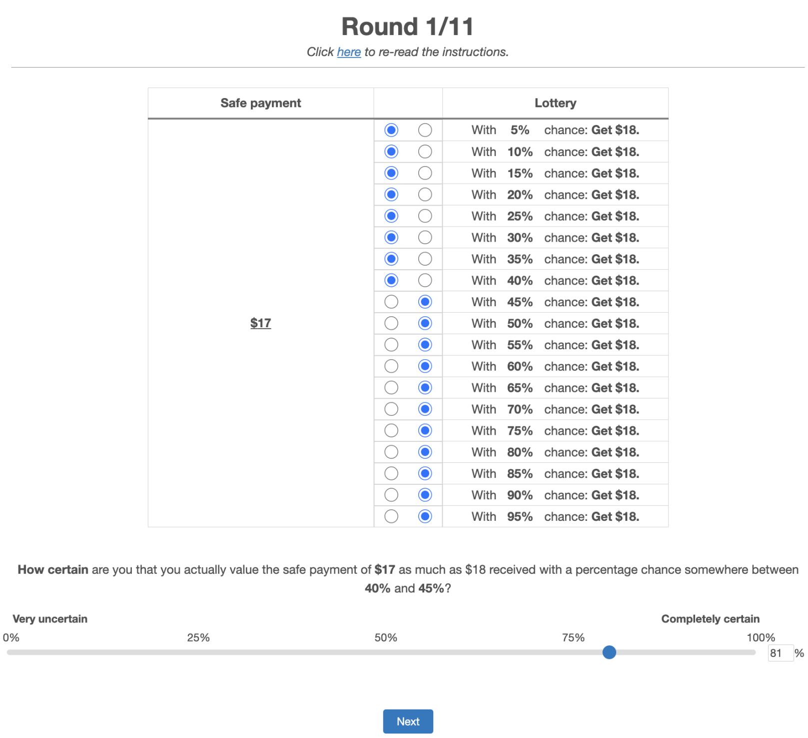


Figure 60: Decision screen for PRE task.

G.14 PRS

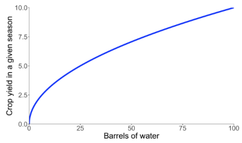
Instructions

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 = $\sqrt{\textbf{Barrels of Water}}$

  - **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 61: The instruction screen for PRS task.

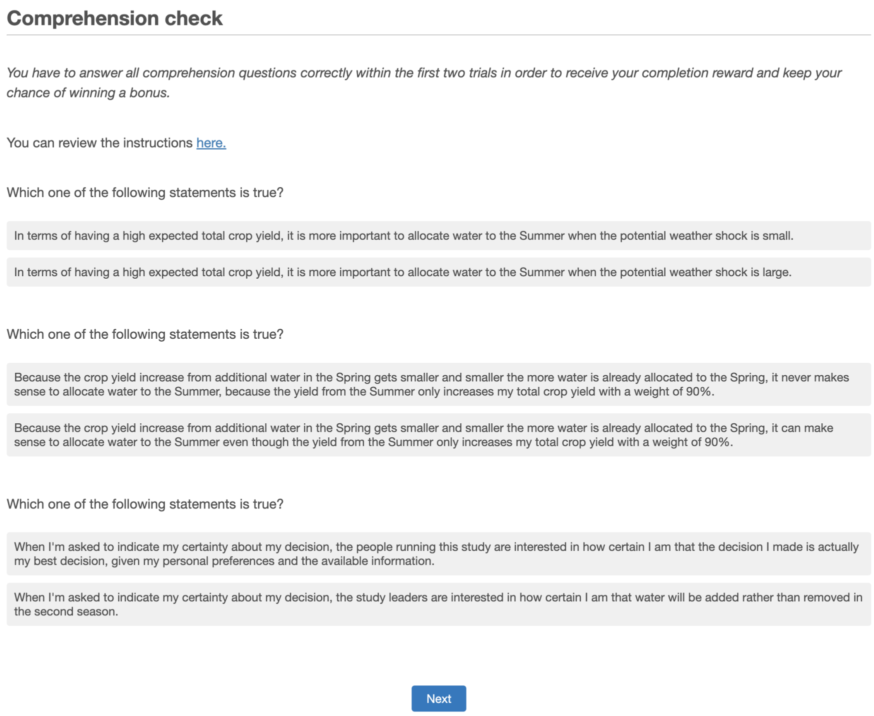


Figure 62: Comprehension check for PRS task.

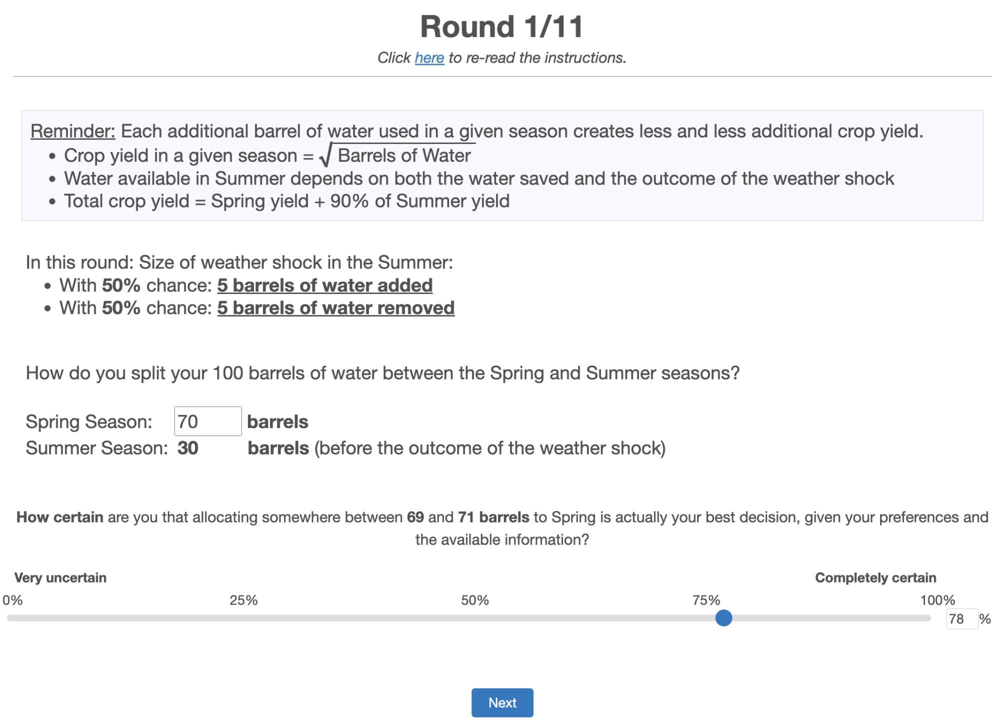
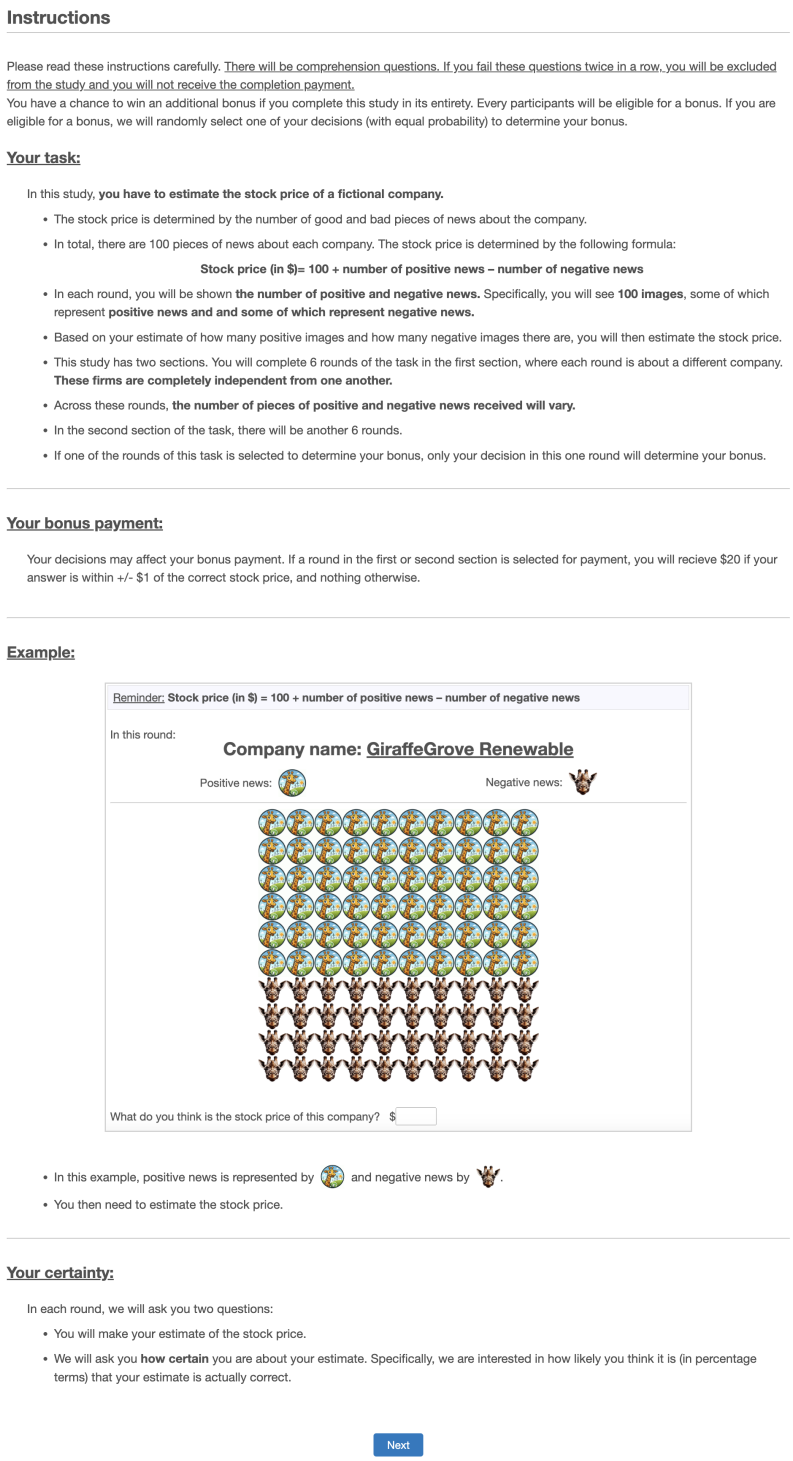


Figure 63: Decision screen for PRS task.

G.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 64: The instruction screen for REC task.

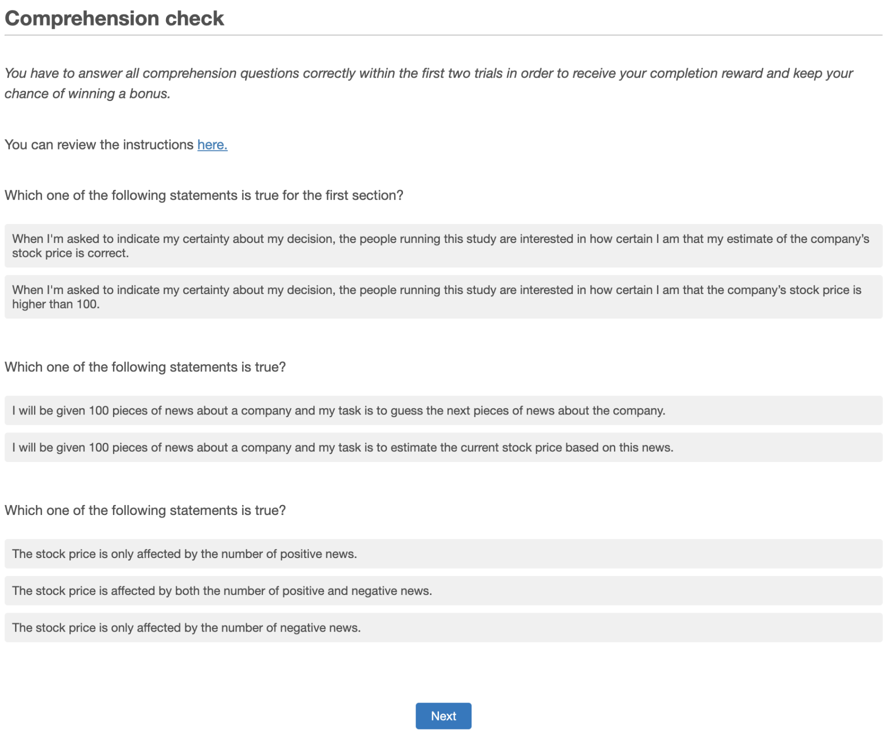


Figure 65: Comprehension check for REC task.

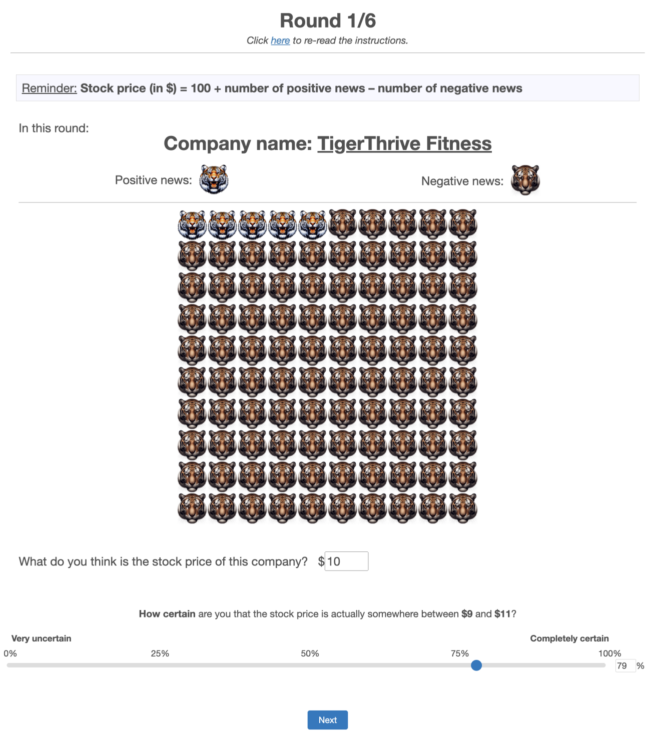
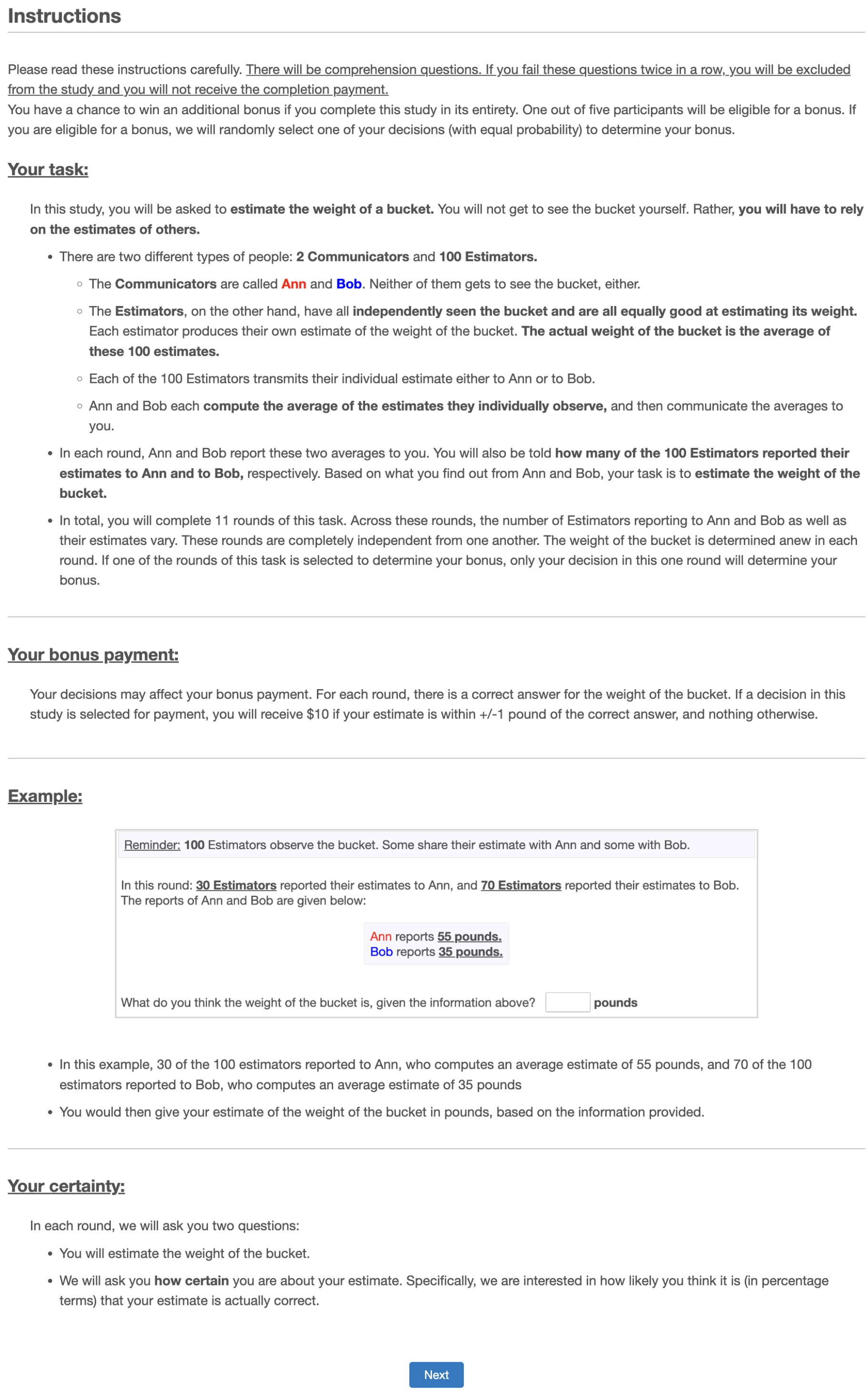


Figure 66: Decision screen for REC task.

G.16 SIA



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 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.

Your bonus payment:

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.

Example:

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

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

Ann reports **55 pounds.**
Bob reports **35 pounds.**

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.

Your certainty:

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 67: The instruction screen for SIA task.

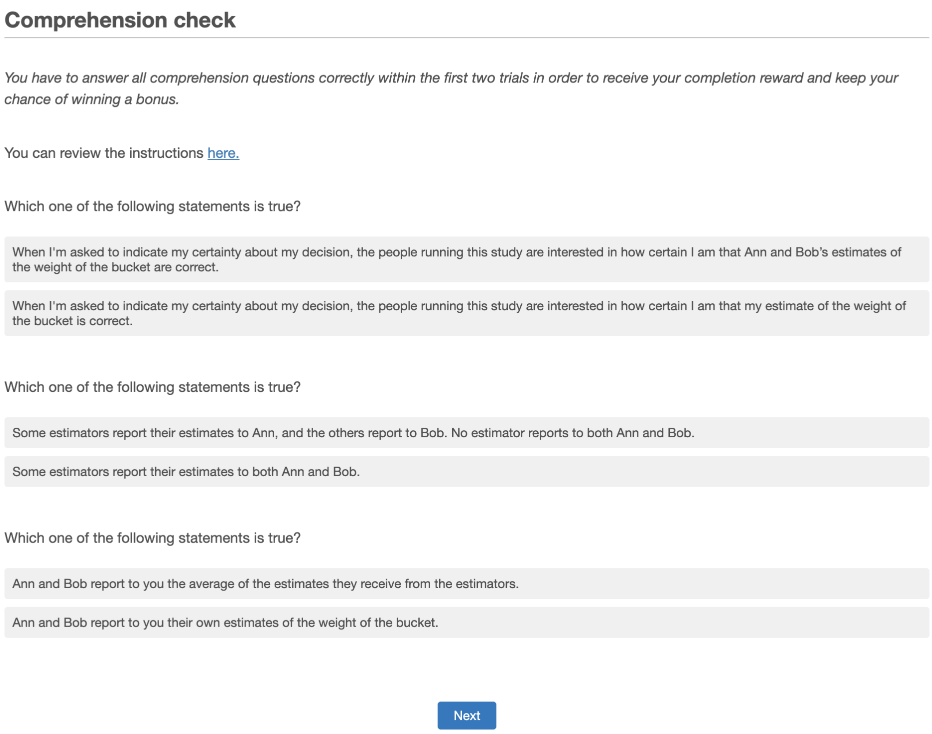


Figure 68: Comprehension check for SIA task.

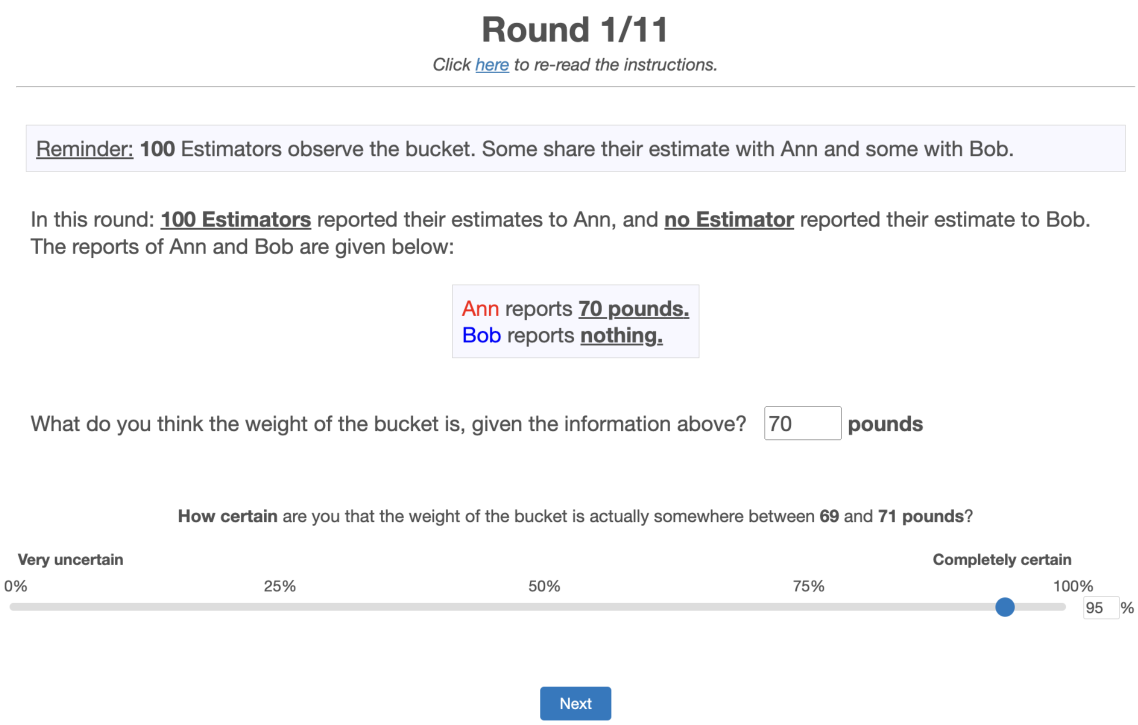


Figure 69: Decision screen for SIA task.

G.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).

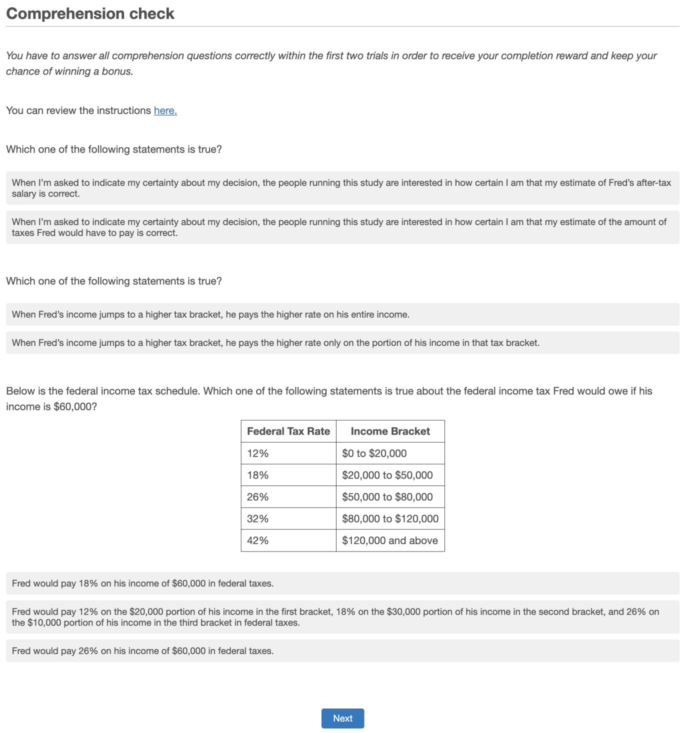
Your certainty:

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 70: The instruction screen for 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.

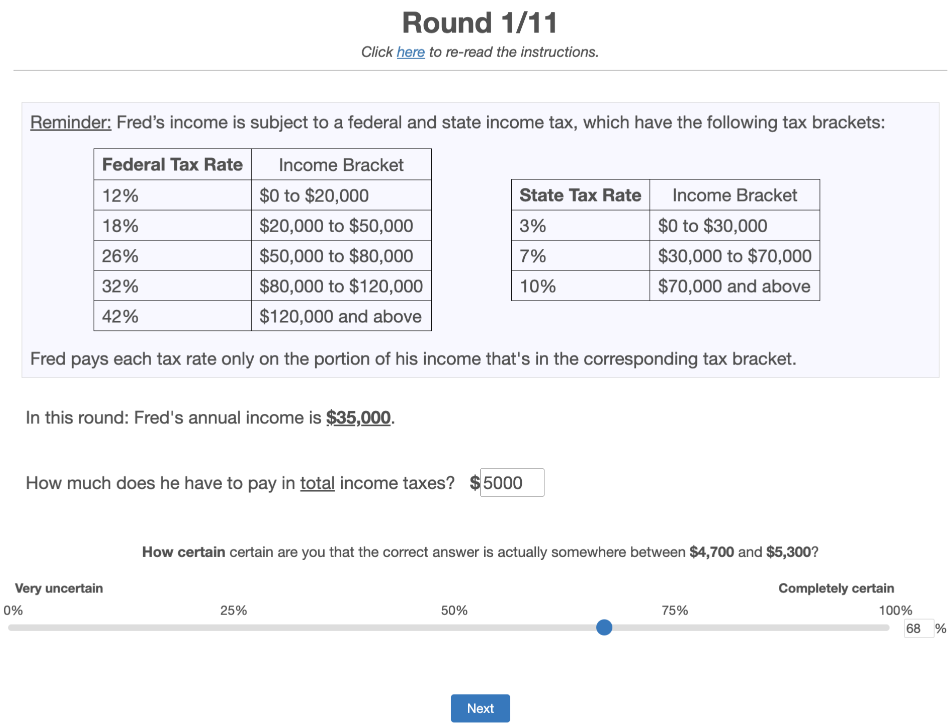
Below is the federal income tax schedule. Which one of the following statements is true about the federal income tax Fred would owe if his income is $60,000?

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 71: Comprehension check for 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 72: Decision screen for TAX task.

G.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.

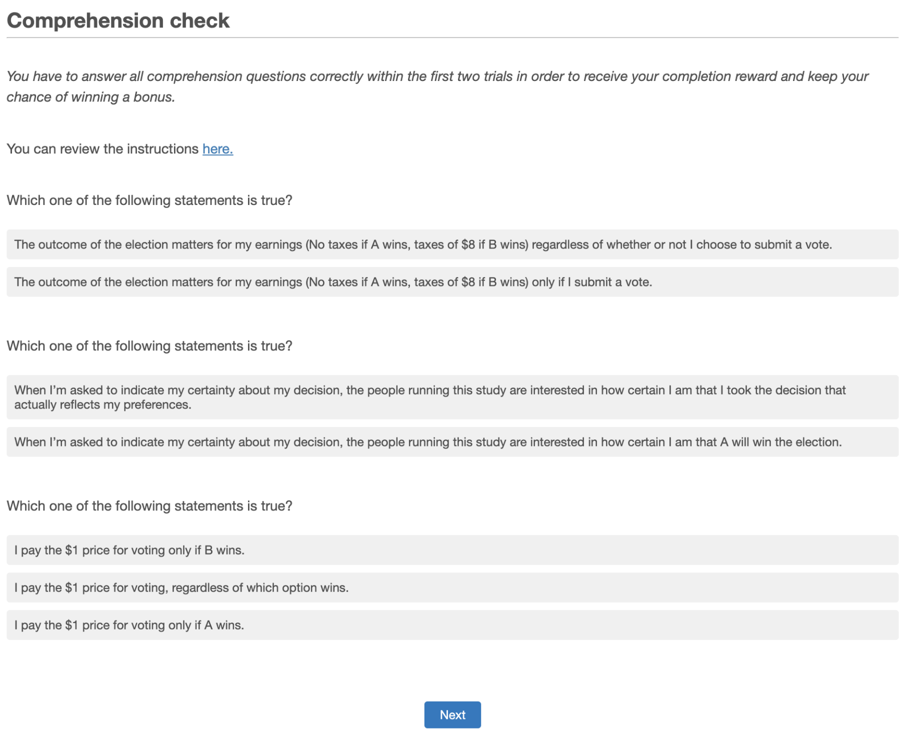
Your certainty:

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 73: The instruction screen for VOT 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 outcome of the election matters for my earnings (No taxes if A wins, taxes of $8 if B wins) regardless of whether or not I choose to submit a vote.

The outcome of the election matters for my earnings (No taxes if A wins, taxes of $8 if B wins) only if I submit a vote.

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 took the decision that actually reflects my 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 A will win the election.

Which one of the following statements is true?

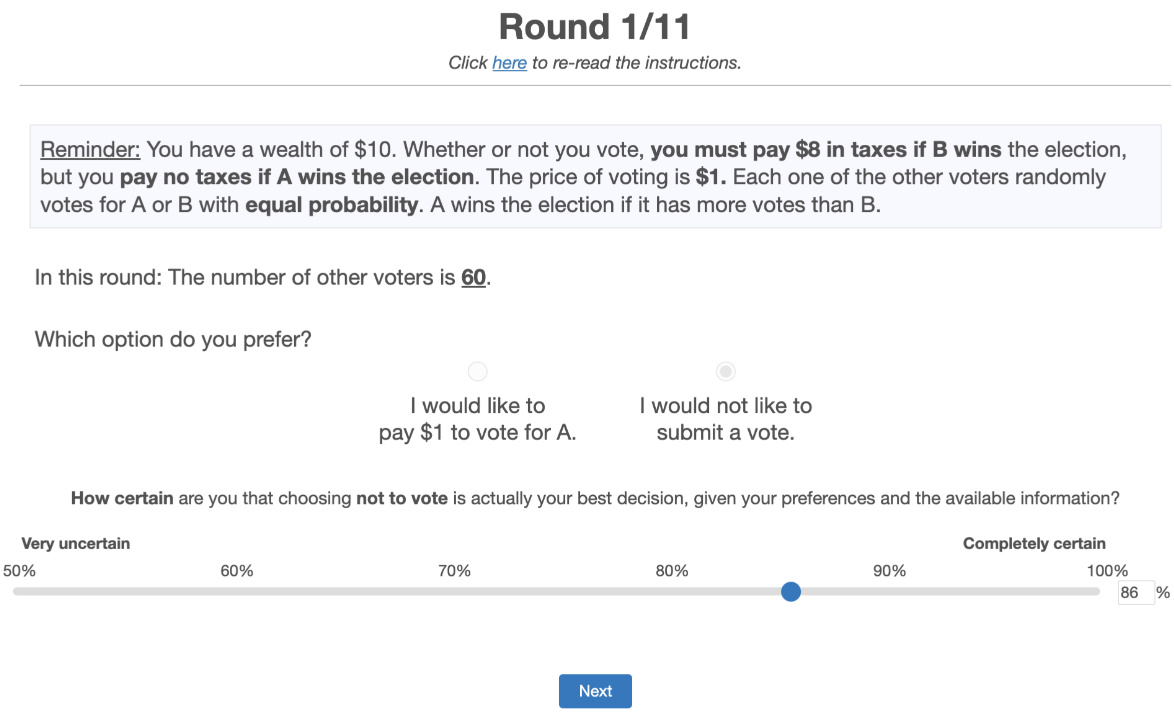
I pay the $1 price for voting only if B wins.

I pay the $1 price for voting, regardless of which option wins.

I pay the $1 price for voting only if A wins.

Next

Figure 74: Comprehension check for VOT task.



Round 1/11

Click here to re-read the instructions.

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 **60**.

Which option do you prefer?

I would like to pay $1 to vote for A.

I would not like to submit a vote.

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

Very uncertain **Completely certain**

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

86 %

Next

Figure 75: Decision screen for VOT task.

G.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.

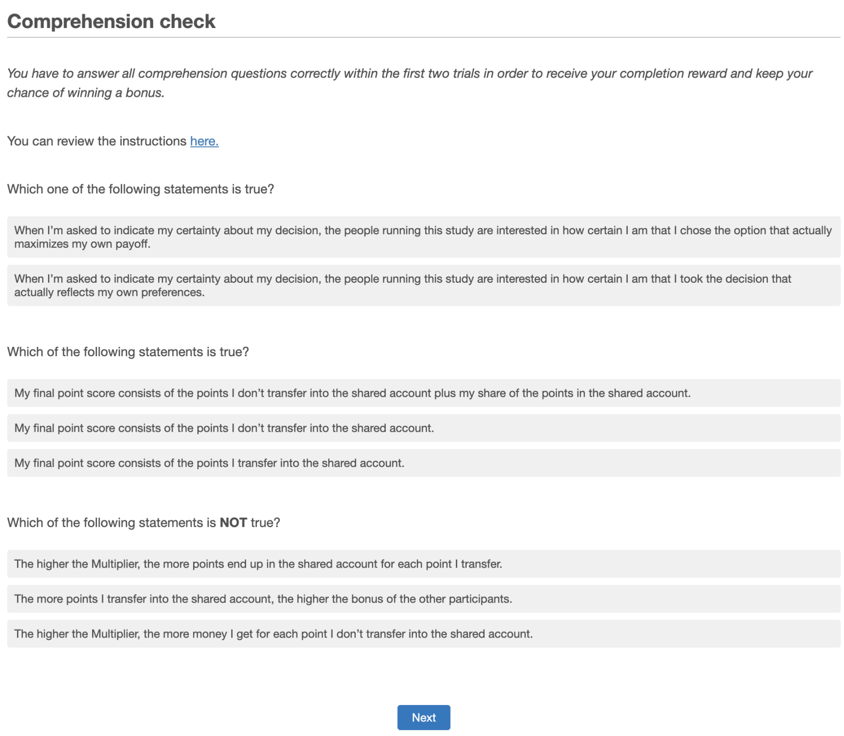
Your certainty:

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 76: The instruction screen for PGG 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 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 I took the decision that actually reflects my own preferences.

Which of the following statements is true?

My final point score consists of the points I don't transfer into the shared account plus my share of the points in the shared account.

My final point score consists of the points I don't transfer into the shared account.

My final point score consists of the points I transfer into the shared account.

Which of the following statements is **NOT** true?

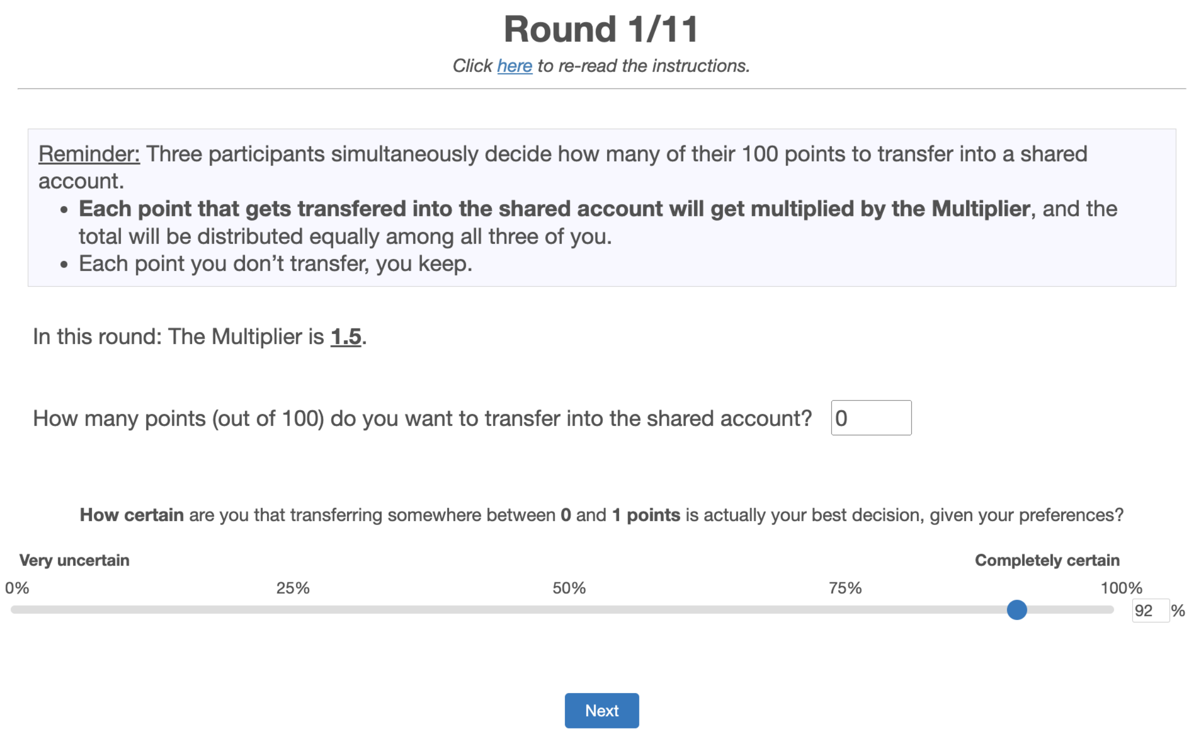
The higher the Multiplier, the more points end up in the shared account for each point I transfer.

The more points I transfer into the shared account, the higher the bonus of the other participants.

The higher the Multiplier, the more money I get for each point I don't transfer into the shared account.

Next

Figure 77: Comprehension check for PGG task.



Round 1/11

Click here to re-read the instructions.

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 **1.5**.

How many points (out of 100) do you want to transfer into the shared account? 0

How certain are you that transferring somewhere between **0** and **1 points** is actually your best decision, given your preferences?

Very uncertain **Completely certain**

0% 25% 50% 75% 100%

92 %

Next

Figure 78: Decision screen for PGG task.

G.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.

Your task:

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.

Example:

Reminder: 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 **6%**.

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.

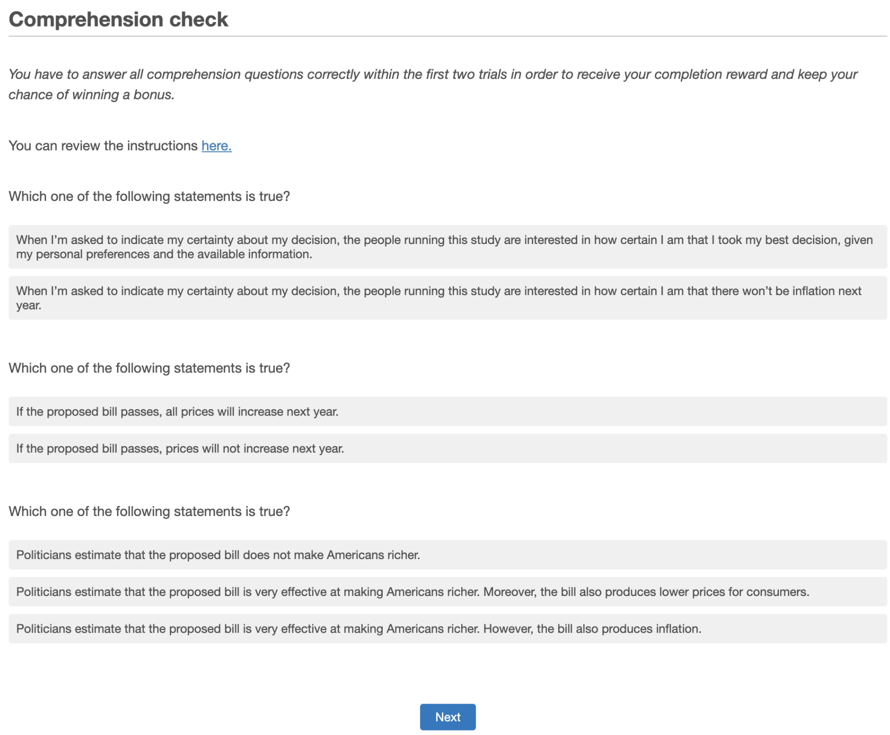
Your certainty:

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 79: The instruction screen for POL 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 I took 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 there won't be inflation next year.

Which one of the following statements is true?

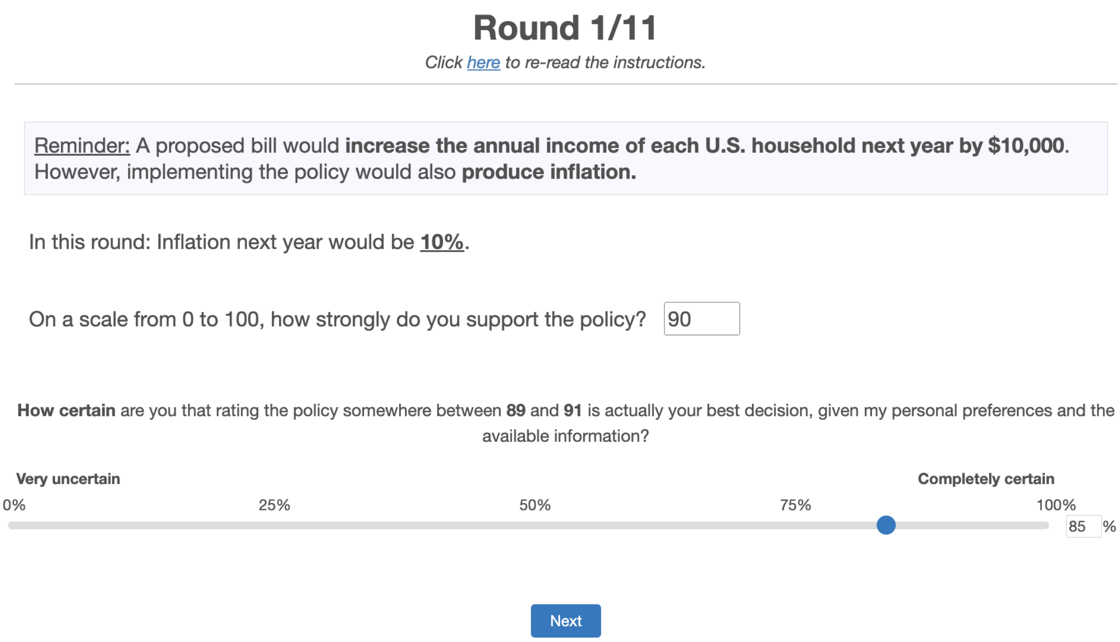
- If the proposed bill passes, all prices will increase next year.
- If the proposed bill passes, prices will not increase next year.

Which one of the following statements is true?

- Politicians estimate that the proposed bill does not make Americans richer.
- Politicians estimate that the proposed bill is very effective at making Americans richer. Moreover, the bill also produces lower prices for consumers.
- Politicians estimate that the proposed bill is very effective at making Americans richer. However, the bill also produces inflation.

Next

Figure 80: Comprehension check for POL task.



Round 1/11

Click here to re-read the instructions.

Reminder: 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 **10%**.

On a scale from 0 to 100, how strongly do you support the policy? 90

How certain are you that rating the policy somewhere between **89** and **91** is actually your best decision, given my personal preferences and the available information?

Very uncertain **Completely certain**

0% 25% 50% 75% 100% 85 %

Next

Figure 81: Decision screen for POL task.

G.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 excluded 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 are 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 82: The instruction screen for STO task.

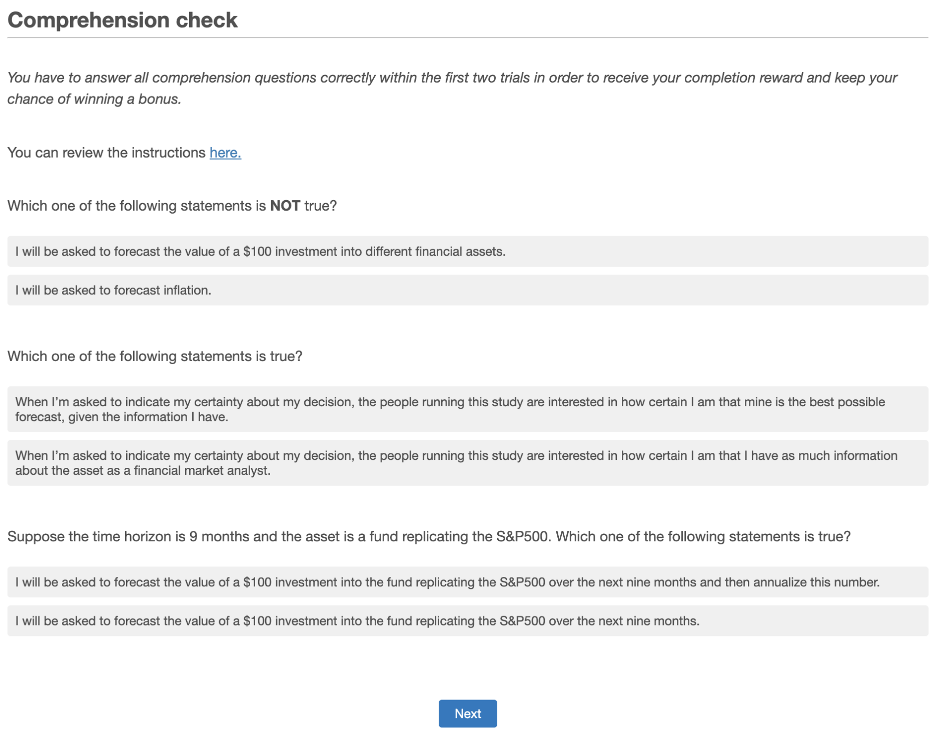


Figure 83: Comprehension check for STO task.

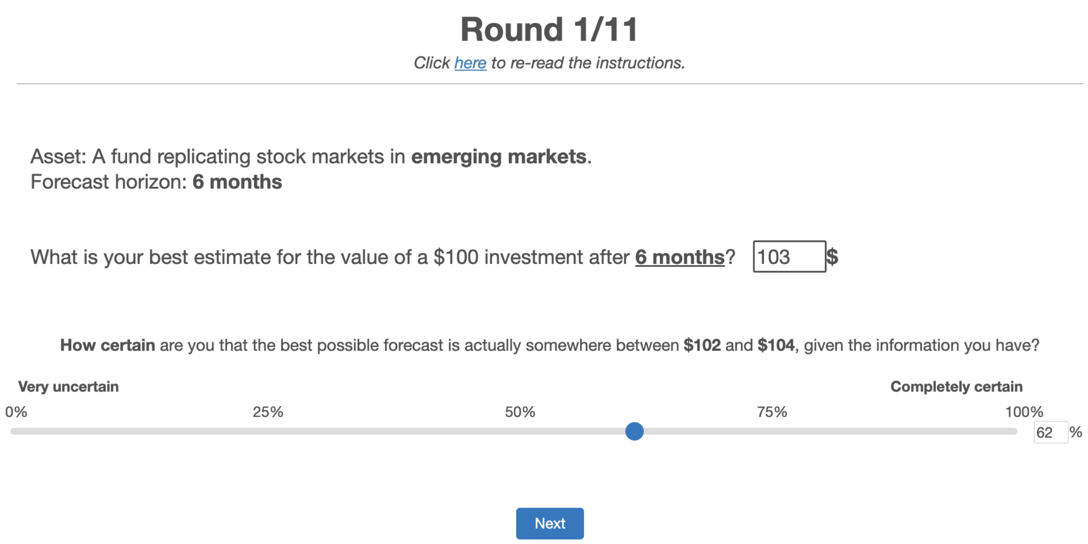


Figure 84: Decision screen for STO task.

G.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 85: The instruction screen for TID task.

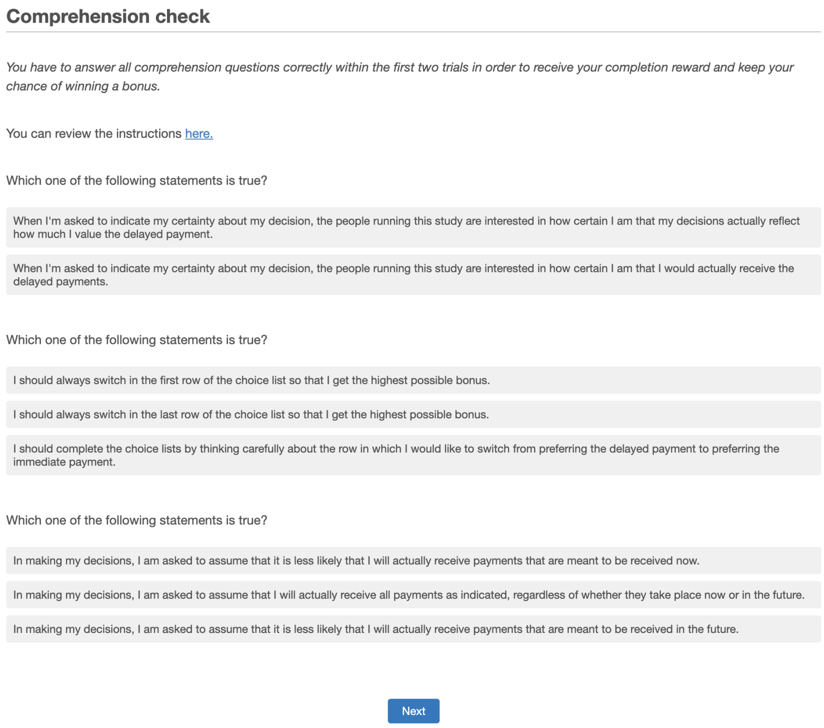


Figure 86: Comprehension check for TID task.

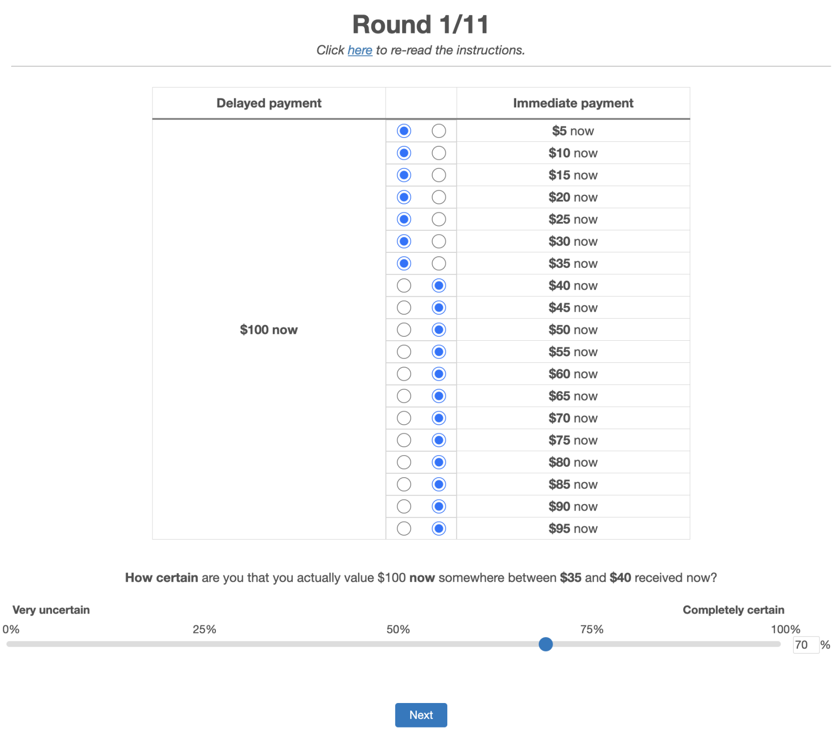


Figure 87: Decision screen for TID task.

G.23 BEU

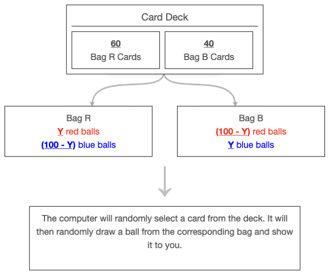
Instructions

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:

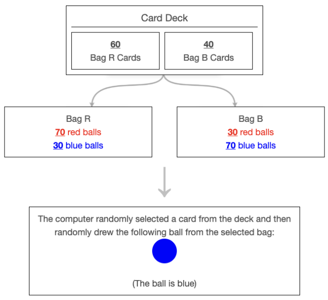


- There is a deck of **100 cards**, 60 of which have **"Bag R"** written on them and 40 of which have **"Bag B"** written on them.
- There are **two bags**, Bag R and Bag B. **Both bags contain 100 balls each,** some of which are red and some of which are blue. Bag R always contains at least as many 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 88: The instruction screen for BEU task.

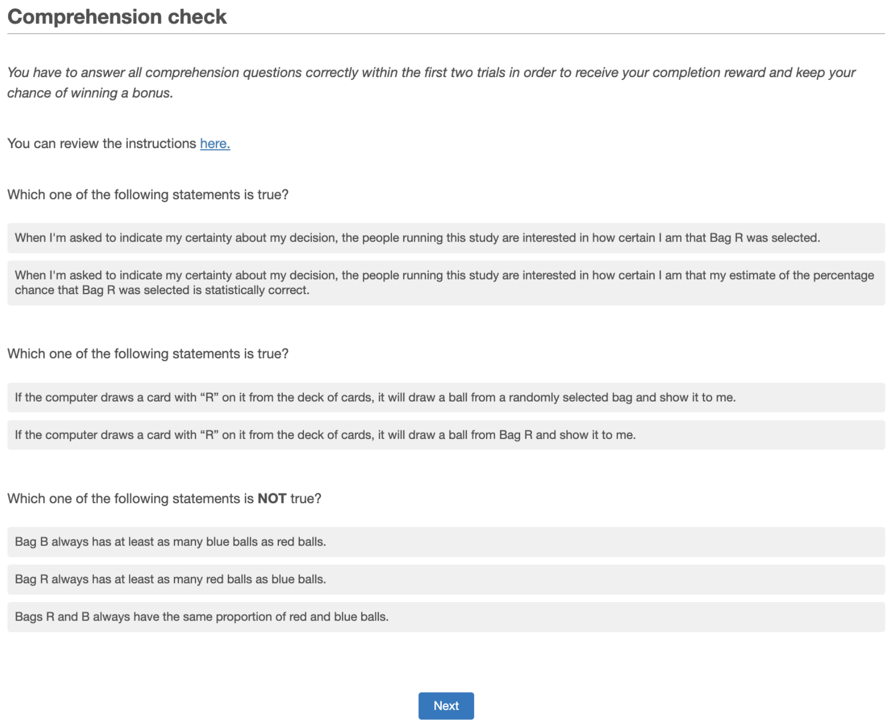


Figure 89: Comprehension check for BEU task.

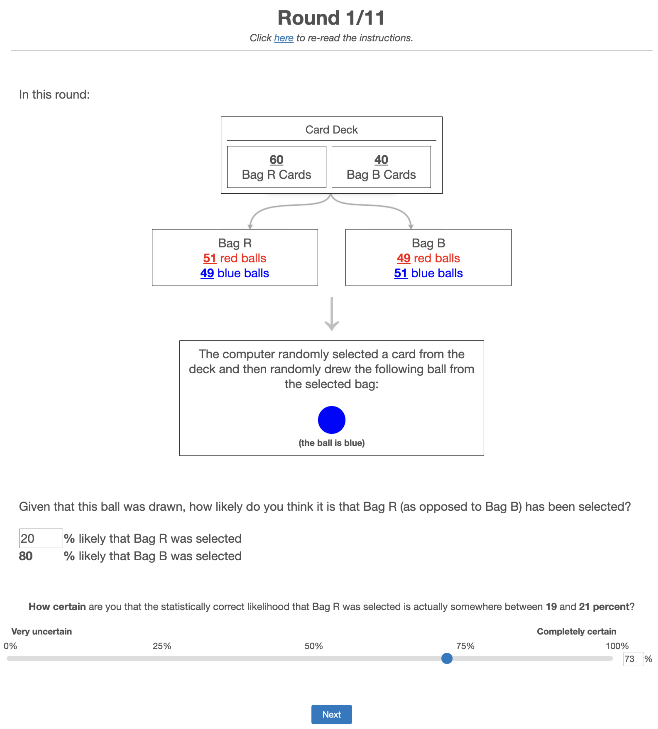


Figure 90: Decision screen for BEU task.

G.24 CEE

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 **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.

Your bonus payment:

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.**

Example:

Lottery		Safe payment
With **80%** chance: **Get $18** With **20%** chance: **Get $0**		$1
		$2
		$3
		$4
		$5
		$6
		$7
		$8
		$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.

Your certainty:

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 91: The instruction screen for CEE task.

Figure 92: Comprehension check for CEE task.

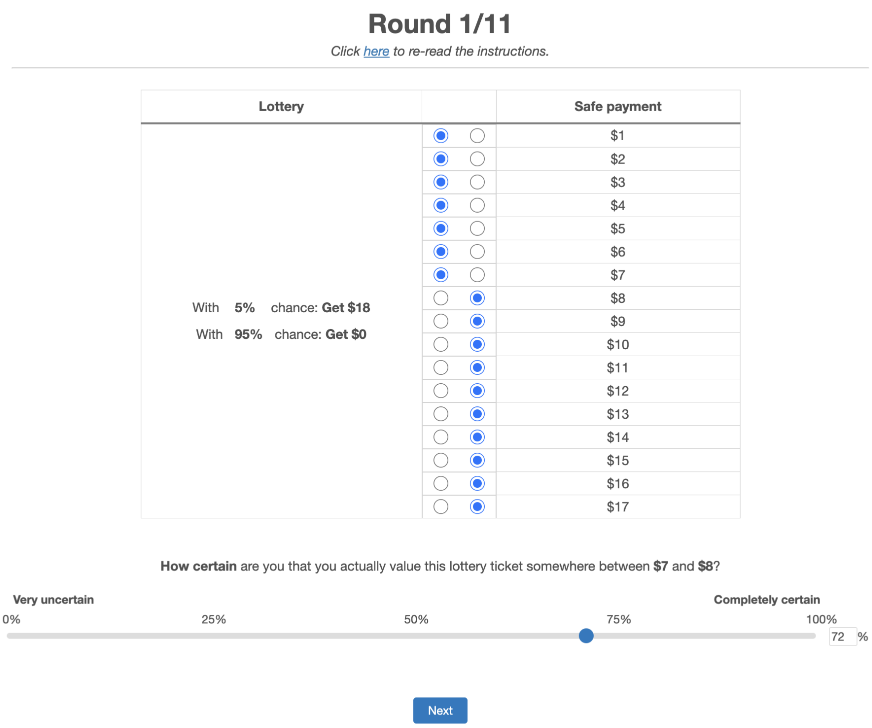


Figure 93: Decision screen for CEE task.

G.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.

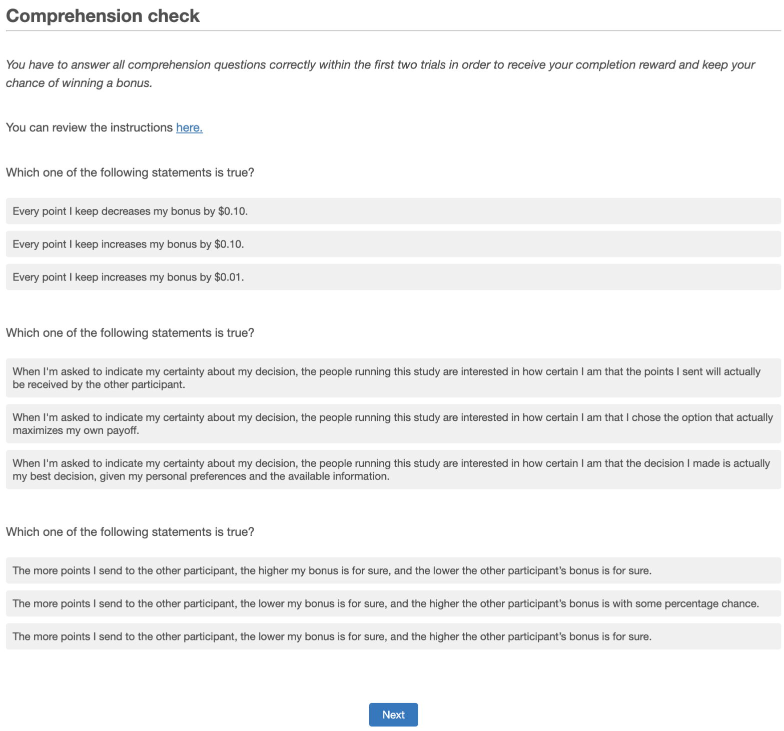
Your certainty:

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 94: The instruction screen for DIG 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?

Every point I keep decreases my bonus by $0.10.

Every point I keep increases my bonus by $0.10.

Every point I keep increases my bonus by $0.01.

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 points I sent will actually be received by the other participant.

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.

Which one of the following statements is true?

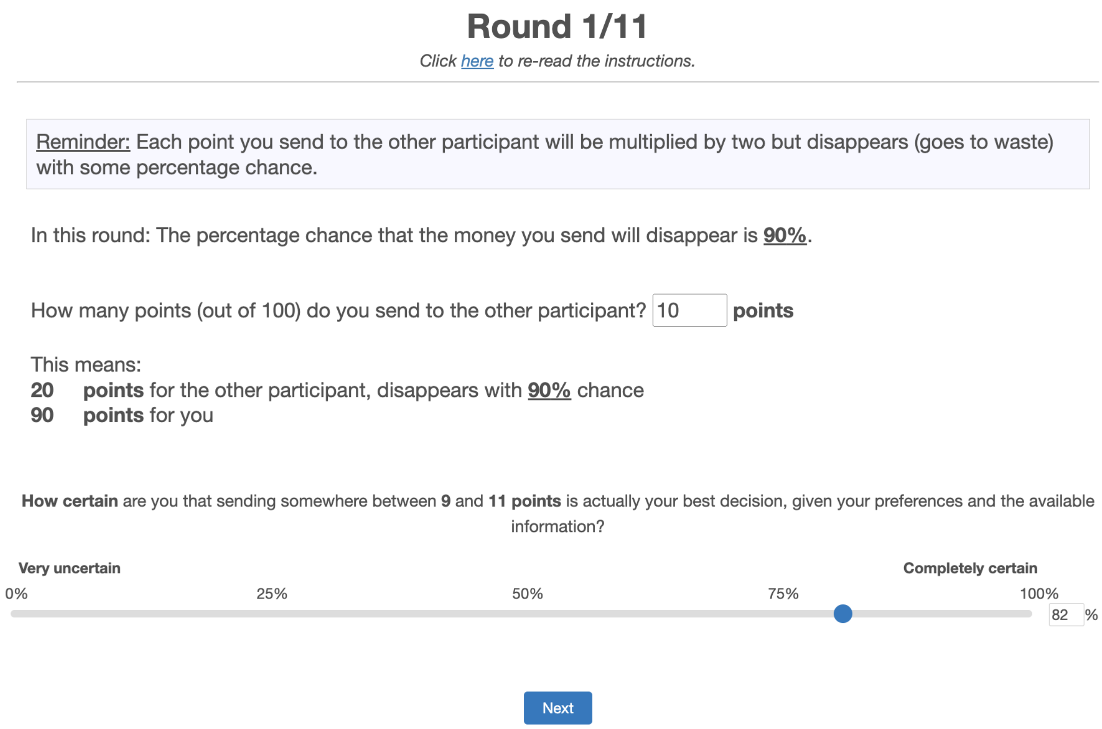
The more points I send to the other participant, the higher my bonus is for sure, and the lower the other participant's bonus is for sure.

The more points I send to the other participant, the lower my bonus is for sure, and the higher the other participant's bonus is with some percentage chance.

The more points I send to the other participant, the lower my bonus is for sure, and the higher the other participant's bonus is for sure.

Next

Figure 95: Comprehension check for DIG task.



Round 1/11

Click here to re-read the instructions.

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 **90%**.

How many points (out of 100) do you send to the other participant? 10 **points**

This means:
20 **points** for the other participant, disappears with **90%** chance
90 **points** for you

How certain are you that sending somewhere between **9** and **11 points** is actually your best decision, given your preferences and the available information?

Very uncertain **Completely certain**
0% 25% 50% 75% 100%
82 %

Next

Figure 96: Decision screen for DIG task.

G.26 EFF

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 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.

Your bonus payment:

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.

Example:

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 **$0.22**.

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.

Your certainty:

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 97: The instruction screen for EFF task.

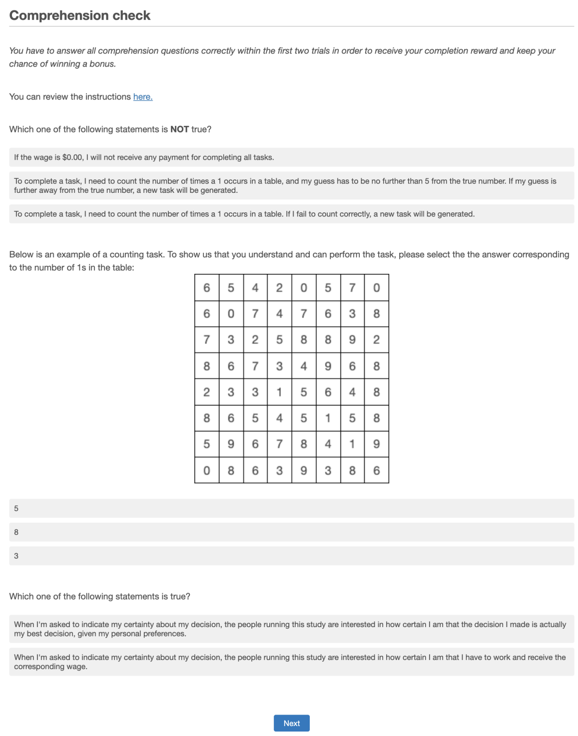


Figure 98: Comprehension check for EFF task.

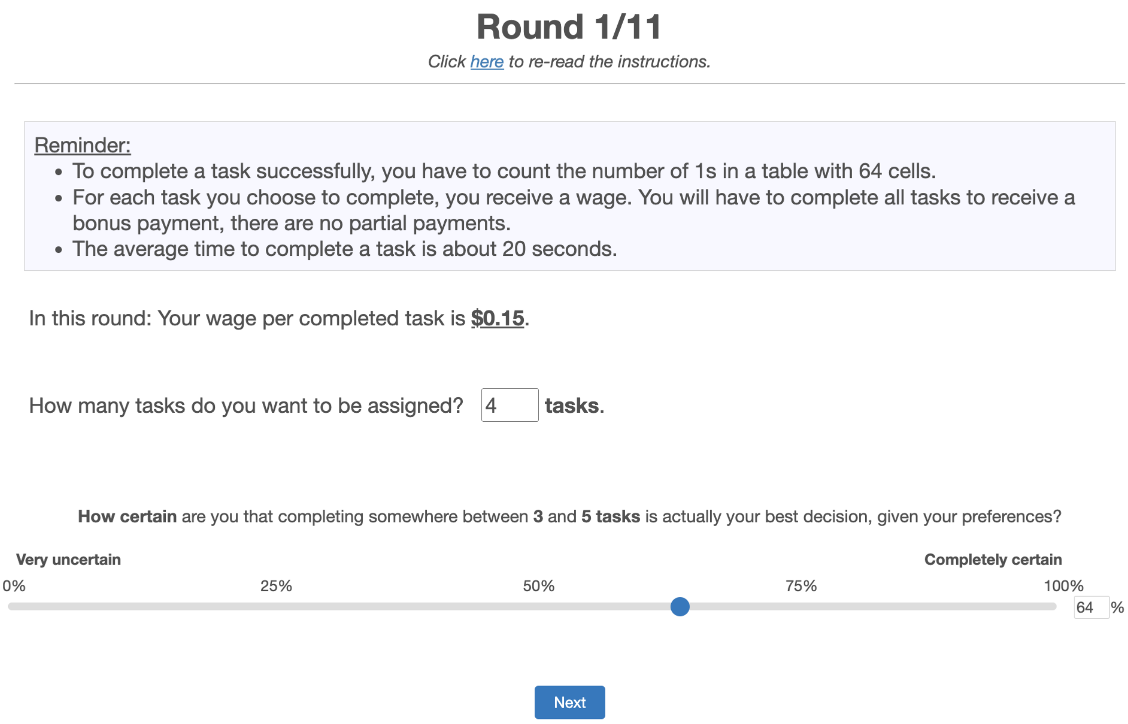


Figure 99: Decision screen for EFF task.

G.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 predictable. Specifically, the change in the firm's earnings from 2023 to 2024 is determined by two components:
  - A **firm trend** equal to the previous change in the firm's earnings from 2022 to 2023.
  - A **market trend** equal to **+5** in every year.
- The relative importance of these two components is given by P, a share between 0 and 100%. In particular, the earnings change is given by the formula

  2024 earnings – 2023 earnings =
  P% × (Firm trend) + (100 – **P**)% × (Market trend).

- 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 relative importance of each component, 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 relative importance 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 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 correct forecast, and nothing otherwise.

Example:

Reminder: The earnings change between 2023 and 2024 is determined by two components:
- A **firm trend** equal to the previous change in the firm's earnings between 2022 and 2023.
- A **market trend** equal to **+5** in every year.

The relative importance of these two components is determined by the share **P**.

In this round: The relative importance of the firm trend is **80%** and that of the market trend is **20%**, which means:

2024 earnings - 2023 earnings =
80% × (Firm trend) + **20%** × (Market trend)

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 importance of the firm trend is 80% and that of the market trend is 20%, 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 correct forecast.

Figure 100: The instruction screen for 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?

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 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?

My task is to forecast the average 2024 earnings of the firm, which are equal to the firm's 2023 earnings; plus P% of the firm trend; plus (100-P)% of the market trend.

My task is to forecast the average 2023 earnings change of the firm.

Which one of the following statements is true?

The market trend is zero and can be ignored.

The market trend is positive and equals 2.

The market trend is positive and equals 5.

Next

Figure 101: Comprehension check for 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 **firm trend** equal to the previous change in the firm's earnings between 2022 and 2023.
- A **market trend** equal to **+5** in every year.

The relative importance of these two components is determined by the share **P**.

In this round: The relative importance of the firm trend is **75%** and that of the market trend is **25%**, which means:

2024 earnings - 2023 earnings =
75% × (Firm trend) + **25%** × (Market trend)

The firm's earnings over the previous two years are given below:

2024 Earnings	?
2023 Earnings	**$128**
2022 Earnings	**$112**

What is your forecast of the earnings of this firm in 2024? $141

How certain are you that the correct forecast of the firm's 2024 earnings is actually somewhere **$140** and **$142**?

Very uncertain **Completely certain**

0% 25% 50% 75% 100%

67 %

Next

Figure 102: Decision screen for FOR task.

G.28 MUL

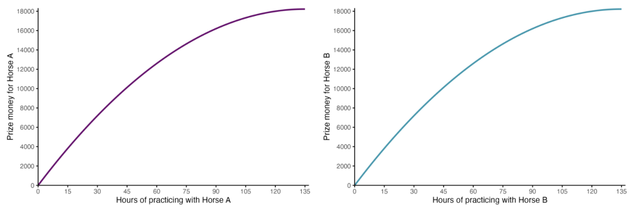
Instructions

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 103: The instruction screen for MUL task.

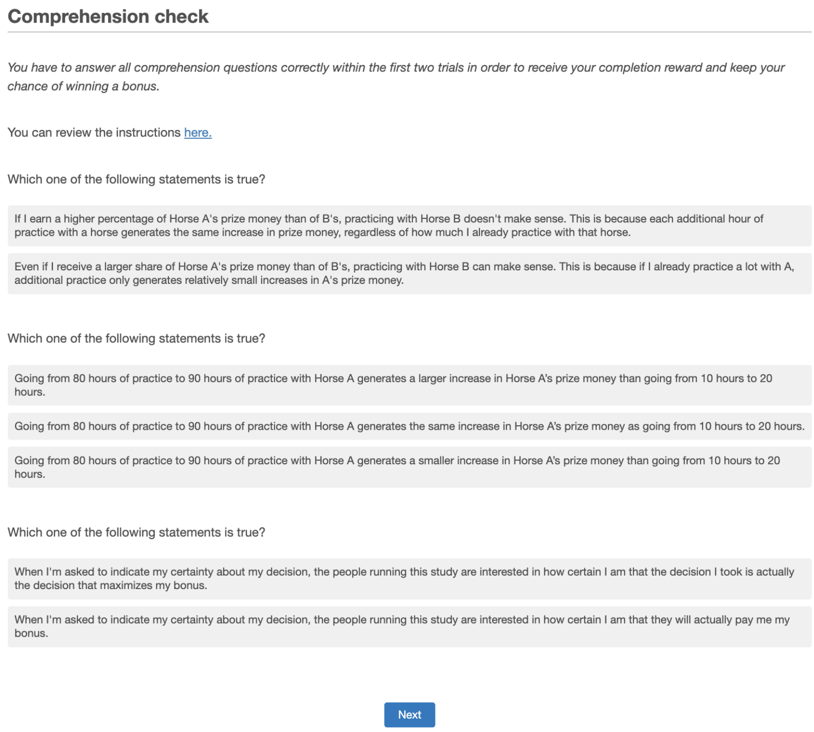


Figure 104: Comprehension check for MUL task.

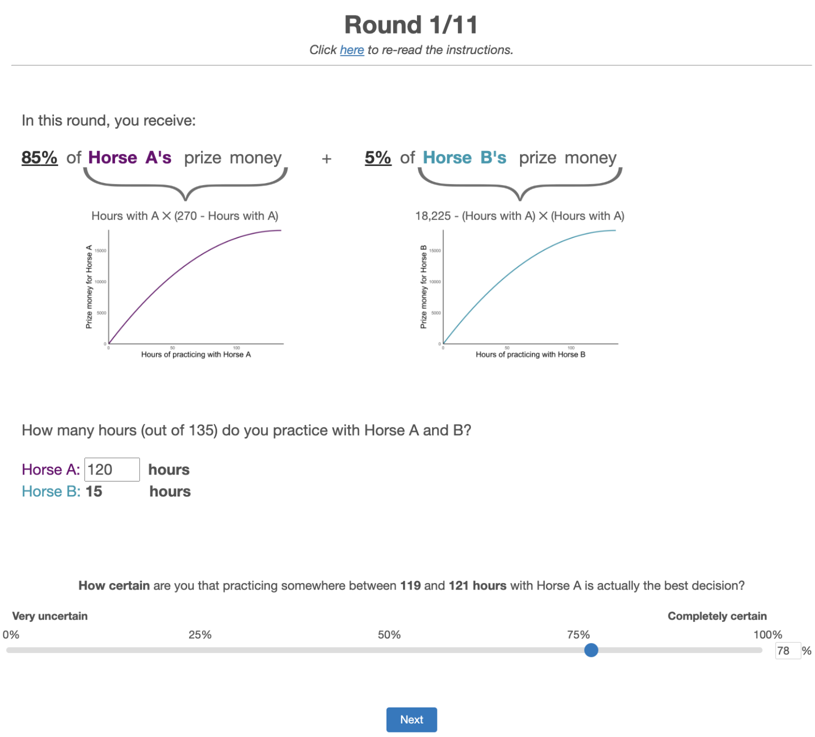


Figure 105: Decision screen for MUL task.

G.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 106: The instruction screen for NEW task.

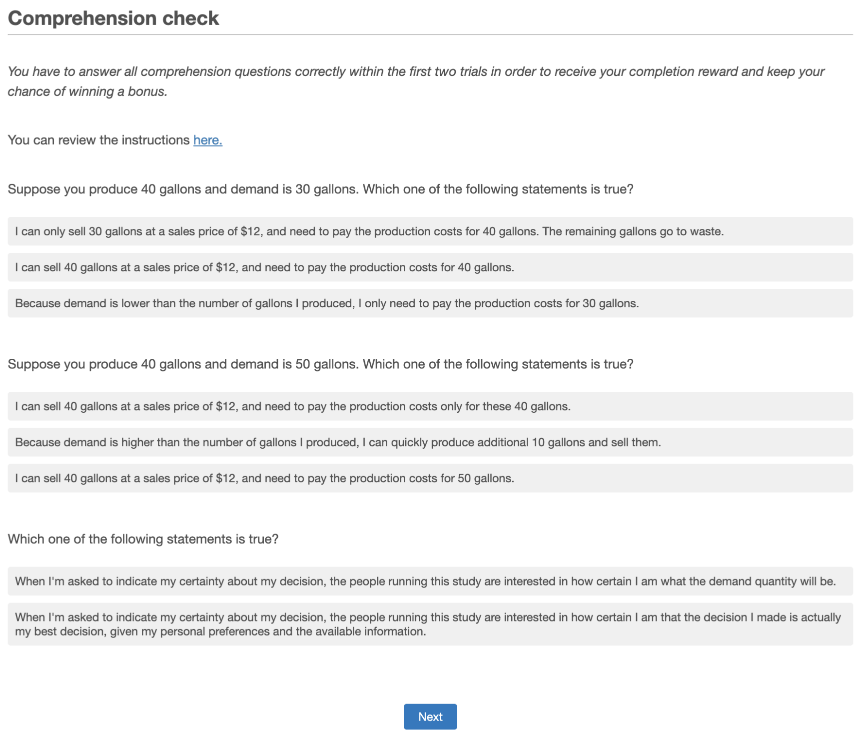


Figure 107: Comprehension check for NEW task.

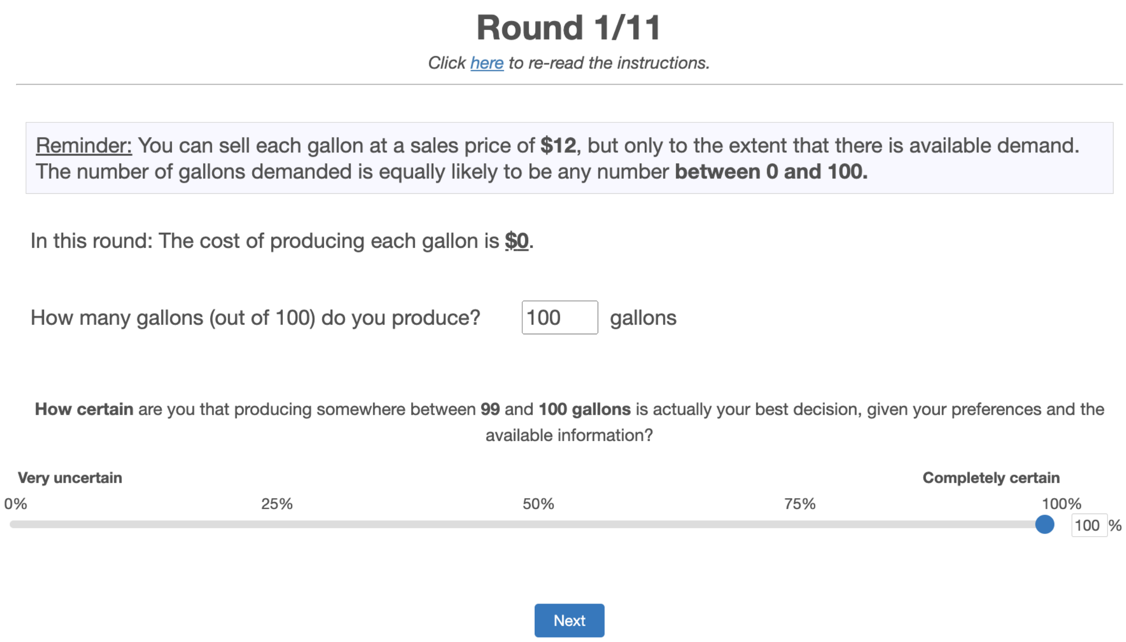


Figure 108: Decision screen for NEW task.

G.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
$4,900/year	◉	○	$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)
	○	◉	$4,500/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 109: The instruction screen for ENS task.

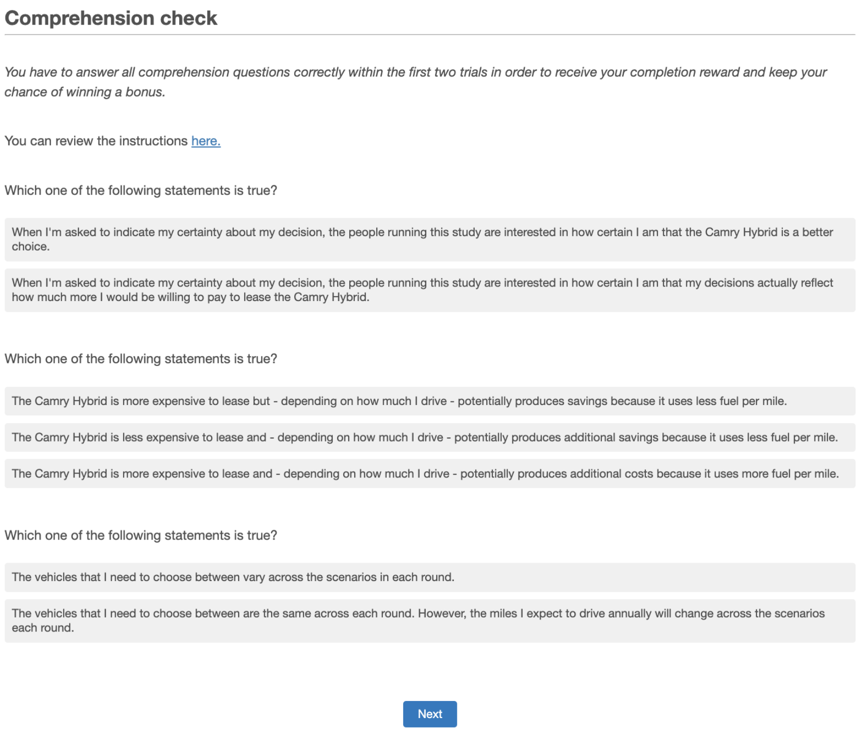


Figure 110: Comprehension check for ENS task.

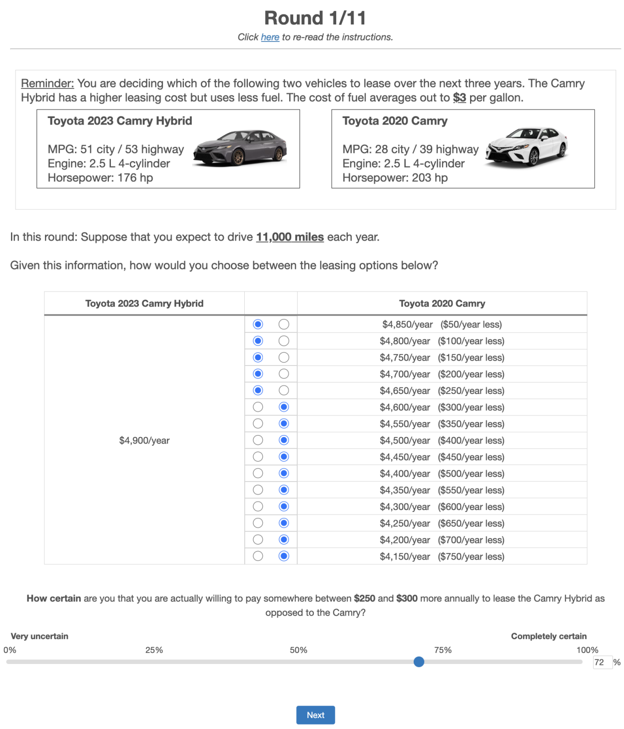


Figure 111: Decision screen for ENS task.

G.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.

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Figure 112: The instruction screen for HEA 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 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 people will really get sick due to the disease.

Suppose there are 10 people expected to get sick. Which of the following statements is true?

If I decide the government should spend $100,000, this is the amount the government will spend for each of the 10 people, meaning the government will spend $1,000,000 in total.

If I decide the government should spend $100,000, this is the amount the government will spend overall, meaning the government will spend $100,000 in total.

Which one of the following statements is true?

People who get the disease will die.

People who get the disease will be sick for 1 year.

People who get the disease will be sick for 1 month.

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Figure 113: Comprehension check for HEA task.

Round 1/11

Click here to re-read the instructions.

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: **10 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?
$ 200000

How certain are you that spending somewhere between **$197,500** and **$202,500** is actually your best decision, given your preferences and the available information?

Very uncertain **Completely certain**

0% 25% 50% 75% 100%

74 %

Next

Figure 114: Decision screen for HEA task.