When Irrelevant Options Matter: Redundancy, Noisy Cognition, and Portfolio Choice*

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Abstract

Adding options that expand no opportunity should not change behavior. We test this by introducing redundant assets, securities replicable from those already available, into a laboratory portfolio problem with an unchanged budget set. In a model of noisy cognition, redundancy spreads a fixed cognitive capacity over more operations, so the decision maker reads relative prices less precisely and shrinks demand toward her prior. Redundancy reduces price responsiveness by 18 percent even when payoff arithmetic is automated; cognitive uncertainty best predicts who attenuates; and observing the choices of unattenuated participants cuts attenuation by 60 to 73 percent, mainly among high-uncertainty subjects.

Keywords: Asset Redundancy, Complexity, Noisy Cognition, Behavioral Attenuation, Cognitive Uncertainty, Social Information, Portfolio Choice

JEL classification: C91, D11, D81, D83, D91, G11, G41

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1 Introduction

Standard theory predicts that adding an option should not change behavior if the feasible choice set remains unchanged. A redundant security, whose payoff can be replicated at the same cost using existing assets, is an example (Ross, 1978; Harrison and Kreps, 1979). Adding it leaves the budget set unchanged, so revealed preference analysis cannot distinguish between the choice problems with and without it. This equivalence assumes that choices depend only on what is feasible, not on how hard it is to choose. Choosing is difficult when the problem is complex, preferences are uncertain, or the optimum is hard to find. Models of limited attention and cognitive noise (Simon, 1955; Sims, 2003; Gabaix, 2014; Woodford, 2020; Khaw et al., 2021) predict that behavior depends on how a problem is represented, and recent experiments show that such difficulty shapes what is measured as risk and time preference (Enke and Graeber, 2023; Oprea, 2024; Enke et al., 2025). Redundancy is an unusually clean presentation manipulation. Most complexity manipulations change the economic problem along with how it appears; redundancy changes only how it appears, while opportunities, information, and the optimum stay fixed.

Redundancy is also pervasive, especially in financial markets, including dual-listed shares, exchange-traded funds tracking the same index, and derivatives replicable from traded assets; all duplicate claims that are already available. We ask the following questions. Do redundant options change behavior? If so, through what cognitive channel, and who is most affected? Can we correct the resulting distortion, and who benefits most? We answer these questions with a two-stage laboratory experiment and a model of portfolio choice under noisy cognition that delivers testable predictions for each stage.

In the first stage, 314 subjects each allocate a budget across assets that pay off in one of two equally likely states. Each subject completes 60 incentivized problems with different relative prices of the two states. Half of the problems are *Simple*: two Arrow securities, one paying in each state. The other half are *Complex*: the same two securities plus two redundant assets. Each redundant asset can be replicated by a portfolio of the two Arrow securities and is priced at the portfolio's cost. The two environments therefore share the same budget set. Because every subject faces both environments, we measure for each individual how her sensitivity to relative prices changes when redundancy is introduced. To separate the cognitive burden of recognizing redundancy from the arithmetic burden of computing payoffs, we use two display conditions. Half of the subjects are randomly assigned to see the state-contingent payoffs implied by their allocation updated on screen in real time (State Payoff, or SP). The other half must compute these payoffs themselves (No State Payoff, or NSP). After every fifth round, we elicit cognitive uncertainty, a

subject's stated uncertainty about whether her chosen allocation is close to her own optimum (Enke and Graeber, 2023). At the end of the session, we collect additional measures, including cognitive ability and implementation error.

Before turning to the data, we develop a model of portfolio choice with noisy cognition. The agent does not act on the relative price but on a noisy internal representation of it, and her optimal response to that noise is to shrink her demand toward her prior. Attenuated price sensitivity is thus the rational response to imprecision, not a failure to optimize. We extend models of noisy cognition (Woodford, 2020; Khaw et al., 2021; Oprea and Woodford, 2026) by linking redundancy to noise. Recovering the relative price from the choice screen requires two kinds of cognitive operations: inferring the state prices, including recognizing which assets are redundant, and computing the payoffs an allocation delivers. Redundancy adds both kinds of operations, and an agent who spreads a fixed processing capacity over more operations forms a noisier representation. The SP display performs the payoff arithmetic.

We build the following predictions. First, introducing redundant assets should reduce demand's responsiveness to relative prices, which we call behavioral attenuation, following Enke et al. (2024). Because the representation is unbiased, the reduction should appear in the slope of demand, not its level. Second, price sensitivity in the Simple problems should be the same under SP and NSP because, with two Arrow securities, there is no arithmetic to remove. In problems with redundant assets, attenuation should be smaller under SP than under NSP, but remain positive because the display leaves price inference untouched. Attenuation under SP therefore measures the cost of recognizing redundancy and inferring prices, and the gap between the conditions measures the cost of computing payoffs. Third, attenuation should be larger for individuals with lower cognitive processing capacity. Because the same capacity governs an agent's posterior uncertainty about her own optimal action, cognitive uncertainty measured in the Simple environment should predict how much an individual's price sensitivity deteriorates when redundancy is introduced. Cognitive uncertainty should also rise within subject when redundancy is introduced.

The data confirm these predictions. In the pooled data, the slope of demand share with respect to the log price ratio falls by 21 percent when the redundant assets are present. The reduction is 18 percent under SP and 24 percent under NSP. Automating the arithmetic dampens the effect, as predicted, though the difference is only marginally significant. The intercept does not move, so the effect is confined to the slope. Simple-round price sensitivity is the same in the two conditions, and attenuation is larger under NSP, though the difference is only marginally significant; in the model's decomposition, price inference accounts for about three quarters of the attenuation and payoff arithmetic

for the rest. The economic magnitude is substantial. Under expected utility, subjects choose in the Complex environment as if their coefficient of relative risk aversion were 35 to 49 percent higher, even though their opportunities are identical. The effect is not driven by a few subjects or by noise: roughly one third of subjects show statistically significant attenuation at the individual level. They do not ignore the redundant assets, allocating close to half their budget to them. Fewer than 2 percent of their Complex-round choices split the budget equally across assets. Thus, attenuation is not a switch to a naive heuristic but a flattening of every choice, as the model implies. Attenuation is also predictable. Cognitive uncertainty rises within subjects from Simple to Complex rounds, and cognitive uncertainty elicited in the Simple problems most strongly correlates with an individual's attenuation, accounting for the largest share of explained variation across subjects, whereas cognitive ability and implementation error contribute little.

If attenuation reflects imprecise inference rather than preference, then information that sharpens the inference should reduce it. In the second stage, 219 subjects repeat four earlier problems while observing the average allocation of a group of previous participants. Subjects are randomized to one of two displays constructed from earlier sessions: the average behavior of participants whose price sensitivity did not change between Simple and Complex problems (Unattenuated Information), or the average behavior of participants who had themselves attenuated (Attenuated Information). Subjects are not told how the participants behind the information were selected.

In the model, the agent takes the display as an unbiased signal of her optimal action and averages it with her own noisy estimate, weighting each by its precision. The noisier her own estimate, the more she relies on the display, so she weights it more in Complex rounds than in Simple ones. Her attenuation then moves toward the attenuation shown in the display, by an amount proportional to the gap between the two. The factor of proportionality is her weight on the display, which does not depend on which display she sees. Three predictions follow. First, Unattenuated Information should reduce attenuation for every subject whose Complex-round demand is no more price-sensitive than the display. Second, Attenuated Information should produce a smaller correction for every subject, and because its recipients lie on both sides of the attenuation it conveys, it yields little average change. Third, the correction under Unattenuated Information should be larger among high-cognitive-uncertainty subjects, who have more baseline attenuation to correct and place more weight on the display.

The Stage 2 results support these predictions. Observing unattenuated behavior reduces attenuation by about 60 to 73 percent from baseline in both conditions, whereas observing attenuated behavior has no significant average effect in either condition. At the individual level, the change in attenuation relates to the gap between the display's

attenuation and the subject's baseline. The change and the gap have the same sign for about 80 percent of subjects, and their correlation ranges from 0.62 to 0.72. Under Unattenuated Information, the correction is more than twice as large for subjects in the top half of the cognitive uncertainty distribution in the SP condition. In the NSP condition, the correction is significant only for subjects in the top half of the cognitive uncertainty distribution. After controlling for Stage 1 choices, we also find that these subjects respond more strongly to the displayed allocation, the second channel the model identifies. Under Attenuated Information, neither group shows a significant change in attenuation.

Our paper connects to three literatures. The first studies complexity and cognitive noise. Individuals with high cognitive uncertainty exhibit attenuated responses across many decision domains (Enke and Graeber, 2023; Enke et al., 2024). Complexity can also account for much of measured risk and time preference (Oprea, 2024; Enke et al., 2025). In tax decisions, it weakens responses to incentives, especially among subjects with lower cognitive ability (Abeler and Jäger, 2015). Experimental manipulations of complexity have used compound lotteries (Halevy, 2007; Gillen et al., 2019), large state spaces (Sonsino et al., 2002; Puri, 2025), and dissimilar payoff structures (Enke and Shubatt, 2023; Shubatt and Yang, 2024); most of these change the economic content of the problem along with its presentation.[1]

The closest design to ours is Carvalho and Silverman (2024), who also introduce redundant assets in a between-subject setting.[2] Our within-subject design measures the complexity effect at the individual level, links it to elicited cognitive uncertainty, and decomposes it into the cost of inferring prices and the cost of computing payoffs. In our model, attenuation, cognitive uncertainty, and the response to information all derive from one source of imprecision. The link to cognitive uncertainty helps predict behavior: confidence elicited in the Simple environment is correlated with both attenuation under redundancy and responses to corrective information. Our design also speaks to the debate over what cognitive uncertainty measures: uncertainty about one's best decision or about the payoff one will receive (Bernheim et al., 2026; Enke and Graeber, 2026). Because redundancy changes the presentation of a choice problem but not its opportunities, it separates decision difficulty from the outcome uncertainty of the chosen portfolio: within subject, cognitive uncertainty rises when redundant assets are added even though the chosen portfolio becomes safer, and the rise survives controls for its riskiness.

The second literature concerns complexity and redundancy in financial markets. Redundant securities take many forms, including dual-listed stocks (Rosenthal, 1983;

[1] Agranov et al. (2026) link subjective perceptions of complexity to behavior using deliberation time.

[2] Relatedly, Eyster and Weizsäcker (2011) show that portfolio choices differ across problems with the same set of attainable returns but different correlations among the available assets.

Gagnon and Karolyi, 2010), ETFs tracking identical indices (Agapova, 2011; Ben-David et al., 2023), closed-end funds with replicable holdings (Lee et al., 1991), and derivatives in complete markets (Ross, 1976). Field evidence documents price gaps between economically equivalent claims (Froot and Dabora, 1999) and overvaluation of simple but dominated securities (Goodman and Puri, 2025). Field evidence, however, cannot separate the demand-side response to redundancy from the incentives of issuers to obfuscate (Carlin, 2009; Carlin and Manso, 2011; Henderson and Pearson, 2011; Célérier and Vallée, 2017; Ghent et al., 2019; Allen and Barbalau, 2024) or from transaction costs, liquidity, and taxes. Our experiment isolates the demand side and shows that redundancy alone reduces the price responsiveness of demand. Most of the reduced responsiveness comes from the difficulty of inferring prices rather than from arithmetic.

The third literature uses social information as a behavioral intervention. Providing information about the behavior of others has been used to raise retirement plan participation (Duflo and Saez, 2003), reduce energy consumption (Allcott, 2011), increase tax compliance (Hallsworth et al., 2017), influence dictator game allocation (Cason and Mui, 1998), and shape financial decisions (Bursztyn et al., 2014). Our experiment complements this literature in two ways. The setting is non-strategic, and the target of the information is a well-defined cognitive distortion, which allows us to treat social information purely as a signal, in the spirit of the observational learning literature (Banerjee, 1992; Bikhchandani et al., 1992), rather than as a carrier of social pressure or image concerns. And the model delivers a precise account of the heterogeneity that field studies document: the effect of social information depends jointly on the behavioral content of the signal and on the recipient's own precision. Information corrects the distortion when it conveys undistorted behavior to uncertain subjects. Otherwise, it may not help and, in the model, can harm. A recipient less attenuated than the display moves toward the behavior shown and becomes more attenuated. For policy, this implies that a clear behavioral benchmark, rather than more disclosure, is what restores price responsiveness, especially for those who report the least confidence.

The remainder of the paper proceeds as follows. Section 2 describes the Stage 1 design and measurement. Section 3 develops the model of portfolio choice with redundant assets and derives its predictions. Section 4 tests them. Section 5 describes the Stage 2 social-information intervention, Section 6 extends the model and derives its predictions, and Section 7 tests them. Section 8 discusses our main results.

2 Stage 1 Experiment: Asset Redundancy

Stage 1 measures how the introduction of redundant assets changes investment behavior, holding the economic problem fixed. This section first defines asset redundancy, then describes the main task, the between-subject variation in computational burden, and the additional measures we elicit from subjects or construct from their choices.

Stage 1 was conducted at Seoul National University with 314 student subjects in 17 sessions. We pre-registered the design, primary outcomes, and three hypotheses in the AEA RCT Registry (AEARCTR-0016214) before data collection (Choi et al., 2025).[3] The experiment was computerized using oTree (Chen et al., 2016). Sessions lasted approximately two hours, and subjects earned an average of 27,000 KRW, including a 10,000 KRW show-up fee.[4] Choices were made in experimental currency units (ECU), with 1 ECU worth 500 KRW.

2.1 Asset Redundancy

We increase the complexity of a portfolio problem by adding redundant assets, following Al-Najjar et al. (2003) and Carvalho and Silverman (2024). In their framework, complexity is the number of payoff-relevant contingencies a decision maker believes she must consider in order to choose well, so a problem becomes more complex when it requires reasoning over more contingencies even if the economic environment is unchanged.

An asset is redundant if its payoff and its cost can be exactly replicated by a combination of other available assets. A redundant asset expands neither the set of attainable state-contingent payoffs nor the opportunities for sharing risk; it provides another representation of allocations that are already attainable at the same cost. It nevertheless adds to complexity in the sense above, because the decision maker must consider more options that map onto the same payoffs. Online Appendix D.1 shows formally that the budget set with redundant assets coincides with the budget set without them.

2.2 Main Task: Within Subject Design

The main task measures, for each subject, how investment behavior changes when redundant assets are introduced. There are two states of the world, State 1 and State 2, each realized with probability one half. Each asset j has a unit price p^j and a pair of unit returns (r_1^j, r_2^j), one for each state. A subject who invests ECU^j in asset j holds ECU^j/p^j

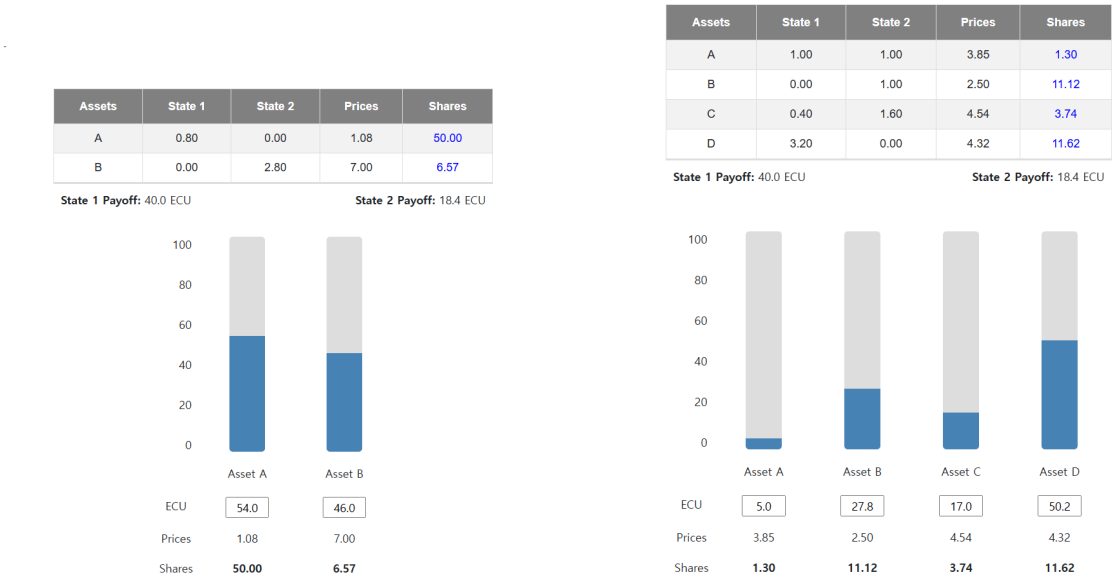
[3] We note at the end of each theory section which of the model's predictions correspond to the registered hypotheses and which do not.

[4] In 2025, the average exchange rate was approximately 1 USD = 1,400 KRW.

units of it, so her payoff in State s is

$$x_s = \sum_j \frac{r_s^j}{p^j} \text{ECU}^j, \qquad s = 1, 2. \tag{1}$$

We refer to x_1 and x_2 as the state payoffs. The subject is paid the payoff of the realized state, so (x_1, x_2) is the state-contingent consumption bundle.



(a) Simple Round

(b) Complex Round

Figure 1: Decision Screen

Notes: This figure shows the sample decision screen. Panel (a) presents the decision screen for the Simple round. Panel (b) presents the decision screen for the Complex round.

In each round, a subject allocates a budget of 100 ECUs across the available assets; the entire budget must be invested. Each asset is displayed as in Figure 1, and the subject sets her investment in an asset either by clicking on the desired level or by typing it. Subjects complete 60 rounds, 30 Simple and 30 Complex, in an order randomized at the subject level, and one round is randomly selected for payment at the end of the session.

A Simple round offers two Arrow securities. We describe the round with the asset paying in State 1 labeled A, although labels are randomized. Asset A pays a positive return only in State 1, with unit returns $(r_1^A, 0)$, and Asset B pays a positive return only in State 2, with unit returns $(0, r_2^B)$. Obtaining one unit of payoff in State 1 therefore costs $p_1 \equiv p^A/r_1^A$ ECUs, and one unit of payoff in State 2 costs $p_2 \equiv p^B/r_2^B$ ECUs; we refer to p_1 and p_2 as the state prices, and to $\log(p_1/p_2)$ as the log price ratio. Across

the 30 Simple rounds, the log price ratios approximate a standard normal distribution, ranging from -1.87 to 1.83 with an average spacing of 0.13. Online Appendix B.2 reports the values of r_1^A, p^A, r_2^B, and p^B in each round. To avoid framing effects, we randomly assign labels A and B in each round for each subject, so the asset paying in State 1 is labeled A in some rounds and B in others. Panel (a) of Figure 1 shows a Simple round.

A Complex round adds two assets, C and D, to the corresponding Simple round. The returns and the price of each are the same convex combination of the returns and the prices of A and B, so that a portfolio of A and B replicates its payoff at exactly its cost; one combination is randomly weighted toward Asset A and the other toward Asset B, with the weights drawn at random. A Complex round therefore has precisely the same set of attainable state-contingent payoffs as its Simple counterpart, with two redundant assets added. The labels A, B, C, and D are again randomized at the subject level in every round. Panel (b) of Figure 1 shows a Complex round.

2.3 Computational Burden: Between-Subject Design

Redundant assets could affect behavior simply by making state payoffs harder to compute.For example, in a Simple round, a subject who invests 50 ECUs in each of Assets A and B obtains a State 1 payoff of $(r_1^A/p^A + r_1^B/p^B) \times 50$. In a Complex round, a subject who invests 25 ECUs in each of the four assets must combine four return-to-price ratios, $(r_1^A/p^A + r_1^B/p^B + r_1^C/p^C + r_1^D/p^D) \times 25$. To test whether the effect of redundancy survives when this arithmetic is removed, we randomly assigned subjects to one of two conditions.

No State Payoff (NSP): 155 subjects completed the 60 rounds without any on-screen calculation of state payoffs. They had to compute payoffs themselves, so the computational burden is highest in this condition, particularly in Complex rounds.

State Payoff (SP): 159 subjects saw the state payoffs implied by their current allocation on the screen, updated in real time as they adjusted their investments. The arithmetic is thereby removed, while the need to recognize which assets are redundant and to infer the state prices remains.

We report results for the SP and NSP conditions side by side, so that each finding can be assessed for robustness to computational burden.

2.4 Additional Measurements

We collect three further measures that may relate to behavior under redundancy, and we construct three more from the main-task choices themselves. We define each measure here and report descriptive statistics in Section 4.

Cognitive Uncertainty. After every fifth round of the main task, we elicit the subject's cognitive uncertainty about the decision just made, following Enke and Graeber (2023). The elicitation occurs 12 times in total, in six Simple and six Complex rounds drawn at random. The screen reminds the subject of her allocation, marks a small margin of ± 1 ECU around it, and asks:

"How certain are you that your optimal decision is within the small margins (± 1) *range of your actual choice, given your preference and the 100 ECU budget constraint?"*

Subjects answer with a probability between 0 and 100 percent using a slider. Our measure of cognitive uncertainty is $100 - X$, where X is the reported certainty.

Cognitive Ability. After the main task, and after Stage 2 in the sessions that included it, subjects solve 12 problems from the Advanced Raven's Progressive Matrices within a 15-minute limit. The task is incentivized at 250 KRW per correct answer.

Implementation Errors. At the end of the session, we measure how accurately subjects can implement a given portfolio. In each of six rounds, three Simple and three Complex, the subject is shown a target pair of state payoffs and asked to reach it as closely as possible within 30 seconds by allocating the assets. The task is not incentivized. Our measure is the average Euclidean distance between the target and the state payoffs actually implemented. Online Appendix B.1 provides a screenshot and the instructions.

The 60 main-task choices yield three further individual-level measures of choice consistency and risk attitude. We compute each separately for the 30 Simple rounds and the 30 Complex rounds.

Consistency with Utility Maximization. Afriat (1967) shows that a set of choices can be rationalized by a well-behaved utility function if and only if it satisfies the Generalized Axiom of Revealed Preference (GARP). We measure the severity of GARP violations by the Critical Cost Efficiency Index (CCEI), the largest proportional scaling of all budget constraints under which the choices satisfy GARP. The CCEI ranges from 0 to 1, with 1 indicating no violations and lower values indicating larger departures from consistency.

Risk Tolerance. Following Choi et al. (2014), we define risk tolerance (RT) as the average, across rounds, of the fraction of the budget allocated to the state with the lower state price. A value of 0.5 corresponds to equal allocation across states, as a highly risk-averse investor would choose; values near 1 indicate allocations concentrated in the cheaper state, as a risk-neutral or risk-seeking investor would choose.

Stochastic Dominance. Also following Choi et al. (2014), we augment each subject's choices with mirror-image observations, obtained by exchanging the prices and the corresponding allocations across the two states in every round, and compute the CCEI on the combined data. Because the two states are equally likely, a choice and its mirror image should be treated symmetrically by any investor who respects first-order stochastic dominance. The resulting SD Mirror score therefore measures joint consistency with GARP and first-order stochastic dominance, with higher values indicating greater consistency.

3 Theory: Portfolio Choice with Redundant Assets

This section develops a portfolio-choice model in which the decision maker's reading of the choice environment is imprecise, building on Woodford (2020) and Khaw et al. (2021). Imprecision leads her to shrink demand toward a prior benchmark, attenuating price sensitivity, and redundancy increases imprecision because recovering the relative price from more assets requires more cognitive operations. All proofs are in Online Appendix D.3.

3.1 Setup

There are two equally likely states, 1 and 2. The agent is an expected utility maximizer with CRRA utility over state-contingent consumption,

$$U(x_1, x_2) = \frac{1}{2}u(x_1) + \frac{1}{2}u(x_2), \qquad u(x) = \frac{x^{1-\rho}}{1-\rho}, \qquad \rho > 0,\ \rho \neq 1, \tag{2}$$

subject to the budget constraint $p_1 x_1 + p_2 x_2 = M$, where p_s is the price of one unit of consumption in state s.

Because the redundant assets in the Complex environment are convex combinations of the two Arrow securities at arbitrage-free prices, the Simple and Complex environments generate the same budget set (Online Appendix D.1). All decision-relevant variation is summarized by the log price ratio $q \equiv \log(p_1/p_2)$, and the agent's choice by the log demand ratio $y \equiv \log(x_1/x_2)$. Under frictionless expected utility maximization, the first-order condition gives

$$y^*(q) = -\frac{1}{\rho}q. \tag{3}$$

The frictionless demand slope with respect to the log price ratio is $-1/\rho$.

3.2 Noisy Cognition and Attenuation

The agent does not act on the true log price ratio q but on a noisy internal representation of it,

$$r = q + \varepsilon, \tag{4}$$

where ε captures imprecision in reading and interpreting the choice environment. A choice rule $y(\cdot)$ maps representations into actions and is chosen optimally subject to the constraint that the agent can condition on r but not on q:

$$\max_{y(\cdot)} \mathbb{E}\Big[\, U\Big(y(r); q\Big)\,\Big], \tag{5}$$

so that $y(r) \in \arg\max_y \mathbb{E}[\, U(y; q) \mid r\,]$ for every r.

Assumption 1 (Gaussian environment and quadratic payoff loss)**.**

(i) The log price ratio is drawn from the prior $q \sim \mathcal{N}(0, \sigma_q^2)$. Conditional on any realization of q, the representation error is drawn from $\varepsilon \sim \mathcal{N}(0, \sigma_\varepsilon^2)$, independent of q.

(ii) The utility consequence of an action is approximated to second order around the frictionless optimum,

$$U(y; q) = U(y^*(q); q) - \frac{\Gamma}{2}\Big(y - y^*(q)\Big)^2,$$

where $\Gamma > 0$ is a constant curvature parameter.

Part (i) matches the design: the distribution of log price ratios is symmetric around zero and identical across the Simple and Complex environments, so the prior is held fixed and only the representation noise can vary with redundancy. Part (ii) is the linear-quadratic-Gaussian structure standard in models of costly information processing (Sims, 2003; Gabaix, 2014) and cognitive imprecision (Woodford, 2020; Khaw et al., 2021); it makes the optimal action the posterior mean of the frictionless action.

Lemma 1 (Noisy cognition)**.** *Under Assumption 1, the solution to (5) is*

$$y(r) = -\frac{\lambda}{\rho} r, \qquad \lambda = \frac{\sigma_q^2}{\sigma_q^2 + \sigma_\varepsilon^2}. \tag{6}$$

The attenuation of the demand slope relative to the frictionless benchmark is

$$B(\sigma_\varepsilon^2) = \frac{1 - \lambda}{\rho} = \frac{1}{\rho} \frac{\sigma_\varepsilon^2}{\sigma_q^2 + \sigma_\varepsilon^2}, \tag{7}$$

which is strictly increasing in the noise σ_ε^2.

A noisier representation leads the agent to place less weight on what she reads and more on the prior, which flattens her demand response. Because $\mathbb{E}[r \mid q] = q$, the population regression of y on q has slope $-\lambda/\rho$ and intercept zero: imprecision attenuates the slope of demand but does not shift its level. Attenuation is thus the rational response to imprecision rather than a failure to optimize.

3.3 Redundancy and Representation Noise

We summarize the burden of recovering the relative price from the choice screen by the number of cognitive operations it requires, of two kinds. *Price inference* requires reading the price and returns of each asset and comparing assets to recognize which are redundant and to extract the two state prices; let $K^P(N)$ be the number of these operations with $N(\geq 2)$ assets, which is positive because at least the two Arrow securities must be read. *Payoff arithmetic* requires translating an allocation into state payoffs by combining one return-to-price ratio per asset in each state; let $K^A(N)$ be the number of these operations. The agent learns the terms of trade between states by working out what alternative allocations deliver, so both kinds of operation feed into her representation of q. The SP display performs the payoff arithmetic and nothing else, so the computational load under condition $\tau \in \{SP, NSP\}$ is

$$K_{SP}(N) = K^P(N), \qquad K_{NSP}(N) = K^P(N) + K^A(N). \tag{8}$$

Assumption 2 (Computational load)**.**

(i) $K^P(N)$ *and* $K^A(N)$ *are strictly increasing in* N*;*

(ii) $K^A(2) = 0$ *and* $K^A(N) > 0$ *for* $N \geq 3$.

Part (i) says that redundancy lengthens both computations. Moving from two to four assets doubles the prices and returns that must be read, adds the comparisons needed to recognize which assets are redundant, and adds a return-to-price ratio to every state payoff that must be evaluated. Part (ii) says that payoff arithmetic is a burden only once at least one redundant asset is present. In a Simple round each Arrow security pays in a single state, so the payoff in a state is the investment in one asset times a return-to-price ratio that can be read directly from the screen; there is nothing to combine, and the SP display adds nothing that the subject cannot see.[5] In a Complex round each state

[5] Payoff arithmetic in the sense of (8) is the combination of contributions from several assets to the same

payoff aggregates contributions from up to four assets, as in (1), and an NSP subject who considers an allocation across several assets must carry out this aggregation herself. By (8), the two parts imply $K_{SP}(2) = K_{NSP}(2) < K_{SP}(4) < K_{NSP}(4)$: the two conditions impose the same load in the Simple environment, redundancy raises the load in both conditions, and it raises it by more under NSP.

We next connect computational load to representation noise. Let $\theta^i > 0$ denote individual i's cognitive imprecision, with higher θ^i corresponding to lower processing capacity.

Lemma 2 (Capacity allocation)**.** *For an individual with cognitive imprecision θ^i, optimal allocation of capacity across $K_\tau(N)$ operations yields*

$$\sigma^2_{\varepsilon,i}(N,\tau) = K_\tau(N)^2\theta^i. \tag{9}$$

With $K_\tau(N)$ operations, the optimal allocation splits capacity equally, so each operation receives a share $1/K_\tau(N)$ and has error variance $K_\tau(N)\theta^i$. Because the operation-level errors are independent, their variances sum to $K_\tau(N)^2\theta^i$. Redundant assets add no information but spread a fixed capacity over more operations, so representation noise increases quadratically with computational load. The Online Appendix D.3 presents the operation-level allocation problem and its derivation.

Combining Lemmas 1 and 2, individual i's attenuation in environment (N,τ) is

$$B^i(N,\tau) = \frac{1}{\rho}\frac{K_\tau(N)^2\theta^i}{\sigma_q^2 + K_\tau(N)^2\theta^i}. \tag{10}$$

The central object in the experiment is the change in attenuation induced by redundancy. We define individual i's *degree of attenuation* as

$$\beta^i = B^i(4,\tau) - B^i(2,\tau), \tag{11}$$

which measures the increase in attenuation when she moves from the Simple to the Complex environment.

Proposition 1 (Redundancy-driven attenuation)**.** *Under Assumptions 1–2:*

(i) $\beta^i > 0$ *in either condition* $\tau \in \{SP, NSP\}$*;*

(ii) $\mathbb{E}[y \mid q = 0] = 0$ *in every environment and condition;*

state payoff. Implementing a chosen allocation with precision is a separate task that may be harder without the display even in Simple rounds; we measure it directly with the implementation-error task of Section 2.4, and it does not enter the representation of q.

(iii) $B^i(2, SP) = B^i(2, NSP)$ *and* $B^i(4, NSP) > B^i(4, SP)$*, and therefore* β^i *in NSP is greater than SP.*

Parts (i) and (ii) predict a flatter demand response under redundancy, with no shift in its level. Part (iii) describes the role of computational burden. In the Simple environment the SP display has nothing to remove, so price sensitivity is the same in the two conditions. In the Complex environment the display removes the payoff arithmetic, so price sensitivity is higher under SP than under NSP, and since the Simple-round benchmark is common, attenuation is larger under NSP. The display does not eliminate the effect of redundancy, because the price-inference operations $K^P(N)$, and their increase from two to four assets, are untouched: β^i in SP is smaller than β^i in NSP but strictly positive. Attenuation under SP measures the cost of recognizing redundancy and inferring state prices, and the gap between β^i in NSP and β^i in SP measures the additional cost of computing payoffs.

Proposition 2 (Heterogeneity)**.** *Under Assumptions 1–2, consider individuals* i *and* j *in the same condition* τ *with* $\theta^i > \theta^j$*.*

(i) $B^i(N, \tau) > B^j(N, \tau)$ *in every environment* (N, τ)*;*

(ii) if $B^i(4, \tau) \leq \frac{1}{2\rho}$*, then* $\beta^i > \beta^j$*.*

Lower capacity means more attenuation in every environment (part (i)), and redundancy amplifies the gap (part (ii)). Because $B^i(N, \tau)$ is bounded above by $1/\rho$, the attenuation produced by an additional unit of noise eventually declines, so part (ii) holds when attenuation is moderate, $B^i(4, \tau) \leq \frac{1}{2\rho}$, that is, when the agent retains at least half of the frictionless slope in the Complex environment. Since θ^i is unobservable, the proposition becomes testable through a proxy that the model itself supplies.

The same primitive θ^i that governs attenuation also governs how uncertain the agent is about her own optimal action. Conditional on the representation r,

$$\mathrm{Var}(y^*(q) \mid r) = \frac{1}{\rho^2} \frac{\sigma_q^2 \, \sigma_{\varepsilon,i}^2(N, \tau)}{\sigma_q^2 + \sigma_{\varepsilon,i}^2(N, \tau)}, \tag{12}$$

which, for any environment (N, τ), is strictly increasing in θ^i. Our elicitation asks subjects for the probability that their optimal decision lies within a small margin of ± 1 ECU of their actual choice, given their own preferences and the budget constraint. We interpret this elicited cognitive uncertainty (CU) as the empirical counterpart of (12): a tighter posterior implies a higher probability that the optimum falls within any fixed margin of the chosen allocation, so CU is a strictly increasing transform of $\mathrm{Var}(y^*(q) \mid r)$ and hence of θ^i.

Corollary 1 (Cognitive uncertainty)**.** *Under Assumptions 1–2, among individuals with* $B^i(4,\tau) \leq \frac{1}{2\rho}$*, individuals with greater cognitive uncertainty exhibit a larger degree of attenuation* β^i*. In particular, cognitive uncertainty measured in the Simple environment predicts* β^i*.*

A subject who reads the choice screen imprecisely will both report low confidence and exhibit a flatter demand response, for the same underlying reason, and her confidence in the Simple environment already reveals the imprecision that redundancy will amplify. Because (12) also increases in computational load, the model has two further implications for CU itself: CU should be higher in Complex than in Simple rounds within subject, since $K_\tau(4) > K_\tau(2)$, and CU in Simple rounds should not differ between the SP and NSP conditions, since $K_{SP}(2) = K_{NSP}(2)$.

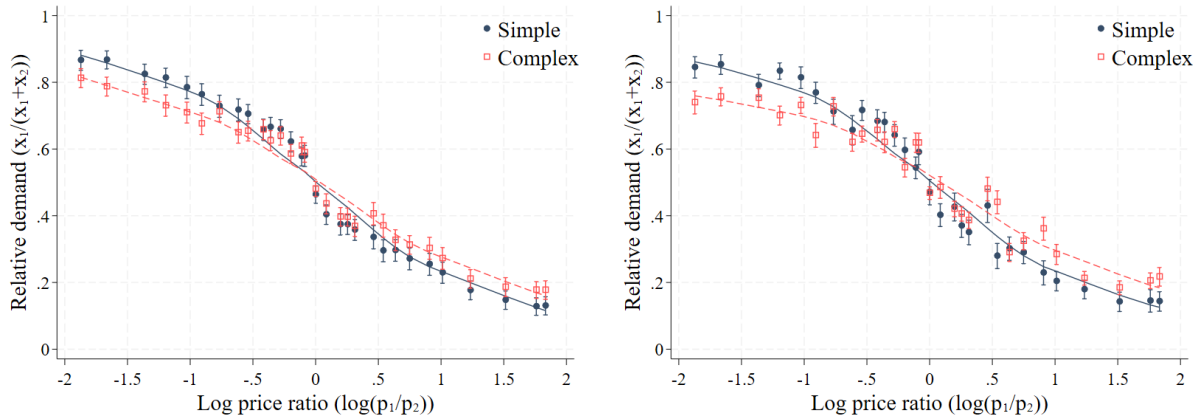
Bernheim et al. (2026) caution against reading low decision confidence as evidence that a choice could have been improved, since in lottery choices it often reflects the riskiness of the chosen option; Section 8.1 shows that the within-subject rise in cognitive uncertainty under redundancy is not accounted for by the riskiness of the chosen portfolio.

Attenuation is costly. The expected utility loss from imprecision, $\frac{\Gamma}{2}\,\mathbb{E}[\mathrm{Var}(y^*(q) \mid r)]$, increases in θ^i and in N and, under the condition in Proposition 2(ii), co-moves with β^i across individuals (Online Appendix C and D.3.6); those who attenuate most lose most from redundancy, which motivates the intervention in Stage 2.

In sum, demand share should respond less to the log price ratio in Complex than in Simple rounds in both conditions, with the reduction confined to the slope (Proposition 1(i) and (ii)). Price sensitivity should be the same across conditions in Simple rounds and lower under NSP in Complex rounds, so that attenuation is larger under NSP yet positive under SP (Proposition 1(iii)). The degree of attenuation should increase with cognitive uncertainty, including cognitive uncertainty measured in Simple rounds (Proposition 2 and Corollary 1). Cognitive uncertainty should rise within subject from Simple to Complex rounds and be equal across conditions in Simple rounds. Online Appendix E relates these predictions, and those of Section 6, to the hypotheses registered before data collection.

4 Results: Stage 1

This section tests the predictions of Section 3 using the Stage 1 data. We first examine whether redundant assets reduce price sensitivity and whether this effect differs between the SP and NSP conditions. We then examine individual differences in attenuation and their relationship with cognitive uncertainty.



(a) State Payoff (SP)

(b) No State Payoff (NSP)

Figure 2: Aggregate Demand across Log Price Ratio

Notes: This figure shows the relationship between the demand share for State 1 ($x_1/(x_1+x_2)$) and the log price ratio $\log(p_1/p_2)$. Panel (a) displays the State Payoff condition, and Panel (b) displays the No State Payoff condition. Blue dots are mean demand shares in Simple rounds and red diamonds are mean shares in Complex rounds; bars indicate 95% confidence intervals. Online Appendix F.1 reports, as a robustness check, the same figure with $\log(x_1/x_2)$ as the dependent variable.

4.1 Redundancy and Price Sensitivity

Throughout the paper, we use the demand share for State 1, $x_1/(x_1+x_2)$, as the outcome variable, rather than the log demand ratio $\log(x_1/x_2)$ on which the propositions are stated. The share is defined for every observation, whereas the log demand ratio is undefined when x_1 or x_2 is zero, which occurs in roughly 16 percent of choices. Because the demand share is a strictly increasing transformation of the log demand ratio, every sign and monotonicity prediction carries over unchanged; Online Appendix D.2 gives the mapping, and Online Appendix F.1 replicates all main results with $\log(x_1/x_2)$ after imputing the undefined values.

Figure 2 shows the average demand share for State 1 at each log price ratio, separately for Simple and Complex rounds, in the SP and NSP conditions. In both conditions, the share falls with the log price ratio, and the Complex averages lie inside the Simple averages on both sides of the log price ratio: when the redundant assets are present, subjects buy less of the cheap state and more of the expensive state. The two curves cross near log price around 0 and are close to symmetric around it. This is the pattern that Lemma 1 and Proposition 1 imply: a flatter slope with no shift in level.

To quantify the degree of attenuation, we estimate the following regression:

$$\left(\frac{x_1}{x_1+x_2}\right)_t^i = \alpha_1 \, \mathbb{1}\{\text{Complex}\}_t^i + \alpha_2 \left[\log\left(\frac{p_1}{p_2}\right)\right]_t^i + \beta \, \mathbb{1}\{\text{Complex}\}_t^i \times \left[\log\left(\frac{p_1}{p_2}\right)\right]_t^i + \delta^i + \epsilon_t^i. \tag{13}$$

where i and t index subjects and rounds, respectively, δ^i is an individual fixed effect, and $\mathbb{1}\{\text{Complex}\}$ equals one in Complex rounds and zero otherwise. The coefficient α_2 measures price sensitivity in Simple rounds, while $\alpha_2 + \beta$ measures price sensitivity in Complex rounds. Thus, β captures the change in the demand slope when redundant assets are introduced. With a negative Simple-round slope, a positive β indicates a less negative slope in Complex rounds. We refer to β as the degree of attenuation. The coefficient α_1 captures the difference in demand between the two environments when the log price ratio is zero.

The model predicts positive attenuation in both conditions and no level shift at equal state prices. It also predicts equal Simple-round price sensitivity between SP and NSP but greater attenuation in NSP. To test these differences, we interact each regressor in (13) with an indicator NSP for assignment to the NSP condition. The coefficient on $\log(p_1/p_2)\times$NSP tests the difference in Simple-round price sensitivity, while the coefficient on $\mathbb{1}\{\text{Complex}\} \times \log(p_1/p_2) \times$ NSP tests the difference in attenuation. Standard errors are clustered at the subject level throughout.

Table 1 reports the regression results. Column (1) pools the SP and NSP samples. Demand share responds strongly to log prices in the Simple environment: the coefficient on $\log(p_1/p_2)$ is -0.244 and significant at the 1 percent level. Introducing redundant assets attenuates this response. The coefficient on $\mathbb{1}\{\text{Complex}\} \times \log(p_1/p_2)$ is 0.050, also significant at the 1 percent level, so the redundancy reduces price sensitivity by 21 percent. The effect is present in both conditions. Under SP, column (2), the interaction coefficient is 0.043, an 18 percent reduction; under NSP, column (3), it is 0.058, a 24 percent reduction.

Proposition 1(ii) predicts a mean demand share of 0.5 at equal state prices in both environments. The constant in Table 1 is close to 0.5. Across columns (1) to (4), the coefficient on $\mathbb{1}\{\text{Complex}\}$ is near zero and insignificant at the 10 percent level, indicating no significant difference between Simple and Complex rounds at a log price ratio of zero.

Column (4) tests whether attenuation is greater in NSP than in SP. The coefficient on $\log(p_1/p_2) \times$ NSP is not significant at the 10% level, indicating no significant difference in Simple-round price sensitivity between the two conditions, consistent with the model's

Table 1: Redundancy and Price Sensitivity

	Dependent Variable: $x_1/(x_1+x_2)$			
	(1) Pooled	(2) SP	(3) NSP	(4) Pooled
$\mathbb{1}\{\text{Complex}\} \times \log(p_1/p_2)$	0.050^{***}	0.043^{***}	0.058^{***}	0.043^{***}
	(0.004)	(0.005)	(0.006)	(0.005)
$\mathbb{1}\{\text{Complex}\}$	0.001	-0.001	0.004	-0.001
	(0.002)	(0.003)	(0.003)	(0.003)
$\log(p_1/p_2)$	-0.244^{***}	-0.246^{***}	-0.241^{***}	-0.246^{***}
	(0.006)	(0.010)	(0.008)	(0.010)
$\mathbb{1}\{\text{Complex}\} \times \log(p_1/p_2) \times$ NSP				0.014^{*}
				(0.007)
$\mathbb{1}\{\text{Complex}\} \times$ NSP				0.005
				(0.004)
$\log(p_1/p_2) \times$ NSP				0.006
				(0.013)
Constant	0.503^{***}	0.503^{***}	0.503^{***}	0.503^{***}
	(0.001)	(0.001)	(0.002)	(0.001)
Individual Fixed Effects	Yes	Yes	Yes	Yes
Observations	18,840	9,540	9,300	18,840
Individuals	314	159	155	314
R^2	0.514	0.536	0.491	0.514

Notes: This table reports estimates of Eq. 13. Column (1) pools observations from the SP and NSP conditions. Columns (2) and (3) report results separately for the SP and NSP conditions, respectively. Column (4) adds interactions of each regressor with an indicator for the NSP condition. All specifications include individual fixed effects, and the constant is the mean of the estimated individual effects. Standard errors clustered at the subject level are reported in parentheses. Online Appendix F.1 reports a robustness check using $\log(x_1/x_2)$ as the dependent variable. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

prediction that the payoff display has nothing to remove in Simple rounds. The coefficient on $\mathbb{1}\{\text{Complex}\} \times \log(p_1/p_2) \times \text{NSP}$ is 0.014 with a p-value of 0.054: attenuation is larger when subjects must compute payoffs themselves.

In the decomposition of Section 3, attenuation under SP measures the cost of recognizing redundancy and inferring state prices, and the gap between conditions measures the additional cost of payoff arithmetic. The first component, 0.043, is about three times the second, 0.014, and significantly larger at the 1% level (F-statistic: 7.04). This interpretation relies on Assumption 2, under which the SP display removes payoff arithmetic without easing price inference.

Three further facts bear on the interpretation. First, subjects do not ignore the redundant assets. They place 44 percent of the budget in Assets C and D under SP and 50 percent under NSP (Online Appendix B.5), so attenuation arises in portfolios that use the redundant assets, not from subjects who treat a Complex round as a Simple one. Second, subjects do not use the redundant assets mechanically. A subject who divides the budget equally across the assets on the menu, the 1/N rule of Benartzi and Thaler (2001), holds an allocation that does not respond to relative prices, so adopting the rule in Complex rounds would flatten the Complex-round slope and mimic attenuation. Fewer than 2 percent of Complex-round choices place every asset within 3 ECUs of the equal split, in either condition. The two accounts differ in how they flatten the Complex-round demand curve. A 1/N heuristic flattens it by mixing: some choices sit at equal spending regardless of the prices, while the rest respond to prices as before. Noisy cognition flattens it by shrinking every choice toward the equal-payoff allocation, so each choice still moves with prices but by less (Lemma 1). The absence of equal-spending choices rules out the 1/N heuristic account and leaves the noisy-cognition account. We further discuss this in Section 8.2. Third, the results do not depend on the outcome metric. With $\log(x_1/x_2)$ as the dependent variable, the proportional reductions in price sensitivity are 22 percent under SP and 34 percent under NSP, the Complex dummy is again insignificant, and the difference in attenuation across conditions is significant at the 5 percent level (Online Appendix F.1).

To express the magnitude in preference terms, we estimate the CRRA parameter ρ by nonlinear least squares, separately for Simple and Complex rounds within each condition. Under utility maximization, the demand share is $x_1/(x_1+x_2) = \left(1+(p_1/p_2)^{1/\rho}\right)^{-1}$, and we choose ρ to minimize the mean squared distance between observed and predicted shares. Under SP, the estimate rises from 0.77 in the Simple environment to 1.04 in the Complex environment, an as-if increase of 35 percent in the CRRA coefficient. Under NSP, the estimates are 0.80 and 1.19, an as-if increase of 49 percent. Both increases are significant at the 1 percent level (F statistics: 61.4 and 79.6 under SP and NSP,

respectively). These estimates do not show that redundancy changes risk preferences. They provide a preference-based benchmark for the size of the attenuation: subjects choose under redundancy as substantially more risk-averse decision makers would, even though the opportunity set is unchanged.

Result 1 (Redundancy-driven attenuation).

(1) Introducing redundant assets reduces the response of demand share to the log price ratio by 21 percent on average, confirming Proposition 1(i). We find no statistically significant level effect, consistent with Proposition 1(ii).

(2) Price sensitivity in Simple rounds does not differ between SP and NSP, and attenuation is larger under NSP than under SP, with the difference significant at the 10 percent level, consistent with Proposition 1(iii).

4.2 Heterogeneity and Cognitive Uncertainty

Proposition 2 and Corollary 1 predict that attenuation varies across individuals and increases with cognitive uncertainty. We examine heterogeneity in price sensitivity and attenuation, and its relationship with measured cognitive uncertainty.

Cognitive uncertainty. Our measure of cognitive uncertainty in Simple rounds, CU Simple, is the subject's average report over the six Simple rounds in which it was elicited, divided by 100 so that it ranges from 0 to 1; CU Complex is the counterpart for the six Complex rounds, and CU Diff is their difference. The model has two implications for these measures themselves. Cognitive uncertainty should rise within subject from Simple to Complex rounds, and it should not differ across conditions in Simple rounds. Both hold. Mean CU Simple is 0.328 under SP and 0.332 under NSP, which are not significantly different at the 10% level ($t = 0.17$), and CU Complex is higher than CU Simple within subject, 0.388 under SP and 0.367 under NSP; the difference between Simple and Complex is significant at the 1 percent level ($t = 6.56$ in SP, $t = 4.11$ in NSP). The correlation between CU Simple and CU Complex across subjects is 0.84, so differences in reported uncertainty are largely a stable individual trait, as the model treats cognitive capacity, θ^i.[6]

In a regression, we let both price sensitivity and attenuation in (13) vary with CU

[6] Online Appendix B.6 plots average CU across log price ratios and it is relatively flat across log prices

Simple:

$$\begin{aligned}\left(\frac{x_1}{x_1+x_2}\right)_t^i = \alpha_0 + \alpha_1 \mathbb{1}\{\text{Complex}\}_t^i + \alpha_2 \left[\log\left(\frac{p_1}{p_2}\right)\right]_t^i \\ + \beta_1 \left[\log\left(\frac{p_1}{p_2}\right)\right]_t^i \times \mathbb{1}\{\text{Complex}\}_t^i \\ + \beta_2 \left[\log\left(\frac{p_1}{p_2}\right)\right]_t^i \times \text{CU}^i + \beta_3 \mathbb{1}\{\text{Complex}\}_t^i \times \text{CU}^i \\ + \gamma \left[\log\left(\frac{p_1}{p_2}\right)\right]_t^i \times \mathbb{1}\{\text{Complex}\}_t^i \times \text{CU}^i + \delta^i + \epsilon_t^i.\end{aligned} \tag{14}$$

where CU^i is CU Simple and δ^i is an individual fixed effect. Simple-round price sensitivity for a subject with uncertainty CU^i is $\alpha_2 + \beta_2 \text{CU}^i$, and her attenuation is $\beta_1 + \gamma\,\text{CU}^i$. The model predicts that subjects with higher cognitive uncertainty are less price sensitive in Simple rounds ($\beta_2 > 0$) and exhibit greater attenuation under redundancy ($\gamma > 0$). The coefficient β_3 tests whether cognitive uncertainty is associated with a shift in demand under redundancy, which the model predicts to be zero. Online Appendix F.2 reports the results using CU Complex and CU Pooled in place of CU Simple.

Table 2 reports the estimates. In the pooled sample, column (1), $\hat{\gamma}$ is 0.084 and significant at the 1 percent level. A subject at the 75th percentile of CU Simple attenuates by 0.021 more than a subject at the 25th percentile; relative to the average attenuation of 0.050 in Table 1, the interquartile range of cognitive uncertainty accounts for about 40 percent of the average effect. Columns (2) and (3) give similar estimates within SP (0.093) and NSP (0.076), each significant at the 1 percent level. The coefficient CU Simple $\times \log(p_1/p_2)$ is positive and significant in every column: moving from the 25th to the 75th percentile of CU Simple flattens the Simple-round slope by 0.028, or about 11 percent of the slope at the median. High-uncertainty subjects are therefore less price sensitive in Simple rounds and lose more sensitivity under redundancy. The coefficient CU Simple $\times$ Complex is small and insignificant throughout, so uncertainty does not significantly shift the level of demand under redundancy. In Online Appendix B.8, we divide subjects into High CU and Low CU groups based on the median of CU Simple within each condition and plot aggregate demand against the log price ratio separately for each group, as in Figure 2. We confirm that attenuation is greater in the High CU group in both the SP and NSP conditions.

Individual heterogeneity. To measure individual attenuation, we estimate Eq. (13) separately for each subject, allowing the intercept and slopes to differ across subjects. The resulting interaction coefficient, $\hat{\beta}^i$, measures individual attenuation.

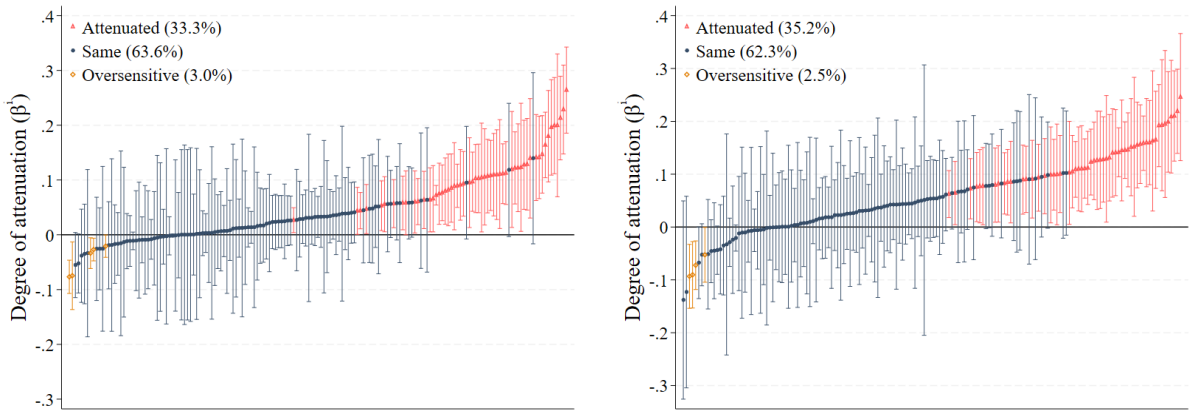
Figure 3 plots $\hat{\beta}^i$ for every subject, ordered from lowest to highest, with 95 percent

Table 2: Cognitive Uncertainty and Behavioral Attenuation

	Dependent Variable: $x_1/(x_1+x_2)$		
	(1) Pooled	(2) SP	(3) NSP
CU Simple $\times \mathbb{1}\{\text{Complex}\} \times \log(p_1/p_2)$	0.084^{***}	0.093^{***}	0.076^{***}
	(0.019)	(0.026)	(0.027)
CU Simple $\times \mathbb{1}\{\text{Complex}\}$	0.005	-0.010	0.020
	(0.011)	(0.015)	(0.017)
CU Simple $\times \log(p_1/p_2)$	0.112^{***}	0.148^{***}	0.077^{*}
	(0.032)	(0.051)	(0.041)
$\mathbb{1}\{\text{Complex}\} \times \log(p_1/p_2)$	0.023^{***}	0.015^{*}	0.033^{***}
	(0.007)	(0.008)	(0.011)
$\mathbb{1}\{\text{Complex}\}$	-0.001	0.002	-0.003
	(0.005)	(0.006)	(0.007)
$\log(p_1/p_2)$	-0.280^{***}	-0.295^{***}	-0.266^{***}
	(0.013)	(0.019)	(0.017)
Constant	0.503^{***}	0.503^{***}	0.503^{***}
	(0.001)	(0.002)	(0.002)
Individual Fixed Effects	Yes	Yes	Yes
Observations	18,840	9,540	9,300
Individuals	314	159	155
R^2	0.524	0.551	0.497

Notes: This table reports estimates of Eq. (14). Column (1) pools observations from the SP and NSP conditions. Columns (2) and (3) report results separately for the SP and NSP conditions. CU Simple is the subject's average cognitive uncertainty over the six Simple rounds in which it was elicited, divided by 100, and ranges from 0 to 1. Online Appendix F.2 reports the results using CU Complex and CU Pooled as alternative measures. All specifications include individual fixed effects, and the constant is the mean of the estimated individual effects. Standard errors clustered at the subject level are reported in parentheses. Online Appendix F.1 reports a robustness check using $\log(x_1/x_2)$ as the dependent variable. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

confidence intervals, for the SP and NSP conditions. We classify subjects into three groups. The *attenuated* group has $\hat{\beta}^i > 0$ with significance at the 5 percent level and is shown in red; the *oversensitive* group has $\hat{\beta}^i < 0$ with significance at the 5 percent level and is shown in yellow; the remaining *same* group, in blue, shows no significant difference between Simple and Complex rounds. The estimate is positive for 75 percent of subjects under SP and 80 percent under NSP. The attenuated group comprises 33.3 percent of subjects under SP and 35.2 percent under NSP, so the share of subjects with significant attenuation does not depend on computational burden. The oversensitive group is about 3 percent in each condition, and more than 60 percent of subjects fall in the same group. Online Appendix B.3 shows examples of each type.



(a) State Payoff (SP)

(b) No State Payoff (NSP)

Figure 3: Individual Heterogeneity in Attenuation

Notes: This figure shows the individual coefficients $\hat{\beta}^i$ from estimating Eq. (13) separately for each subject. Panel (a) presents the State Payoff condition, and Panel (b) presents the No State Payoff condition. Each point is an individual estimate, and the bars indicate 95% confidence intervals. Red denotes the attenuated group, yellow the oversensitive group, and blue the same group. Online Appendix F.1 reports the same figure with $\hat{\beta}^i$ estimated from $\log(x_1/x_2)$.

The magnitude of attenuation also places the typical subject in the region where Proposition 2(ii) assumes. Complex-round price sensitivity is on average 79 percent of Simple-round sensitivity, so a subject retains at least half of the frictionless slope in the Complex environment unless the Simple environment already removes more than a third of it.

Correlates of individual attenuation. We now examine whether cognitive uncertainty remains associated with individual attenuation after controlling for other char-

acteristics that may affect investment choices. These controls capture cognitive ability (CA), implementation error (IE), choice consistency (CCEI and SD Mirror), and risk tolerance (RT), as defined in Section 2.4. We also assess their relative contributions to the explained variation in $\hat{\beta}^i$.

For CCEI, RT, and SD Mirror, we use only the Simple-round measures as baseline controls, since their Complex-round counterparts may themselves reflect attenuation. Online Appendix B.4 reports full descriptive statistics. We estimate

$$\hat{\beta}^i = \alpha_0 + \alpha_1 \,\text{CU Simple}^i + \alpha_2 \,\text{CU Diff}^i + \mathrm{X}^{i\prime}\alpha + \epsilon^i, \tag{15}$$

The controls X^i include CA, the implementation error, risk tolerance, choice consistency, gender, age, and indicators for STEM and business or economics majors. Columns (3) and (4) additionally include CCEI Simple, RT Simple, and SD Mirror Simple.

To compare the relative importance of these variables, we compute a Shapley decomposition of the regression's R^2. This averages each variable's additional explanatory power across all possible orders of inclusion. The contributions are reported as percentages of the explained variation and sum to 100 percent in each column.

Table 3 reports the estimates. CU Simple is positively and significantly associated with $\hat{\beta}^i$ in every column. In columns (1) and (2), a 0.1 increase in CU Simple is associated with 0.009 greater attenuation under SP and 0.007 under NSP. CU Simple and CU Diff together account for 59 and 62 percent of the explained variation, respectively. In columns (3) and (4), which add the Simple-round choice measures, the coefficient on CU Simple is unchanged or larger. The two uncertainty measures still account for 45 and 33 percent of the explained variation, respectively, more than any other variable.

CU Diff is significant only in column (3). The within-subject rise in uncertainty is less informative than its level, which is what the model implies: the level reveals θ^i, whereas the rise reflects the common increase in load that all subjects face.

Cognitive ability, implementation error, and demographics are not significantly associated with attenuation in columns (1) and (2) and contribute little to the explained variation. IE Diff becomes significant in columns (3) and (4), with opposite signs across conditions. Among the choice measures, RT Simple has the largest coefficient and accounts for 19 and 30 percent of the explained variation. Subjects who are less risk averse in Simple rounds, and therefore have steeper Simple-round demand, lose more slope under redundancy. The model predicts this association. By (11), β^i is the product of $1/\rho$ and a term that depends only on θ^i and the computational load, so for a given θ^i a less risk-averse subject has a steeper frictionless slope and loses more of it under redundancy. Risk tolerance therefore scales attenuation without being a source of it, and its coefficient

Table 3: Factors Explaining Heterogeneity in Attenuation

	Dependent variable: $\hat{\beta}_i$							
	SP		NSP		SP		NSP	
	(1)		(2)		(3)		(4)	
	Coef.	Shapley	Coef.	Shapley	Coef.	Shapley	Coef.	Shapley
CU Simple	0.091***	53.1	0.072**	39.6	0.110***	39.1	0.080**	21.8
	(0.029)		(0.030)		(0.031)		(0.031)	
CU Diff	0.060	6.3	−0.072	22.5	0.087**	6.2	−0.073	10.9
	(0.041)		(0.052)		(0.039)		(0.056)	
CA	−0.018	4.2	0.022	2.2	−0.023	2.7	−0.014	0.6
	(0.029)		(0.037)		(0.028)		(0.035)	
IE Simple	0.002	6.5	0.016	7.0	−0.001	3.6	0.020*	5.1
	(0.006)		(0.011)		(0.006)		(0.010)	
IE Diff	−0.009	15.6	0.017	9.0	−0.011**	10.3	0.021**	5.9
	(0.006)		(0.010)		(0.005)		(0.010)	
RT Simple					0.129***	18.9	0.182***	29.6
					(0.036)		(0.057)	
SD Mirror Simple					−0.090	5.9	0.089**	9.1
					(0.057)		(0.040)	
CCEI Simple					0.070	1.8	−0.075	3.5
					(0.081)		(0.048)	
Demographics	Yes	14.4	Yes	19.6	Yes	11.5	Yes	13.5
Constant	0.065		0.042		−0.021		−0.056	
	(0.050)		(0.062)		(0.070)		(0.071)	
Observations	159		155		159		155	
R-squared	0.147		0.103		0.237		0.207	

Notes: This table reports estimates of Eq. (15). The dependent variable is individual-level attenuation, $\hat{\beta}^i$, estimated from Eq. (13) separately for each subject. Columns (1) and (2) include measures not directly constructed from investment choices. Columns (3) and (4) additionally include measures constructed from Simple-round choices. For each variable, the Coef. column reports the coefficient with heteroskedasticity-robust standard errors in parentheses, and the Shapley column reports the Shapley value as a percentage of explained variation. Demographics include age, gender, and indicators for STEM and business or economics majors. Online Appendix F.1 reports a robustness check using $\log(x_1/x_2)$ estimating $\hat{\beta}^i$. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

in Table 3 does not compete with cognitive uncertainty as an explanation. Part of the association may also be mechanical: a subject whose Simple-round slope is overestimated by sampling error will display both a high RT Simple and a high $\hat{\beta}^i$, since $\hat{\beta}^i$ is the difference between her Complex and Simple slopes. The coefficient on CU Simple is not subject to the mechanical concern, because CU Simple is elicited rather than constructed from choices.

Result 2 (Heterogeneity and cognitive uncertainty).

(1) Cognitive uncertainty elicited in Simple rounds predicts attenuation under redundancy. Higher cognitive uncertainty predicts greater attenuation in Complex rounds, consistent with Proposition 2 and Corollary 1.

(2) Attenuation is heterogeneous and systematic: about one third of subjects exhibit statistically significant attenuation at the individual level in both conditions.

(3) The cognitive uncertainty measures jointly account for the largest share of explained variation in individual attenuation

We further connect this heterogeneity in attenuation to potential welfare loss. In Online Appendix C, we convert each subject's Complex-round choices into certainty equivalents evaluated at her Simple-round preferences. The attenuated group incurs a welfare loss of about 4 percent of the budget, whereas the remaining subjects incur essentially none, and a 0.1 increase in $\hat{\beta}^i$ is associated with a 3 to 4 percentage point larger loss. Those who attenuate most lose most, which motivates the corrective intervention of Stage 2.

5 Stage 2 Experiment: Social Information

Stage 1 establishes that redundancy attenuates price sensitivity and that the effect is concentrated among subjects who are uncertain about their own optimum. Stage 2 asks whether this distortion can be corrected. If attenuation reflects a noisy reading of the environment rather than a change in preferences, then a signal about what the optimal action looks like should sharpen the reading and reduce attenuation. Observing the choices of others is a natural candidate for such a signal: it is cheap to provide, widely used as a behavioral intervention (Thaler and Sunstein, 2009), and because a subject's payoff does not depend on what others do, it can matter only as information about the problem itself (Banerjee, 1992; Bikhchandani et al., 1992). Its usefulness, however, should depend on what it conveys. A display of price-sensitive behavior gives an attenuated subject something to move toward, whereas a display of attenuated behavior does not.

Stage 2 therefore varies the behavioral content of the social information while holding everything else about the decision fixed.

Procedure. Stage 2 experiment was run in the last 11 of the 17 sessions, immediately after the Stage 1 main task and before the measures of cognitive ability and implementation error. The 219 subjects in these sessions, 112 in SP and 107 in NSP, took part. The 95 subjects from the first six sessions, 47 in SP and 48 in NSP, did not; their Stage 1 decisions were used to construct the social information shown to later participants, so every display reports the actual average behavior of previous participants.

Each subject plays four rounds, two Simple and two Complex, drawn from the 60 rounds she completed in Stage 1. The two Simple rounds are the ones with extreme log price ratios, $\log(p_1/p_2) = 1.76$ and -1.67, and the two Complex rounds are their counterparts at the same price ratios. We use the extreme prices because attenuation is a difference in slopes, and the gap between an attenuated and an unattenuated allocation is widest there; the two prices in each environment identify a subject's slope in that environment. The decision problem is identical to Stage 1 in every respect but one: the screen includes a row labeled "Others' choice" that reports the average investment in each asset among a group of previous participants. Subjects are told that the row summarizes how dozens of participants in a previous experiment chose on average; they are not told how these participants were selected. To reduce the chance that subjects simply recall their earlier choice, asset labels are re-randomized in Stage 2. Payment follows the Stage 1 rule, with one round selected at random from the 64 rounds a subject has played, so the four Stage 2 rounds are incentivized in the same way as the rest. The full instructions are in Online Appendix A.

Because each Stage 2 round repeats a Stage 1 round at the same prices, the design yields a within-subject measure of the effect of social information: the change in a subject's attenuation between her original decision and her decision after observing the display.

Treatments. Subjects are randomly assigned to one of two treatments that differ only in which previous participants the display averages over. The assignment is made within each SP and NSP condition, and each display is built from previous participants in the same condition, so each treatment is observed under both levels of computational burden and every subject sees the behavior of participants who faced the same screen she faces.

Attenuated Information. The display averages the choices of previous participants in the *attenuated* group of Section 4.2, those whose individual degree of attenuation $\hat{\beta}^i$

was positive and significantly different from zero at the 5 percent level. By construction, the displayed behavior is less price-sensitive in the Complex rounds than in the Simple rounds.

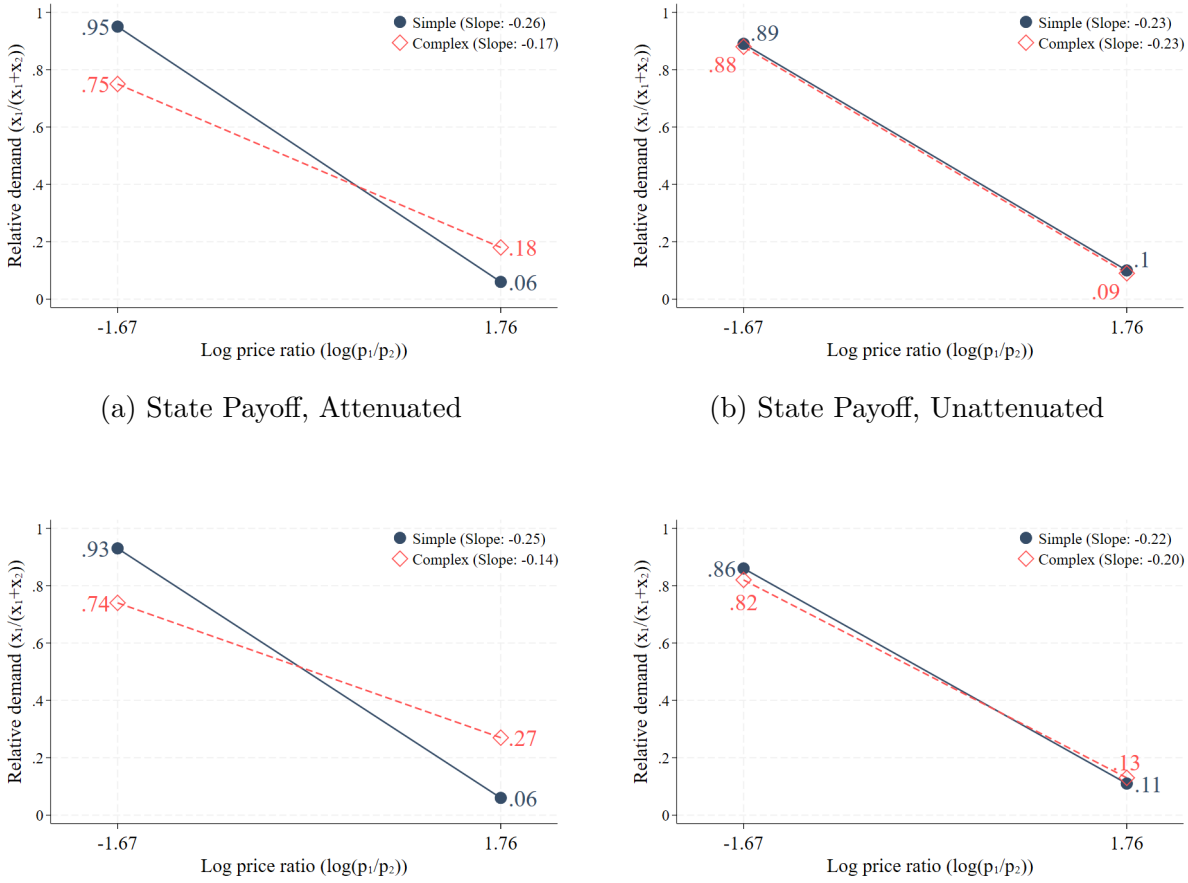
Unattenuated Information. The display averages the choices of previous participants in the *same* group of Section 4.2, those whose $\hat{\beta}^i$ was not significantly different from zero. By construction, the displayed behavior has similar price sensitivity in the Complex and Simple rounds.

Figure 4 shows the content of the four displays, plotting the demand share for State 1 implied by each display against the log price ratio, with circles for Simple rounds and diamonds for Complex rounds. Under Attenuated Information, the displayed demand is markedly flatter in Complex than in Simple rounds: the slopes are -0.26 and -0.17 in the SP condition (panel (a)) and -0.25 and -0.14 in the NSP condition (panel (c)). Under Unattenuated Information, the Simple and Complex slopes are close to each other in both conditions (panels (b) and (d)). In Complex rounds, the unattenuated display is therefore more price-sensitive than the attenuated one, which is the ordering the model of Section 6 relies on. The two treatments thus present subjects with the same kind of information, an average of real previous choices at the same prices, differing only in whether that average is itself attenuated.

Two features of the design are worth emphasizing before turning to the model. First, the social information is truthful in both treatments: no display is fabricated, the two treatments differ only in the selection of participants whose behavior is averaged, and subjects are unaware of that selection, so they have no reason to trust one display more than the other. Second, the treatments are not a comparison of information against no information. Every Stage 2 subject receives social information, and her own Stage 1 decisions at the same prices serve as the no-information baseline. We compare the effects of Attenuated and Unattenuated Information and examine how these effects vary across subjects.

6 Theory: Social Information

We extend the model of Section 3 to the Stage 2 environment by treating the displayed behavior of previous participants as a second signal about the optimal action, which the agent combines with her own noisy representation of the problem by Bayesian updating. Because the setting is non-strategic, the display affects behavior only through what it reveals about the optimum.



(a) State Payoff, Attenuated

(b) State Payoff, Unattenuated

(c) No State Payoff, Attenuated

(d) No State Payoff, Unattenuated

Figure 4: Summary of Social Information Treatments

Notes: This figure plots the demand share for State 1 implied by each display, $x_1/(x_1 + x_2)$, against the log price ratio $\log(p_1/p_2)$. Circles are Simple rounds and diamonds are Complex rounds, and the line through each pair gives the price sensitivity of the displayed behavior in that environment. Panels (a) and (b) show the State Payoff condition and panels (c) and (d) the No State Payoff condition.

6.1 The Display

The social information in treatment $S \in \{\text{Attenuated}, \text{Unattenuated}\}$ reports the average choice of a group of previous participants selected on their own Stage 1 attenuation. Let $d^S(N)$ denote the log demand ratio implied by the display in the environment with $N \in \{2, 4\}$ assets, and let $-\pi^S(N)/\rho$ denote its slope with respect to the log price ratio. Because the display averages Stage 1 choices at the prices the subject faces, the displayed quantity is a deterministic function of q,

$$d^S(N) = -\frac{\pi^S(N)}{\rho}\, q. \tag{16}$$

It is external to the subject: it does not depend on her own representation error, and its conditional mean given q is $-\pi^S(N)q/\rho$, which equals the frictionless action $y^*(q)$ only when $\pi^S(N) = 1$. In analogy with β^i in (11), define the *attenuation content* of the display as

$$\beta^S \equiv \frac{\pi^S(2) - \pi^S(4)}{\rho}, \tag{17}$$

which is the amount by which the displayed behavior is less price-sensitive in the Complex environment than in the Simple one. Let U and A denote the Unattenuated and Attenuated treatments. To capture the treatment distinction, we assume $\pi^U(2) = \pi^U(4) \equiv \pi^U$ and $\pi^A(2) > \pi^A(4)$, with $\pi^A(4) \leq \pi^U$: in Complex rounds, the attenuated display is no more price-sensitive than the unattenuated one. Thus, $\beta^U = 0$ and $\beta^A > 0$. The displays in Figure 4 closely match these properties.

6.2 Perception and Use of the Display

We now model how cognitively imprecise agents use this social information.

Assumption 3 (Perceived social signal)**.** *The agent treats the display as an unbiased signal about her frictionless optimal action $y^*(q) = -q/\rho$. Under her subjective model,*

$$d^S(N) \,\big|\, q \;\sim\; \mathcal{N}(y^*(q),\, 1/h)\,, \tag{18}$$

with the error in the signal independent of q and of her own representation error ε. The parameter $h > 0$ is the perceived precision of the social information.

Assumption 3 describes the agent's perception, not the construction of the display. By (16), the display is in fact an attenuated function of q whenever $\pi^S(N) < 1$, and under Attenuated Information it is more attenuated in Complex than in Simple rounds. Subjects do not know how the participants generating the displayed choices were selected,

so they have no basis for discounting one display relative to the other; this is why we take h to be common across treatments, and it is what allows β^S to differ from zero without subjects adjusting for it.

Individual i now conditions on two signals, her internal representation r and the displayed behavior $d^S(N)$. Under the quadratic approximation of Assumption 1, Bayesian updating gives the following choice rule.

Lemma 3 (Optimal use of social information)**.** *Under Assumptions 1 and 3, in an environment with $N \in \{2, 4\}$ assets, the optimal choice is*

$$y = w^i(N)\left(-\frac{\lambda^i(N)}{\rho}r\right) + \big(1 - w^i(N)\big)\, d^S(N), \qquad w^i(N) = \frac{1}{1 + h\,\mathrm{Var}(y^*(q) \mid r)}, \quad (19)$$

where $\lambda^i(N)$ is the shrinkage factor from Lemma 1 in environment N.

The agent's action is a precision-weighted average of what she would have chosen on her own and what the display shows. The weight on the display, $1 - w^i(N)$, increases with her posterior uncertainty, which in turn increases with cognitive imprecision θ^i by (12). Thus, subjects who read the environment less precisely place more weight on social information. The weight does not depend on the treatment, because h is common, but it does depend on the environment: by Assumption 2, representation noise and hence posterior variance are greater in the Complex environment, so $w^i(4) < w^i(2)$ and the same subject places more weight on the display in Complex than in Simple rounds. The change in attenuation therefore depends on the display's attenuation content and on this difference in weights.

6.3 Predictions

The empirical object in Stage 2 is the change in a subject's attenuation once she sees the display. Let $\beta^i_{\text{Baseline}}$ denote individual i's degree of attenuation in her Stage 1 decisions at the four Stage 2 price ratios, and β^i_{Social} the corresponding measure from her Stage 2 decisions. In the model, $\beta^i_{\text{Baseline}}$ is the β^i of (11), which by Lemma 1 equals $(\lambda^i(2) - \lambda^i(4))/\rho$. Define

$$\Delta\beta^i \equiv \beta^i_{\text{Social}} - \beta^i_{\text{Baseline}}. \quad (20)$$

Proposition 3 (Effect of social information)**.** *Under Assumptions 1–3,*

$$\Delta\beta^i = (1 - w^i(2))\Big(\beta^S - \beta^i_{\text{Baseline}}\Big) + \frac{w^i(2) - w^i(4)}{\rho}\Big(\lambda^i(4) - \pi^S(4)\Big). \quad (21)$$

Consequently:

(i) Under Unattenuated Information, $\Delta\beta^i < 0$ for every subject whose Complex-round baseline choice is no more price-sensitive than the display, $\lambda^i(4) \leq \pi^U$.

(ii) For every subject, Attenuated Information produces a smaller reduction in attenuation than Unattenuated Information.

The first term in (21) pulls the subject's attenuation toward that of the display, by a fraction $1 - w^i(2)$ of the gap. The second term arises because she leans on the display more in Complex rounds: her Complex-round slope moves toward the display's by more than her Simple-round slope does, which reduces attenuation when the display's Complex-round behavior is more price-sensitive than her own, $\pi^S(4) > \lambda^i(4)$, and raises it otherwise. Under Unattenuated Information, $\beta^U = 0$, so the first term is negative for every attenuated subject and the second reinforces it under the condition in part (i). For a given subject, Attenuated Information produces a smaller reduction on both counts: its attenuation content is positive, and its Complex-round display is less price-sensitive (part (ii)). Because each subject sees a single display, part (ii) is tested across subjects: with random assignment to treatment, the pointwise inequality implies that the average reduction in attenuation is smaller under Attenuated than under Unattenuated Information.

Equation (21) also describes the individual-level response. The second term does not involve the gap $\beta^S - \beta^i_{\text{Baseline}}$, so $\Delta\beta^i$ is linear in the gap with slope $1 - w^i(2)$, the weight the subject places on the display. By Lemma 3, this slope lies strictly between zero and one, is the same under Attenuated and Unattenuated Information because h is common, and increases in θ^i. Subjects in the two treatments therefore lie on one line, on opposite sides of zero: a subject more attenuated than the display becomes less attenuated and one less attenuated than it becomes more so. Under Attenuated Information these movements offset in the aggregate, which is why one mechanism predicts a large average effect in the Unattenuated arm and a small one in the Attenuated arm.

The model also predicts who responds most to corrective information.

Proposition 4 (Heterogeneous correction)**.** *Under Assumptions 1–3, let H and L be two individuals in the same condition with $\theta^H > \theta^L$ and $B^H(4, \tau) \leq \frac{1}{2\rho}$. If $\pi^U \geq \lambda^L(4)$, then under Unattenuated Information,*

$$\Delta\beta^H < \Delta\beta^L < 0.$$

Individuals with greater cognitive imprecision respond more strongly to Unattenuated Information for two reinforcing reasons. They begin with greater attenuation and so have more room for correction (Proposition 2(ii)), and their noisier representation leads them

to place more weight on the display (Lemma 3). The condition $\pi^U \geq \lambda^L(4)$ requires the Unattenuated display to be at least as price-sensitive in Complex rounds as the less imprecise of the two recipients.[7] As in Stage 1, θ^i is not observable, but cognitive uncertainty is increasing in it, so the testable form of Proposition 4 is that the corrective effect of Unattenuated Information, $|\Delta\beta^i|$, is larger among subjects with higher cognitive uncertainty.

In sum, Unattenuated Information should reduce attenuation for subjects whose Complex-round baseline choices are no more price-sensitive than the display, and the average reduction should be smaller under Attenuated Information (Proposition 3); the change in attenuation should increase in the gap between the display's attenuation and the subject's own, with a slope between zero and one that is common to the two treatments and larger for subjects with higher cognitive uncertainty (equation (21)); and the correction under Unattenuated Information should be larger among subjects with higher cognitive uncertainty (Proposition 4). The registry anticipated the two arms of Stage 2 but not these directional predictions, which should be read as theory-guided rather than pre-registered tests (Online Appendix E).

7 Results: Stage 2

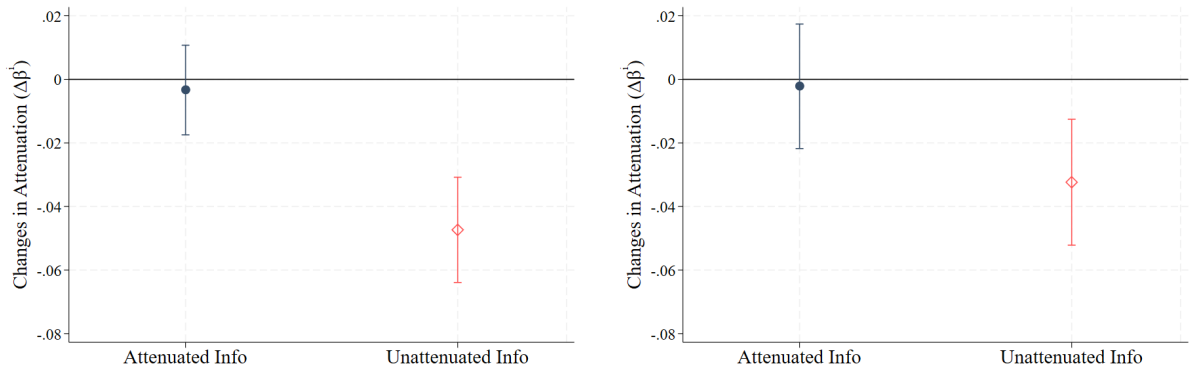
This section tests Propositions 3 and 4. Because each Stage 2 round repeats a Stage 1 round at the same prices, a subject's own Stage 1 choices provide her no-information baseline, and the effect of social information is measured within subject.

We estimate $\hat{\beta}^i_{\text{Baseline}}$ by applying the individual-level regression in Eq. (13) to a subject's four Stage 1 rounds at the Stage 2 price ratios, and $\hat{\beta}^i_{\text{Social}}$ by applying it to her four Stage 2 rounds. With two price ratios per environment, each estimate is the difference between her Complex-round and Simple-round slopes, each slope computed from two choices. The empirical counterpart of Eq. (20) is $\Delta\hat{\beta}^i = \hat{\beta}^i_{\text{Social}} - \hat{\beta}^i_{\text{Baseline}}$; a negative value means that the display reduced the subject's attenuation.

7.1 Effect of Social Information

Figure 5 reports the average $\Delta\hat{\beta}^i$ by treatment, with 95 percent confidence intervals, under SP (panel (a)) and NSP (panel (b)). Unattenuated Information reduces attenuation by 0.044 under SP and 0.036 under NSP; relative to the average baseline attenuation of 0.060, these are reductions of 73 and 60 percent. Attenuated Information produces no significant change in either condition, and its effect differs significantly from that

[7] Section 7 reports how often it holds in the data.



(a) State Payoff (SP)

(b) No State Payoff (NSP)

Figure 5: Average Treatment Effect of Social Information

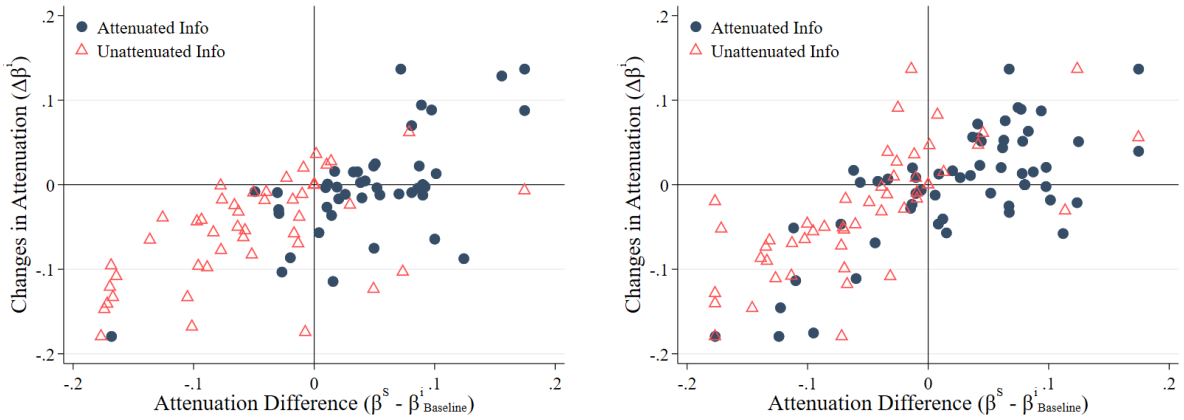
Notes: This figure shows the average change in the degree of attenuation, $\Delta\hat{\beta}^i$, under Attenuated and Unattenuated Information, with 95% confidence intervals. Panel (a) shows the State Payoff condition and panel (b) the No State Payoff condition. Online Appendix F.1 reports a robustness check using $\log(x_1/x_2)$ to estimate $\Delta\beta^i$.

of Unattenuated Information at the 5% level ($t = 3.96$ under SP and $t = 2.12$ under NSP). Proposition 3(i) predicts a reduction for subjects whose Complex-round baseline choice is no more price-sensitive than the unattenuated display, $\lambda^i(4) \leq \pi^U$. Comparing each subject's Complex-round baseline slope with the slope of the display she saw, the condition holds for 67 percent of subjects in the Unattenuated Information.

Equation (21) predicts that $\Delta\hat{\beta}^i$ increases in the gap between the attenuation content of the display a subject saw and her own baseline attenuation, $\hat{\beta}^S - \hat{\beta}^i_{\text{Baseline}}$, where $\hat{\beta}^S$ is computed from the displayed allocations in the same way as $\hat{\beta}^i_{\text{Baseline}}$, with a slope between zero and one that is common to the two treatments. Figure 6 plots the two. Subjects in the Attenuated arm (blue circles) lie mostly to the right of zero, because the display is more attenuated than their own baseline, and subjects in the Unattenuated arm (red triangles) lie to the left. The two variables have the same sign for 77 percent of subjects under SP and 78 percent under NSP. Their correlation is 0.64 in the Attenuated arm and 0.62 in the Unattenuated arm under SP, and 0.71 and 0.72 under NSP; in neither condition do the two correlations differ significantly (Fisher z-test: $p = 0.823$ under SP and $p = 0.984$ under NSP), as Equation (21) implies when the perceived precision h is common to the two displays.

Result 3 (Effect of social information).

(1) Unattenuated Information reduces attenuation by 60 to 73 percent of its baseline



(a) State Payoff (SP)

(b) No State Payoff (NSP)

Figure 6: Individual-level Effect of Social Information

Notes: This figure shows the individual-level effect of Attenuated and Unattenuated information under the State Payoff and No State Payoff conditions. On the X-axis, we have the attenuation difference defined as $\beta^S - \beta^i_{\text{Baseline}}$. On the Y-axis, we have the change in the degree of attenuation ($\Delta\beta^i$). Each dot represents an individual who participated in the experiment. Online Appendix F.1 reports a robustness check using $\log(x_1/x_2)$ to estimate both the X- and Y-axes.

level in both conditions, consistent with Proposition 3(i).

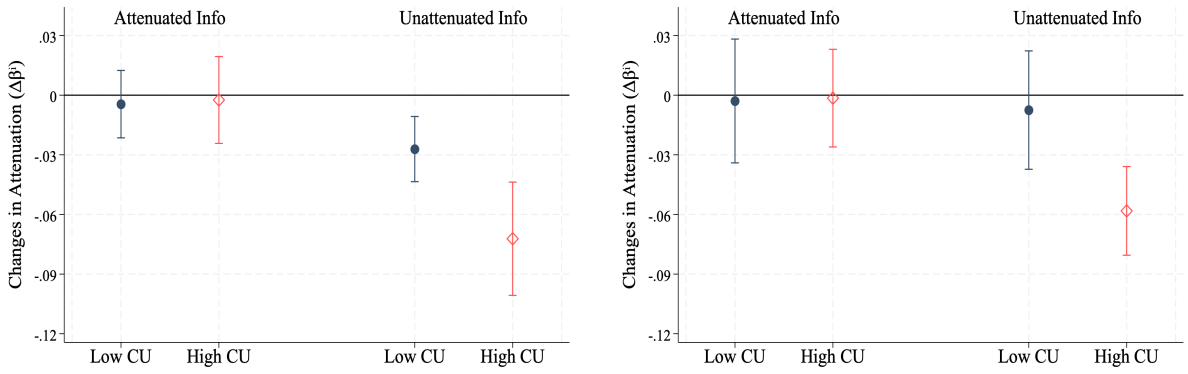
(2) Attenuated Information produces no significant average change, and its effect is smaller than that of Unattenuated Information, consistent with Proposition 3(ii).

(3) At the individual level, the change in attenuation is positively correlated with the gap between the display's attenuation and the subject's own, and the correlation does not differ significantly between the two treatments, consistent with Equation (21).

7.2 Heterogeneity by Cognitive Uncertainty

Proposition 4 predicts that subjects with greater cognitive imprecision respond more to Unattenuated Information, with cognitive uncertainty as the observable proxy. In Figure 7, we split subjects into High CU and Low CU groups at the median of CU Simple and compute the average $\Delta\hat{\beta}^i$ in each group by treatment and condition.

Under Attenuated Information, neither group shows a significant change in either condition. Under Unattenuated Information, the correction is concentrated among High CU subjects. In the SP condition, attenuation falls by 0.027 in the Low CU group and by 0.072 in the High CU group; both changes are significant, and the difference between the



(a) State Payoff (SP)

(b) No State Payoff (NSP)

Figure 7: Heterogeneous Treatment Effect across Cognitive Uncertainty

Notes: This figure shows the average change in the degree of attenuation, $\Delta\hat{\beta}^i$, by treatment, separately for subjects below (Low CU; blue dots) and above (High CU; red diamonds) the median of cognitive uncertainty in Simple rounds, with 95% confidence intervals. Panel (a) shows the State Payoff condition and panel (b) the No State Payoff condition. Online Appendix F.1 reports a robustness check using $\log(x_1/x_2)$ to estimate $\Delta\beta^i$.

groups is significant at the 1% level (t-statistic: 2.79). In the NSP condition, the High CU group reduces attenuation by 0.058, whereas the change in the Low CU group, -0.008, is not significantly different from zero (t-statistic: -0.49). Proposition 4 attributes the larger correction to two channels: a larger baseline attenuation and a larger weight on the display. The first is visible directly: High CU subjects attenuate more at baseline (Table 2). In Online Appendix B.9, we provide evidence for the second channel: after controlling for Stage 1 choices, High CU subjects respond more strongly to displayed allocations. We also report how the treatment effect varies continuously with CU in Online Appendix B.7.

Result 4 (Heterogeneous correction).

(1) The correction under Unattenuated Information is more than twice as large among High CU as among Low CU subjects under SP, and significant only among High CU subjects under NSP, consistent with Proposition 4; High CU subjects both have more attenuation to correct and place more weight on the display.

(2) Under Attenuated Information, neither group changes significantly in either condition.

Cognitive uncertainty measured in Simple rounds thus helps identify both subjects

whose price responses are more affected by redundancy and those who benefit more from Unattenuated Information.

8 Discussion

Our findings show that redundant assets affect portfolio choice even when the feasible set, information, and optimum remain unchanged. Cognitive uncertainty helps identify both who is most affected by redundancy and who benefits most from corrective information. We discuss the interpretation of cognitive uncertainty and consider alternative explanations for these findings.

8.1 Interpreting Cognitive Uncertainty

Bernheim et al. (2026) and Enke and Graeber (2026) have recently discussed the interpretation of cognitive uncertainty. Bernheim et al. (2026) suggest that subjects may report uncertainty about the payoff they will receive rather than about whether they have made the best decision. Enke and Graeber (2026) reply that outcome uncertainty is one reason a decision is hard rather than a different object: cognitive uncertainty rises with the strength of the tradeoff a decision requires, and the dispersion of outcomes is one source of that tradeoff. Under the outcome-uncertainty interpretation, cognitive uncertainty is a function of the payoff dispersion of the chosen portfolio and does not depend on the environment in which the portfolio was chosen. Our design separates the two because the same budget sets appear in both environments and the chosen portfolio is observed.

The central result is the within-subject effect of redundancy on cognitive uncertainty conditional on the chosen portfolio. Online Appendix G.1 regresses the 12 cognitive uncertainty reports per subject on an indicator for Complex rounds, the riskiness of the chosen portfolio, $|x_1 - x_2|/(x_1 + x_2)$, an indicator for corner allocations, individual fixed effects, and log price ratio fixed effects with riskiness entered linearly or quadratically (Table G.1 in Online Appendix G.1). The Complex coefficient is around 0.06 under SP and 0.04 under NSP and is significant at the 1 percent level (Average CU Simple is around 0.33 for both SP and NSP). Redundancy raises cognitive uncertainty within the subject even though, at the same budget set, the subject's Complex-round portfolio has, on average, 20.5% lower riskiness than her own Simple-round portfolio (Simple: 0.51; Complex: 0.40). Under the outcome-uncertainty interpretation, a safer portfolio should come with lower cognitive uncertainty. The result is inconsistent with that interpretation and is consistent with what our model predicts.

Figure G.1 in Online Appendix G.1 plots the relationship between cognitive uncer-

tainty and the ex-post riskiness of the chosen portfolio. Cognitive uncertainty is lowest at corner allocations, where payoff variance is maximal. Within the interior, cognitive uncertainty rises from the equal-payoff allocation, peaks at intermediate riskiness, and falls toward the corners. The interior rise is consistent with the outcome-uncertainty interpretation, but equally with the tradeoff interpretation, under which difficulty increases with the dissimilarity of state payoffs; it therefore does not discriminate between the two. The overall shape matches Enke and Graeber (2023), where cognitive uncertainty is lowest at degenerate lotteries and highest where the tradeoff is most pronounced.

The within-subject result holds under both SP and NSP. We conclude that cognitive uncertainty in our setting measures what the elicitation asks: uncertainty about the best decision rather than about the realized payoff. The Complex-round allocations are also improvable in the sense of Bernheim et al. (2026): a planner who knew the subject's Simple-round preferences would allocate differently, and Section 7 shows that information alone moves subjects toward that allocation.

8.2 1/N Allocation Rule

A widely documented investment heuristic is the 1/N allocation rule, under which the investor divides the budget equally across the assets on the menu, regardless of their returns or prices (Benartzi and Thaler, 2001; Huberman and Jiang, 2006; DeMiguel et al., 2009; Gathergood et al., 2023). The rule is an alternative explanation for attenuation. An equal split does not respond to relative prices; therefore, its estimated slope falls, even if no subject reads the environment less precisely. We examine the proportion of subjects who follow the 1/N allocation rule. In our experiment, the Simple condition includes two assets, so the 1/N rule implies allocating 50 ECUs to each asset. The Complex condition includes four assets, so the rule implies allocating 25 ECUs to each asset.

To allow for small deviations from the exact 1/N allocation, we classify a choice as consistent with the rule if every asset receives an amount within δ ECUs of the equal split. For example, when $\delta = 1$, a Simple-round choice qualifies if each asset receives between 49 and 51 ECUs, and a Complex-round choice if each receives between 24 and 26 ECUs.

Table 4 reports the percentage of choices consistent with the 1/N allocation rule. In Simple rounds, about 3 percent of choices are exact equal splits, and the share rises to 8 to 12 percent at $\delta = 3$. In Complex rounds, fewer than 2 percent of choices are consistent with the rule at every tolerance between 0 and 3, in both conditions.

Table 4: Percentage of Choices Consistent with the 1/N Allocation Rule

Condition		δ						
		0.0	0.5	1.0	1.5	2.0	2.5	3.0
(1) SP	Simple	3.58	5.11	6.73	7.86	9.03	9.76	11.59
	Complex	1.03	1.03	1.05	1.09	1.15	1.21	1.33
(2) NSP	Simple	3.31	4.18	5.23	5.93	6.77	7.43	8.36
	Complex	1.46	1.46	1.48	1.52	1.63	1.71	1.83

Notes: This table presents the percentage (%) of choices consistent with the 1/N allocation rule in the Simple and Complex environments. Row (1) reports the results for the SP condition, and Row (2) reports the results for the NSP condition. δ is a boundary around the 1/N allocation.

8.3 Correlation Neglect

Correlation neglect offers another possible explanation for the effect of redundant assets. Eyster and Weizsäcker (2011) show that investors may treat asset returns as independent, misperceiving the benefits of diversification. In our experiment, adding redundant assets could therefore change perceived portfolio risk even though the available payoff distributions remain unchanged.

Correlation neglect cannot, however, generate attenuation in our setting. A neglector misperceives both environments. In a Simple round, the two Arrow securities are perfectly negatively correlated, and a neglector who treats them as independent already understates the hedging benefit of holding both, so her demand is distorted before any redundant asset appears, and the within-subject comparison differences this distortion out. The misperception that redundancy adds moves demand in the direction opposite to attenuation. A neglector treats the two redundant assets as two further independent gambles, each with a smaller perceived variance than either Arrow security. Four independent assets appear to offer more scope for diversification than two, so the perceived cost of bearing risk falls and she concentrates more of her budget in the cheaper state. Redundancy lowers the risk a neglector perceives at any allocation, so she behaves as if she were less risk averse, and her Complex-round demand is at least as steep as her Simple-round demand.

The calibration confirms the intuition. Using a mean–variance model in Eyster and Weizsäcker (2011), we fit the model assuming investors perceive all asset covariances as zero and estimate a single risk-aversion parameter from average Simple-round choices separately for SP and NSP. We then use the fitted parameter to predict Complex-round choices. In SP and NSP conditions, the model predicts a steeper demand response in Complex rounds, whereas the observed response is flatter. Correlation neglect therefore

predicts the wrong sign and cannot account for the attenuation. Online Appendix G.2 provides details of the calibration procedure and results.

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Online Appendix for "When Irrelevant Options Matter: Redundancy, Noisy Cognition, and Portfolio Choice"

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November 2, 2026

A Experimental Instructions

Welcome! You are about to participate in an experiment on economic decision-making under uncertainty. During the experiment, you will make several decisions. After carefully reading these instructions and making your decisions, you may earn additional payments.

At the end of the experiment, the computer will randomly select one round, and your earnings will depend on your decision in that round and chance. Earnings will be paid in ECU (Experimental Currency Unit) and converted at the following rate: **1 ECU = 500 KRW**. In addition, you will receive a participation fee of **10,000 KRW**.

During the experiment, please do not use your mobile phone or any other electronic devices. Communication with other participants is strictly prohibited.

A.1 Stage 1 Instructions

In this experiment, you will participate in two stages: Stage 1 and Stage 2. The following instructions describe Stage 1. Instructions for Stage 2 will be provided after the completion of Stage 1.

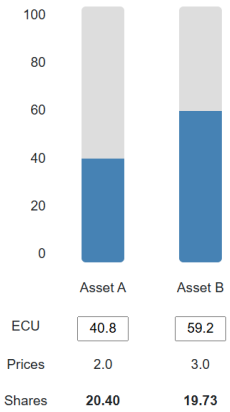
Stage 1 consists of 60 independent rounds. In each round, you will have 100 ECU to allocate across either 2 assets or 4 assets. Among the 60 rounds, 30 involve 2 assets and the other 30 involve 4 assets. The order of rounds is randomly determined.

You may invest between 0 and 100 ECU in each asset, with a minimum increment of 0.1 ECU. The total investment must always equal 100 ECU. The outcome of each round depends on which of the two possible states occurs, each with equal probability (50%).

Round Information: 2 Assets. Each round, you will see a "table" and a "choice bar"; the figure below illustrates an example with two assets.

Assets	State 1	State 2	Prices	Shares
A	3.0	1.0	2.00	20.40
B	0.0	4.0	3.00	19.73

State 1 Payoff: 61.2 ECU **State 2 Payoff:** 99.3 ECU



The table provides information on each asset's returns and prices.

- **Asset column**: Shows the name of each asset.
- **State 1 column**: Shows the return per unit of the asset if State 1 is realized.
- **State 2 column**: Shows the return per unit of the asset if State 2 is realized.
- **Prices column**: Indicates the price per unit.
- **Shares column**: Shows the total number of units of each asset you currently hold through investment.
- The footnote below the table shows the possible payoffs in each state given your investment.

Using the choice bar, you will decide how to allocate 100 ECU across the assets. There are two ways to do so.

- First, you can click or drag the bars to adjust the investment amount for each asset.
- Second, you can directly enter the desired investment amount in the input boxes below the bars.
- Since the total investment across all assets must always sum to 100 ECU, changing the investment in one asset will automatically adjust the investment in the other asset.
- Below the bars, you will again see the price per unit and the number of units you currently hold.

In each round, the number of assets, their returns, and their prices will change, so please review the table carefully before making your investment decision. After you decide, click the **Next** button to confirm your investment and proceed to the next round.

Investment Example: 2 Assets. An illustrative example is provided below to help your understanding. After checking the returns and prices of each asset in the table, suppose that you invest 40.8 ECU in Asset A and 59.2 ECU in Asset B.

The number of *Shares* for each asset is calculated by dividing the invested ECU by the asset price. This implies that you hold 20.40 units of Asset A ($= 40.8/2.0$) and 19.73

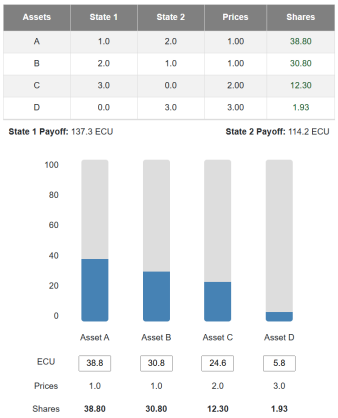
units of Asset B (= 59.2/3.0).

Using these holdings, the payoffs in each state are calculated as follows.

If State 1 is realized: multiplying the 20.40 units of Asset A by its return of 3.0 yields 61.2 ECU, while multiplying the 19.73 units of Asset B by its return of 0.0 yields 0.0 ECU. Therefore, the total payoff is $61.2 + 0.0 = 61.2$ ECU (see the State 1 Payoff in the table footnote).

If State 2 is realized: applying the return of 1.0 to the 20.40 units of Asset A yields 20.4 ECU, and applying the return of 4.0 to the 19.73 units of Asset B yields 78.9 ECU. Therefore, the total payoff is $20.4 + 78.9 = 99.3$ ECU (see the State 2 Payoff in the table footnote).

Round Information & Investment Example: 4 Assets. In rounds with four assets, all rules remain the same, except that you will allocate 100 ECU across four assets (Assets A, B, C, and D). An example with four assets is shown below.



Assets	State 1	State 2	Prices	Shares
A	1.0	2.0	1.00	38.80
B	2.0	1.0	1.00	30.80
C	3.0	0.0	2.00	12.30
D	0.0	3.0	3.00	1.93

State 1 Payoff: 137.3 ECU **State 2 Payoff:** 114.2 ECU

Suppose that you invest 38.8 ECU in Asset A, 30.8 ECU in Asset B, 24.6 ECU in Asset C, and 5.8 ECU in Asset D. This implies that you hold 38.8 units of Asset A (= 38.8/1.0), 30.8 units of Asset B (= 30.8/1.0), 12.3 units of Asset C (= 24.6/2.0), and 1.93 units of Asset D (= 5.8/3.0).

If State 1 is realized: $38.8 + 2 \times 30.8 + 3 \times 12.3 + 0 \times 1.93 = 137.3$ ECU (see the State 1 Payoff in the table footnote).

If State 2 is realized: $2 \times 38.8 + 30.8 + 0 \times 12.3 + 3 \times 1.93 = 114.2$ ECU (see the State 2 Payoff in the table footnote).

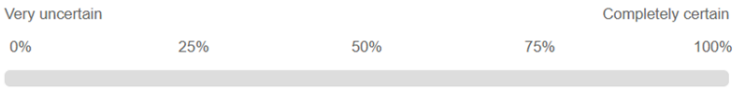
In each round, the number of assets, their returns, and their prices will change, so please review the table carefully before making your investment decision. After you decide, click the **Next** button to confirm your investment and proceed to the next round.

Confidence Question. In certain rounds (Rounds 5, 10, 15, . . . , 60), we will additionally ask about your level of confidence in your investment decision. You will be asked to state, in probabilistic terms, how likely you believe it is that your investment decision was actually optimal.

Below is an example of a confidence question. Suppose that, in a two-asset round, you invest 40.8 ECU in Asset A and 59.2 ECU in Asset B.

In this question, you will see a summary of your investment decision, along with a column labeled "Small margins" that displays a narrow range around your chosen investment amounts $(+1/-1)$.

Assets	State 1	State 2	Prices	Shares	Investments	Small margins
A	3.0	1.0	2.0	20.40	40.8 ECU	39.8-41.8 ECU
B	0.0	4.0	3.0	19.73	59.2 ECU	58.2-60.2 ECU



- You invested 40.8 ECU in Asset A, and the small margin for Asset A $(+1/-1)$ is 39.8–41.8 ECU.
- You invested 59.2 ECU, and the small margin for Asset B $(+1/-1)$ is 58.2–60.2 ECU.

Taking your preferences into account and assuming that the budget constraint is satisfied (i.e., the total investment across the two assets sums to 100 ECU), please report, in probabilistic terms, how confident you are that your optimal decision lies within the ranges shown in the "Small margins" column.

0% means "very uncertain," and 100% means "very confident." Please activate the slider by clicking (or touching) it, and then provide your answer. The confidence question follows the same structure in rounds with four assets.

Payoff Determination. After completing Stage 1 (60 rounds), you will play Stage 2 (4 rounds). At the end of the experiment, one round will be randomly selected out of the 64 rounds. With equal probability (50%), State 1 or State 2 will be realized, and your payoff from that round will be your final earning. Because any round can determine your payoff, please make each decision carefully.

Before starting the main rounds, you will be asked to solve 2 quiz questions. If any part of the instructions is unclear, please send a message to the experimenter.

A.2 Stage 2 Instructions

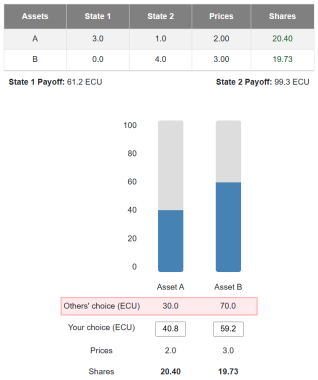
In Stage 2, you will play four rounds. The basic setup is the same as in Stage 1: you are given 100 ECU and asked to make an investment decision over two or four assets.

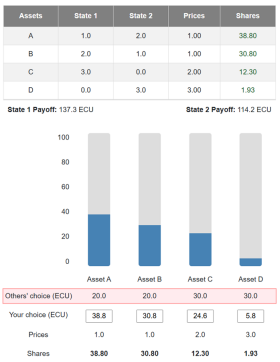
In addition, you will receive information about how dozens of participants from a previous experiment chose on average. An example of this information is shown below.

Example 1: 2 Assets. In each round, in addition to the original choice bars, you will be provided with information about the choices made by previous participants. This information is highlighted in red in the example below. For instance, if previous participants invested, on average, 30 in Asset A and 70 in Asset B, this will be shown in the row labeled "Others' choice."

After reviewing this information, you should make your own choice in the same way as in Stage 1.

Example 2: 4 Assets. Similarly, in rounds with four assets, you will also be able to see information about the average choices made by previous participants. For example, if previous participants invested 20, 20, 30, and 30 in Assets A, B, C, and D, respectively, this will be displayed in the row labeled "Others' choice."





Payoff Rule. After the experiment is completed, one round will be randomly selected from a total of 64 rounds (60 rounds in Stage 1 and 4 rounds in Stage 2). Then, with a 50% (random) probability, either State 1 or State 2 will be realized, and you will receive as your payment the payoff implied by your choice in the selected round under the realized state. In other words, because each round has a chance of being selected for your final payment, please make your decisions carefully.

Raven Tests. In this part, you will be given 12 quiz questions to solve within 15 minutes. For each question, observe the patterns that change across the rows and columns of the figures, and then select the figure that correctly completes the final blank.

The remaining time will be displayed at the top of each page, and once the 15-minute time limit is exceeded, the quiz will end automatically. In this part, you will receive an additional reward of 0.5 ECU for each correct answer.

Final Quiz. In this part, you will be given a total of six quiz questions. In each quiz, you are given a target ECU for each state, and your task is to combine investment amounts across assets to make the total ECU as close as possible to the target.

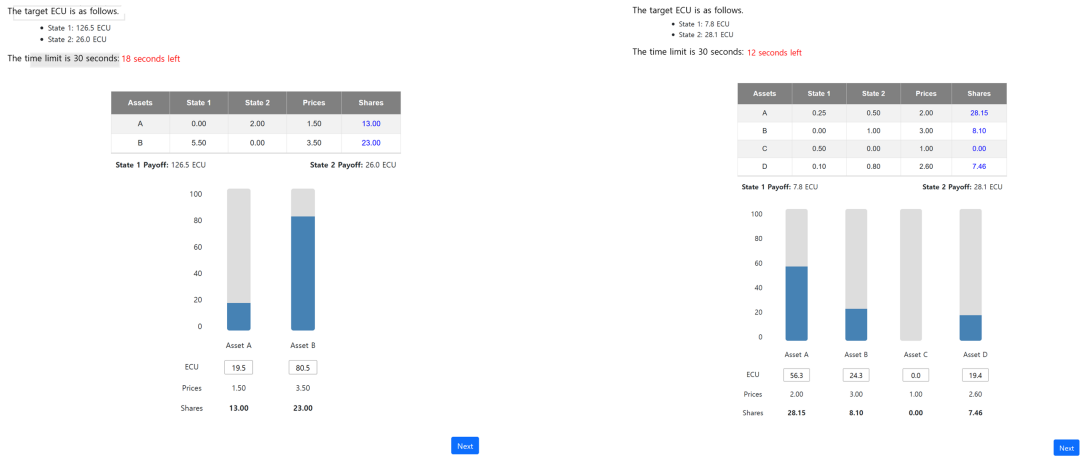
The task consists of six rounds, three Simple and three Complex. Each round has a time limit of 30 seconds, so please quickly choose the asset investment amounts to get as

close as possible to the target ECU.

B Experimental Details

B.1 Screens for Measuring Implementation Errors

In this subsection, we present the final quiz screen in Online Appendix A. The final quiz is used to measure implementation errors. This screen corresponds to the SP treatment. The only difference in the NSP treatment is that the state payoff information is not automatically computed, as in the main stage.



(a) Simple Quiz (b) Complex Quiz

Figure B.1: Screen for Measuring Implementation Error

B.2 Parameters for Stage 1 Experiment

In this subsection, we report the parameter values we used for assets A and B for 30 rounds. Table B.1 shows the set of parameters we used for the experiment.

Table B.1: Budget Sets Parameters

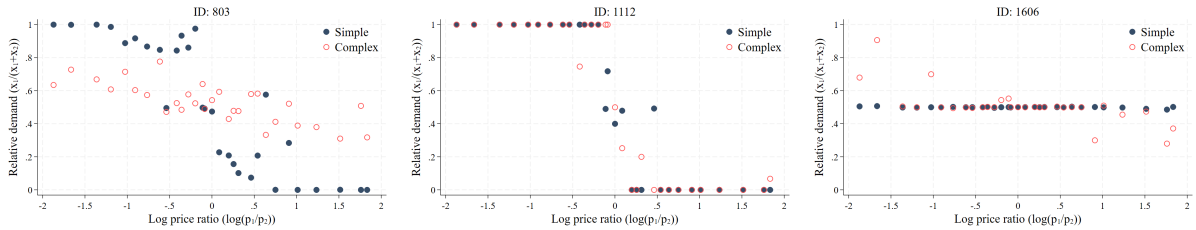
set	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
r_1^A	0.40	0.50	0.80	0.80	0.80	1.00	1.25	1.25	1.60	1.60	1.60	1.60	2.20	2.60	2.80
p^A	2.44	1.55	1.92	1.08	1.40	1.25	6.25	2.00	1.60	2.08	2.48	3.28	7.26	4.81	4.76
r_2^B	5.60	4.20	5.80	2.80	4.00	0.50	5.00	4.00	5.20	5.60	1.00	4.60	4.20	5.00	5.00
p^B	5.88	5.25	8.12	7.00	7.00	1.55	5.50	7.80	33.80	15.68	2.05	6.90	5.04	8.50	9.50

set	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
r_1^A	3.20	3.40	3.40	3.40	3.40	3.60	3.60	3.80	3.80	3.80	4.80	4.80	5.00	5.00	5.40
p^A	3.36	13.43	8.67	3.74	4.76	5.40	7.20	6.27	5.51	10.45	11.04	5.76	9.75	31.25	6.21
r_2^B	4.60	3.80	2.40	5.80	3.00	2.40	3.40	1.25	1.00	2.60	0.40	0.40	1.25	2.80	4.60
p^B	25.53	4.37	3.24	24.94	7.20	5.16	5.27	2.25	2.20	3.38	0.58	1.34	2.00	2.80	17.48

B.3 Individual Scatter Plots

In this subsection, we present scatter plots of selected subjects' portfolio choices. These plots illustrate the relationship between the log price ratio ($\log(p_1/p_2)$) and relative demand $x_1/(x_1 + x_2)$. We present one selected subject for each of three behavioral types—attenuated, same, and oversensitive types—in both SP and NSP.

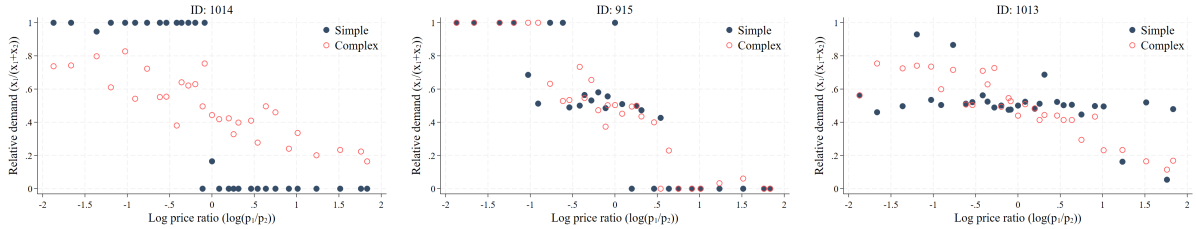
B.3.1 SP



(a) Attenuated Type (b) Same Type (c) Oversensitive Type

Figure B.2: Selected Scatter Plots in SP

B.3.2 NSP



(a) Attenuated Type (b) Same Type (c) Oversensitive Type

Figure B.3: Selected Scatter Plots in NSP

B.4 Summary Statistics of Additional Variables

In this subsection, we present the summary statistics of the variables listed in Section 4 of the main text.

Table B.2: Summary Statistics of Individual-Level Variables

		SP ($N = 159$)				NSP ($N = 155$)			
Variable	Environment	Mean	P25	P50	P75	Mean	P25	P50	P75
CU	Simple	0.328	0.192	0.323	0.458	0.332	0.210	0.308	0.443
	Complex	0.388	0.237	0.393	0.537	0.367	0.223	0.370	0.493
CA	-	0.801	0.750	0.833	0.917	0.846	0.750	0.917	0.917
IE	Simple	5.799	0.077	0.235	0.936	24.281	4.722	17.723	43.576
	Complex	3.371	0.111	0.226	1.977	17.168	7.638	13.391	23.065
CCEI	Simple	0.915	0.883	0.962	0.992	0.841	0.786	0.886	0.953
	Complex	0.911	0.883	0.942	0.973	0.873	0.829	0.913	0.972
RT	Simple	0.726	0.633	0.705	0.823	0.718	0.640	0.690	0.786
	Complex	0.685	0.575	0.635	0.763	0.667	0.583	0.630	0.722
SD Mirror	Simple	0.867	0.802	0.943	0.984	0.760	0.679	0.819	0.906
	Complex	0.870	0.834	0.909	0.951	0.803	0.716	0.848	0.928
CRRA (ρ)	Simple	1.620	0.375	0.808	1.389	1.197	0.470	0.884	1.257
	Complex	1.947	0.576	1.371	2.429	1.794	0.764	1.426	2.295

B.5 Distribution of Redundant Assets Demand

In this subsection, we present the distribution of demand for redundant assets. On average, about 44% of ECUs are invested in redundant assets in the SP condition and 50% in the NSP condition.

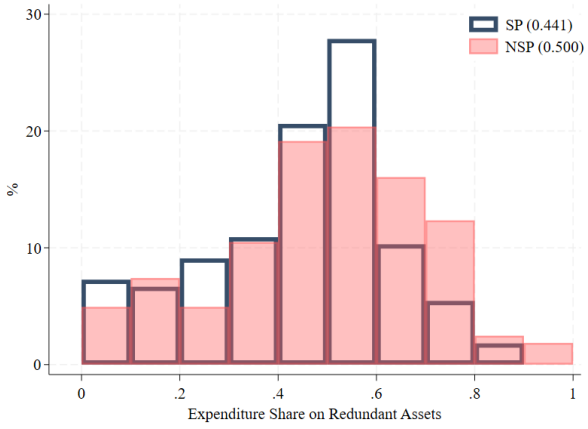
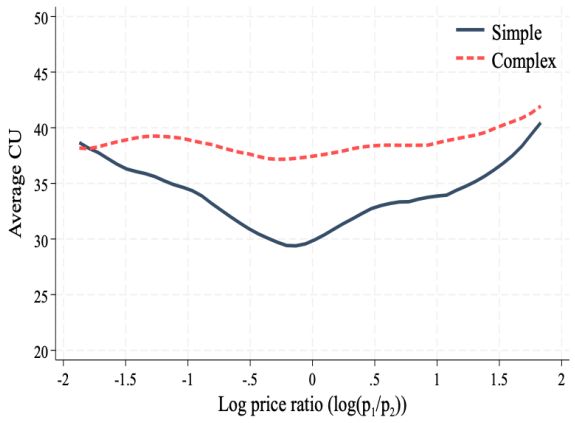


Figure B.4: Expenditure Share on Redundant Assets

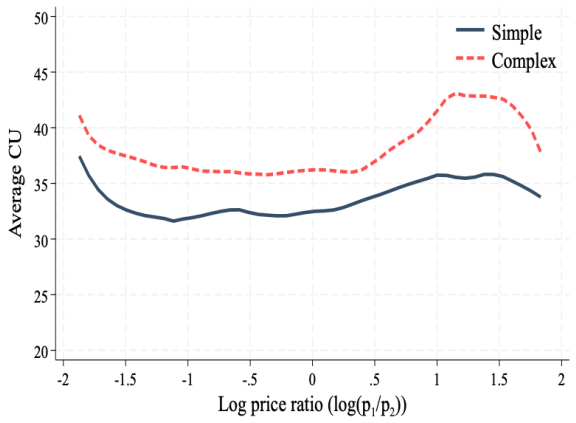
B.6 Cognitive Uncertainty across Log Prices

In this subsection, we report average cognitive uncertainty (CU) across log price ratios. CU tends to be lowest around intermediate price ratios and higher toward the extremes, especially in the Simple condition. The Complex condition exhibits higher and rela-

tively flatter CU overall, with some increase at high positive log price ratios in the NSP treatment.



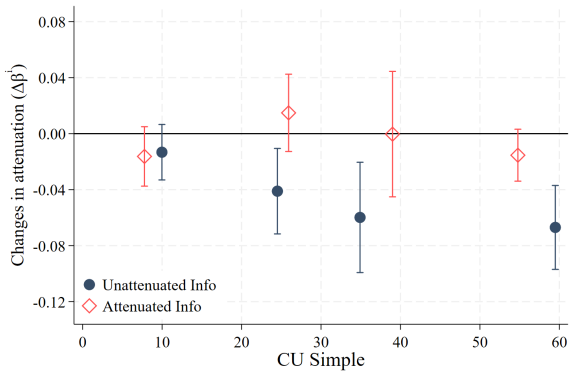
(a) SP



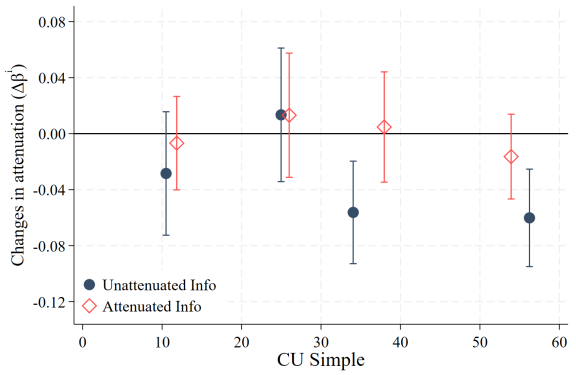
(b) NSP

B.7 Cognitive Uncertainty and Social Information

In this subsection, we examine how the treatment effect of social information varies with CU. We divide the sample into four CU groups separately for each information treatment within the SP and NSP conditions and plot the mean change in attenuation for each group. The patterns are consistent with those reported in the main text.



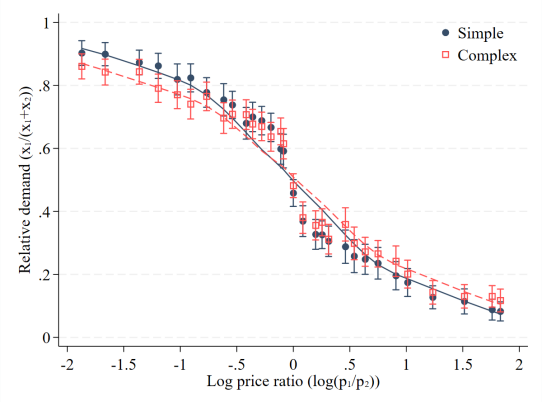
(a) SP



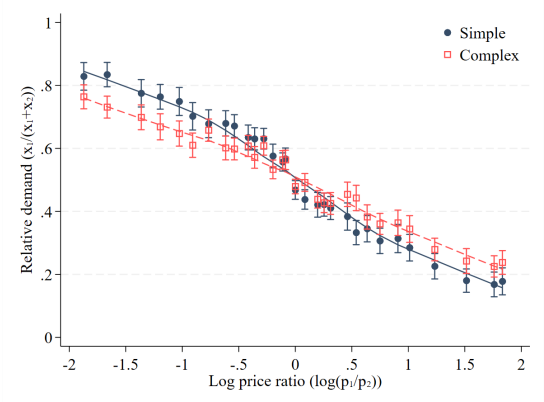
(b) NSP

B.8 Aggregate Demand across Cognitive Uncertainty

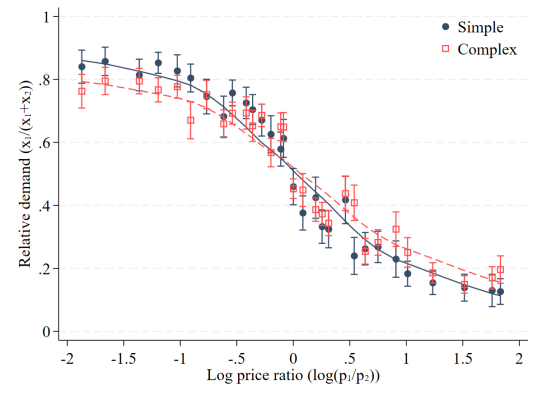
In this subsection, we examine how aggregate demand varies with the log price ratio by cognitive uncertainty. Within each condition, we divide subjects into high- and low-CU groups based on the median of CU Simple and reproduce Figure 2 separately for each group. The high CU group exhibits significant attenuation in both the SP and NSP conditions, whereas the low CU group exhibits relatively little attenuation.



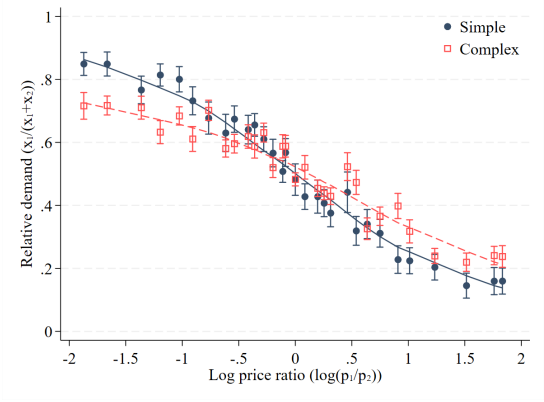
(a) SP, Low CU



(b) SP, High CU



(c) NSP, Low CU



(d) NSP, High CU

B.9 Cognitive Uncertainty and Responses to Displayed Allocations

We examine whether High CU subjects respond more strongly to displayed allocations after controlling for their matched Stage 1 choices. We use the four Stage 2 rounds and the corresponding four Stage 1 rounds for each of the 219 participants. High CU is defined using the same condition-specific median of CU Simple as in Figure 7. We pool the SP and NSP conditions and both information treatments, and estimate the following regression separately for Simple and Complex rounds:

$$\begin{aligned} s^i_{\text{Social},t} = a_j + a_{H,j} H^i + b\, d^i_t + b_H\, d^i_t H^i \\ + c\, s^i_{\text{Baseline},t} + c_H\, s^i_{\text{Baseline},t} H^i + \epsilon^i_t, \end{aligned} \tag{22}$$

where $s^i_{\text{Social},t}$ is the Stage 2 demand share for State 1, $s^i_{\text{Baseline},t}$ is the demand share in the matched Stage 1 round, d^i_t is the displayed demand share, and H^i indicates High CU. The task index j identifies each condition–price combination. Task fixed effects and their interactions with High CU allow average choices to differ across tasks and CU groups, while the baseline-choice interaction allows persistence in individual choices to differ between the groups. Standard errors are clustered at the subject level.

Table B.3: Cognitive Uncertainty and Responses to Displayed Allocations

	(1) Simple rounds	(2) Complex rounds
Displayed demand share	0.061	0.161
	(0.237)	(0.133)
Displayed demand share × High CU	0.722**	0.334*
	(0.364)	(0.174)
Stage 1 demand share	0.722***	0.490***
	(0.078)	(0.067)
Stage 1 demand share × High CU	−0.135	−0.193**
	(0.103)	(0.096)
Task fixed effects	Yes	Yes
Task fixed effects × High CU	Yes	Yes
Observations	438	438
Subjects	219	219
R^2	0.944	0.942

Notes: The dependent variable is the Stage 2 demand share for State 1. Both columns pool the SP and NSP conditions and the Attenuated and Unattenuated treatments. Each subject contributes two observations per column. High CU indicates CU Simple above the condition-specific median. Task fixed effects identify condition–price combinations. Displayed shares use the two-decimal values underlying Figure 4. Subject-clustered standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table B.3 shows that High CU subjects respond more strongly to displayed allocations after controlling for matched Stage 1 choices. The response coefficient is 0.783 for High CU subjects and 0.061 for Low CU subjects in Simple rounds, a difference of 0.722 ($p = 0.049$). In Complex rounds, the corresponding coefficients are 0.494 and 0.161, a difference of 0.334 ($p = 0.056$). These results provide suggestive evidence consistent with the model's second channel: subjects with greater cognitive uncertainty place more weight on social information. Because the regressions use demand shares rather than log demand ratios, the coefficients should not be interpreted as direct estimates of the model's precision weights.

C Welfare Analysis

We investigate the welfare consequences of attenuation. To quantify welfare loss, we first estimate the individual-level CRRA utility parameters ρ^i_{simple} and ρ^i_{complex} using data from the 30 Simple rounds and 30 Complex rounds, respectively, where the CRRA utility function is given by $u(x) = \frac{x^{1-\rho}}{1-\rho}$.

For each subject i and round t, we compute the optimal allocations implied by ρ^i_{simple} and ρ^i_{complex}. We then evaluate both allocations using ρ^i_{simple} as the normative benchmark, yielding utility levels $U^i_{t,\text{simple}}$ and $U^i_{t,\text{complex}}$, respectively. Because utility levels themselves

are not directly comparable in monetary terms, we convert them into certainty equivalents:

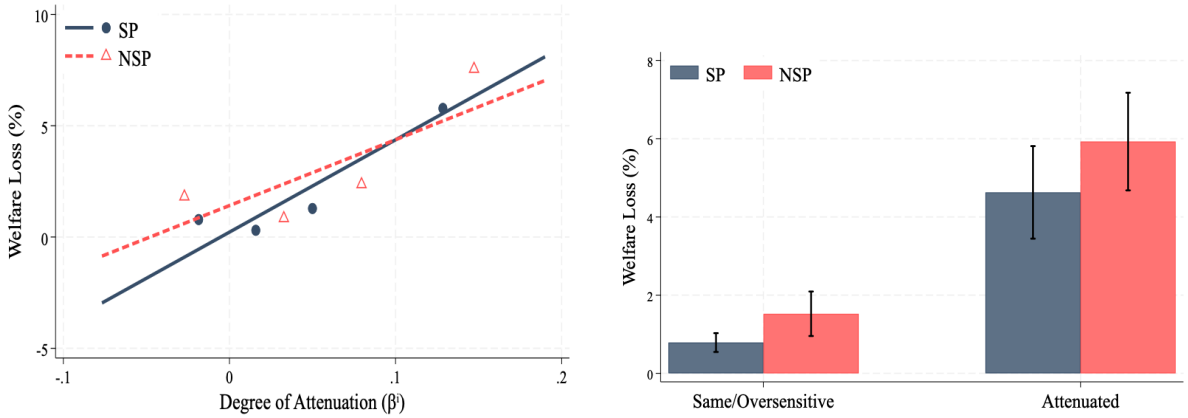
$$CE^i_{t,\text{simple}} = \left[(1-\rho^i_{\text{simple}})U^i_{t,\text{simple}}\right]^{\frac{1}{1-\rho^i_{\text{simple}}}},$$

$$CE^i_{t,\text{complex}} = \left[(1-\rho^i_{\text{simple}})U^i_{t,\text{complex}}\right]^{\frac{1}{1-\rho^i_{\text{simple}}}}.$$

Here, $CE^i_{t,\text{simple}}$ and $CE^i_{t,\text{complex}}$ denote the certainty equivalents of the optimal allocations under the Simple and Complex preferences, respectively. We define the welfare loss from attenuation as the percentage reduction in the certainty equivalent:

$$\Delta W^i_t = \frac{CE^i_{t,\text{simple}} - CE^i_{t,\text{complex}}}{CE^i_{t,\text{simple}}} \times 100,$$

and then compute the individual's average welfare loss across the 30 rounds, denoted by ΔW^i. Thus, ΔW^i represents the welfare loss from complexity as an equivalent percentage loss of total income.



(a) Correlation with Attenuation

(b) Average Welfare Loss

Figure C.1: Welfare Loss and Attenuation

Notes: We examine the correlation between the degree of attenuation and welfare loss. In Panel (a), we plot the degree of attenuation (β^i) on the x-axis and welfare loss (ΔW^i) on the y-axis. We present a binned scatter plot with four equal-sized bins and include a fitted line. In Panel (b), we divide the sample into two groups, as in Fig 3. The first group is the Attenuated group. The second group combines the Same and Oversensitive groups. We then plot the average welfare loss for each group with 95% confidence intervals.

We then plot the correlation between the degree of attenuation and welfare loss. Fig C.1(a) presents the binned scatter plot and the fitted line. The horizontal axis shows β^i, which proxies for the degree of attenuation, and the vertical axis shows ΔW^i. For a binned scatterplot, we divide the β^i into 4 equal-sized groups and plot the corresponding means of the x and y values. In the SP condition, a 0.1 increase in the degree of attenuation is associated with an increase of 4.1 percentage points in welfare loss. In the NSP

condition, the corresponding increase in welfare loss is 3.0 percentage points. Both slope coefficients are statistically significant at the 1% level.

In Fig C.1(b), we compute the average welfare loss across attenuation groups, following the classification in Fig 3. We note that the Oversensitive group is relatively small (around 2%). We divide the sample into two groups: the Attenuated group and the Other group, which combines the Same and Oversensitive subjects. In the SP condition, the welfare loss for the attenuated group is 3.8 percentage points higher than for the Same/Oversensitive groups. Likewise, in the NSP condition, welfare loss is 4.4 percentage points higher for the Attenuated group than for the Same/Oversensitive group. Both differences are significant at the 1% level. These results show that the degree of attenuation is significantly correlated with welfare loss in the Complex rounds. They also show that complexity reduces overall welfare, but its effects are concentrated in the Attenuated group.

Lastly, we examine the correlation between CU Simple and welfare loss. The correlation is 0.09 and significant at the 10% level, indicating a positive association.

D Theoretical Proofs and Extensions

D.1 Equivalence of the Simple and Complex Problems

In this subsection, we show that adding a redundant asset does not change the set of attainable state-contingent payoffs. For simplicity, we consider a complex problem with three assets, where the third asset is redundant. The same argument extends directly to the four-asset case.

Consider first the simple problem. There are two equally likely states, and the subject can purchase two Arrow securities. Asset 1 pays one unit in state 1 and zero in state 2. Asset 2 pays zero in state 1 and one unit in state 2. Their prices are p_1 and p_2, respectively. Given endowment M, the subject chooses state-contingent payoffs (x_1, x_2) by solving

$$\max_{x_1,x_2} U(x_1, x_2) \quad \text{s.t.} \quad p_1 x_1 + p_2 x_2 = M.$$

Now consider a complex problem with one additional asset. The third asset is a redundant asset. It pays λ units in state 1 and $1-\lambda$ units in state 2, where $\lambda \in [0, 1]$. Its price is

$$p_3 = \lambda p_1 + (1-\lambda) p_2.$$

Thus, the third asset has exactly the same payoff and cost as a portfolio that combines λ units of asset 1 and $1-\lambda$ units of asset 2.

Let (a_1, a_2, y) denote the holdings of the two Arrow securities and the redundant asset.

The state-contingent payoffs are then

$$x_1 = a_1 + \lambda y, \qquad x_2 = a_2 + (1 - \lambda)y.$$

The budget constraint in the complex problem is

$$p_1 a_1 + p_2 a_2 + p_3 y = M.$$

Substituting $p_3 = \lambda p_1 + (1 - \lambda)p_2$, we obtain

$$\begin{aligned} p_1 a_1 + p_2 a_2 + p_3 y &= p_1 a_1 + p_2 a_2 + [\lambda p_1 + (1 - \lambda)p_2]\, y \\ &= p_1(a_1 + \lambda y) + p_2(a_2 + (1 - \lambda)y) \\ &= p_1 x_1 + p_2 x_2. \end{aligned}$$

Therefore, the complex budget constraint is equivalent to

$$p_1 x_1 + p_2 x_2 = M.$$

Hence, every feasible allocation in the complex problem corresponds to a feasible state-contingent payoff allocation in the simple problem.

Conversely, any feasible allocation (x_1, x_2) in the simple problem can be replicated in the complex problem by choosing

$$a_1 = x_1, \qquad a_2 = x_2, \qquad y = 0.$$

This allocation produces the same state-contingent payoffs and satisfies the same budget constraint.

Thus, the simple and complex problems generate the same set of attainable state-contingent payoffs. The redundant asset does not change the economic opportunity set. It only changes the representation of the choice problem by adding another asset that must be evaluated. Therefore, any difference in behavior between the simple and complex problems cannot be attributed to different risk-sharing opportunities. Instead, it reflects the additional decision-making complexity created by the redundant asset.

D.2 The Demand-Share Mapping

This subsection describes the relationship between our two dependent variables: the log demand ratio $\log(x_1/x_2)$, used for theoretical predictions, and the demand share $x_1/(x_1 +$

x_2), used for empirical analysis. The relationship between $\log(x_1/x_2)$ and $x_1/(x_1+x_2)$ is

$$\frac{x_1}{x_1+x_2} = \frac{1}{1+e^{-\log(x_1/x_2)}}.$$

By construction, demand share $x_1/(x_1+x_2)$ is a strictly increasing logistic transformation of $\log(x_1/x_2)$.

Two properties follow. First, the relationship is strictly increasing. Thus, within each decision problem, the transformation preserves the ordering of price sensitivity, although it changes the scale.

Second, the relationship is locally compressive near boundary allocations ($x_1 \approx 0$ or $x_2 \approx 0$), which helps address the problem of exploding log demand ratios near the boundaries. Near the boundaries, a given change in log demand ratio $\log(x_1/x_2)$ produces an increasingly smaller change in demand share $x_1/(x_1+x_2)$. Boundary choices account for 22.5% of observations in SP Simple, 17.4% in SP Complex, 17.4% in NSP Simple, and 8.17% in NSP Complex, and are significantly more frequent in Simple under both conditions ($p < 0.01$). This suggests that demand shares $x_1/(x_1+x_2)$ may compress price responsiveness more strongly in Simple than in Complex.

Together, these properties motivate using the demand share as an alternative measure of portfolio choice in the main analysis. Also, the empirical comparison is consistent with a more conservative assessment of attenuation. For example, in the SP condition, 33.3% of subjects are classified as attenuated using the demand share $x_1/(x_1+x_2)$ (Figure 3), compared with 45.6% using the log demand ratio $\log(x_1/x_2)$ (Figure F.2).

D.3 Proofs of the Lemmas, Propositions, and Corollaries

D.3.1 Proof of Lemma 1.

Under Assumption 1(ii), the optimal action minimizes $\mathbb{E}[(y - y^*(q))^2 \mid r]$, so $y(r) = \mathbb{E}[y^*(q) \mid r]$. By Assumption 1(i), Gaussian updating gives

$$\mathbb{E}[q \mid r] = \lambda r,$$

where $\lambda = \sigma_q^2/(\sigma_q^2 + \sigma_\varepsilon^2)$. Since $y^*(q) = -q/\rho$, we obtain $y(r) = -\lambda r/\rho$. Moreover, $\mathbb{E}[r \mid q] = q$ implies $\mathbb{E}[y \mid q] = -\lambda q/\rho$. Thus,

$$B(\sigma_\varepsilon^2) = \frac{1-\lambda}{\rho} = \frac{\sigma_\varepsilon^2}{\rho(\sigma_q^2+\sigma_\varepsilon^2)},$$

which is strictly increasing in σ_ε^2 since $B'(\sigma_\varepsilon^2) = \sigma_q^2/[\rho(\sigma_q^2+\sigma_\varepsilon^2)^2] > 0$. ■

D.3.2 Proof of Lemma 2.

Let $K_\tau(N)$ denote the computational load under each display condition τ with N assets. Agent i has total processing capacity $\Omega^i > 0$ and allocates $\omega_k > 0$ to each operation $k = 1, \ldots, K_\tau(N)$, subject to $\sum_{k=1}^{K_\tau(N)} \omega_k = \Omega^i$. Each operation generates an independent error with variance σ_0^2/ω_k, where $\sigma_0^2 > 0$ is common across operations. The representation error is the sum of these errors, so the agent solves

$$\min_{\omega_1,\ldots,\omega_{K_\tau(N)}>0} \sigma_0^2 \sum_{k=1}^{K_\tau(N)} \omega_k^{-1} \quad \text{s.t.} \quad \sum_{k=1}^{K_\tau(N)} \omega_k = \Omega^i.$$

By the Cauchy–Schwarz inequality, $(\sum_{k=1}^{K_\tau(N)} \omega_k)(\sum_{k=1}^{K_\tau(N)} \omega_k^{-1}) \geq K_\tau(N)^2$, with equality if and only if all ω_k are equal. Hence the unique minimizing allocation is $\omega_k = \Omega^i/K_\tau(N)$, and the minimized variance is $\sigma_0^2 K_\tau(N)^2/\Omega^i$. Defining $\theta^i \equiv \sigma_0^2/\Omega^i$, we obtain $\sigma^2_{\varepsilon,i}(N,\tau) = K_\tau(N)^2\theta^i$. ■

D.3.3 Proof of Proposition 1.

Fix individual i. By Lemmas 1 and 2, $B^i(N,\tau)$ is strictly increasing in $\sigma^2_{\varepsilon,i}(N,\tau)$.

Part (i). By Eq. (8), $K_{SP}(N) = K^P(N)$ and $K_{NSP}(N) = K^P(N) + K^A(N)$. Assumption 2(i) therefore implies $K_\tau(4) > K_\tau(2)$, hence $\sigma^2_{\varepsilon,i}(4,\tau) > \sigma^2_{\varepsilon,i}(2,\tau)$ and $\beta^i = B^i(4,\tau) - B^i(2,\tau) > 0$ in both conditions.

Part (ii). By Lemma 1 and $\mathbb{E}[r \mid q] = q$,

$$\mathbb{E}[y \mid q, N, \tau] = -\frac{\sigma_q^2}{\rho[\sigma_q^2 + \sigma^2_{\varepsilon,i}(N,\tau)]}\, q.$$

Thus expected demand is zero at $q = 0$ in every environment and condition.

Part (iii). By Assumption 2(ii), $K^A(2) = 0$ and $K^A(4) > 0$. Eq. (8) thus gives $K_{SP}(2) = K_{NSP}(2)$ and $K_{SP}(4) < K_{NSP}(4)$. Consequently, $B^i(2, SP) = B^i(2, NSP)$ and $B^i(4, SP) < B^i(4, NSP)$. Subtracting the common Simple attenuation shows that β^i is smaller under SP than under NSP, and part (i) ensures that it is strictly positive in both conditions. ■

D.3.4 Proof of Proposition 2.

Fix condition τ. Recall that $B^i(N,\tau) = \sigma^2_{\varepsilon,i}(N,\tau)/[\rho(\sigma_q^2 + \sigma^2_{\varepsilon,i}(N,\tau))]$.

Part (i). Both the representation-error variance and attenuation are strictly increasing in cognitive imprecision. Hence $\theta^i > \theta^j$ implies $B^i(N,\tau) > B^j(N,\tau)$.

Part (ii). Differentiating $\beta^i = B^i(4,\tau) - B^i(2,\tau)$ with respect to θ^i gives

$$\frac{\partial \beta^i}{\partial \theta^i} = \frac{\varphi(\sigma^2_{\varepsilon,i}(4,\tau)) - \varphi(\sigma^2_{\varepsilon,i}(2,\tau))}{\rho\theta^i},$$

where $\varphi(v) = \sigma_q^2 v/(\sigma_q^2+v)^2$. Since $\varphi'(v) = \sigma_q^2(\sigma_q^2 - v)/(\sigma_q^2+v)^3$, φ is strictly increasing on $[0, \sigma_q^2]$. The condition $B^i(4,\tau) \leq 1/(2\rho)$ is equivalent to $\sigma^2_{\varepsilon,i}(4,\tau) \leq \sigma_q^2$. Since $K_\tau(2) < K_\tau(4)$, the derivative is strictly positive whenever $0 < \theta^i \leq \sigma_q^2/K_\tau(4)^2$. Both θ^j and θ^i lie in this interval, so $\beta^i > \beta^j$. ■

Remark on Proposition 2(ii). The condition $B^i(4,\tau) \leq 1/(2\rho)$ requires retaining at least half of the frictionless price responsiveness in Complex rounds. Outside this region, the comparative statics for the degree of attenuation β^i can reverse. We cannot verify the condition directly because the frictionless slope is unobserved. If Simple-round responsiveness is close to that benchmark, so that $\rho B^i(2,\tau) \approx 0$, it can be assessed approximately using a Complex-to-Simple log-demand slope ratio of at least one half. Aggregate attenuation of 20–25% is consistent with this approximate criterion; 70.7% of subjects have a Complex-to-Simple log-demand slope ratio of at least one half.

D.3.5 Proof of Corollary 1.

The posterior variance is

$$\mathrm{Var}(y^*(q) \mid r) = \frac{\sigma_q^2 \sigma^2_{\varepsilon,i}(N,\tau)}{\rho^2(\sigma_q^2 + \sigma^2_{\varepsilon,i}(N,\tau))},$$

which is strictly increasing in $\sigma^2_{\varepsilon,i}(N,\tau) = K_\tau(N)^2\theta^i$, and hence in θ^i. Under the maintained interpretation of CU as a common strictly increasing transformation of posterior variance, higher CU within a given environment and condition implies higher θ^i. Proposition 2(ii), under its stated condition, therefore implies greater β^i, including when CU is measured in Simple rounds. ■

Remark on Corollary 1. Holding θ^i fixed, $K_\tau(4) > K_\tau(2)$ implies higher CU in Complex than in Simple rounds, while $K_{SP}(2) = K_{NSP}(2)$ implies equal CU in Simple rounds across conditions. Consistent with these predictions, CU rises significantly from Simple to Complex within each condition ($t = 6.56$ under SP and $t = 4.11$ under NSP, both $p < 0.001$), while Simple-round CU does not differ significantly across conditions ($t = 0.17$, $p = 0.863$). Moreover, $K_{NSP}(4) > K_{SP}(4)$ implies higher CU in Complex rounds under NSP than under SP and a larger increase from Simple to Complex. However, we do not find significantly higher Complex-round CU, or a significantly larger Simple-to-Complex increase, under NSP than under SP at the 5% level.

D.3.6 Derivation of the Welfare Remark.

Fix individual i and environment (N, τ). Since $y(r) = \mathbb{E}[y^*(q) \mid r]$, the expected utility loss under the quadratic approximation in Assumption 1(ii) is

$$\frac{\Gamma}{2}\mathbb{E}[(y - y^*(q))^2] = \frac{\Gamma\sigma_q^2\sigma_{\varepsilon,i}^2(N,\tau)}{2\rho^2(\sigma_q^2 + \sigma_{\varepsilon,i}^2(N,\tau))}.$$

This loss is strictly increasing in $\sigma_{\varepsilon,i}^2(N,\tau) = K_\tau(N)^2\theta^i$, and hence in θ^i and N. By Proposition 2(ii) and Corollary 1, welfare loss is positively correlated with both β^i and CU measured in Simple rounds. In Online Appendix C, we show the empirical test results. ■

D.3.7 Proof of Lemma 3.

Fix individual i and condition τ, and suppress τ in the Stage 2 notation. In environment N, Assumption 1 implies that the posterior of $y^*(q)$ given r is Gaussian with mean $-\lambda^i(N)r/\rho$ and variance given by Eq. (12). Under Assumption 3, the agent treats $d^S(N)$ as a signal of $y^*(q)$ with precision h and error independent of q and her own representation error. Gaussian updating under this perceived model gives

$$\mathbb{E}[y^*(q) \mid r, d^S(N)] = w^i(N)\left(-\frac{\lambda^i(N)}{\rho}r\right) + \Big(1 - w^i(N)\Big)d^S(N),$$
$$w^i(N) = \frac{1}{1 + h\,\mathrm{Var}(y^*(q) \mid r)}.$$

Under Assumption 1(ii), the optimal action is this posterior mean, yielding Eq. (19). By Lemma 2, Assumption 2, and Eq. (12), posterior variance is greater in Complex rounds, so $w^i(4) < w^i(2)$. Because h is common across treatments, $w^i(N)$ does not depend on S. ■

D.3.8 Proof of Proposition 3.

Fix individual i, condition τ, and treatment S. By Lemma 3, $\mathbb{E}[r \mid q] = q$, and Eq. (16), expected Stage 2 demand has slope

$$-\frac{w^i(N)\lambda^i(N) + (1 - w^i(N))\pi^S(N)}{\rho}.$$

Taking the Complex–Simple slope difference and rearranging gives

$$\beta^i_{\text{Social}} = w^i(2)\beta^i_{\text{Baseline}} + \Big(1 - w^i(2)\Big)\beta^S + \frac{w^i(2) - w^i(4)}{\rho}\Big[\lambda^i(4) - \pi^S(4)\Big].$$

Subtracting $\beta^i_{\text{Baseline}}$ yields Eq. (21).

Part (i). Under Unattenuated Information, $\beta^U = 0$ and $\pi^U(4) = \pi^U$, so

$$\Delta\beta^i = -\Big(1 - w^i(2)\Big)\beta^i_{\text{Baseline}} + \frac{w^i(2) - w^i(4)}{\rho}\Big[\lambda^i(4) - \pi^U\Big].$$

The first term is strictly negative: Proposition 1(i) gives $\beta^i_{\text{Baseline}} > 0$, and $w^i(2) < 1$. The second term is nonpositive under the stated condition $\lambda^i(4) \leq \pi^U$, since $w^i(2) > w^i(4)$. Hence $\Delta\beta^i < 0$.

Part (ii). Assumption 3 makes perceived precision h common across treatments, so the weights $w^i(N)$ are also common. Switching from Unattenuated to Attenuated Information therefore increases $\Delta\beta^i$ by

$$\Big(1 - w^i(2)\Big)\beta^A + \frac{w^i(2) - w^i(4)}{\rho}\Big[\pi^U - \pi^A(4)\Big].$$

The first term is strictly positive because $\beta^A > 0$ and $w^i(2) < 1$. The second is nonnegative because $w^i(2) > w^i(4)$ and $\pi^A(4) \leq \pi^U$. Thus Attenuated Information produces a smaller reduction in attenuation than Unattenuated Information for each individual. ■

D.3.9 Proof of Proposition 4.

Fix condition τ. Under Unattenuated Information, substituting the weights from Lemma 3 into Eq. (21) and rearranging gives

$$-\Delta\beta^i = \beta^i_{\text{Baseline}}\left[1 - \left(1 + \frac{h\sigma_q^2}{\rho^2}(1 - \pi^U)\right) w^i(2)w^i(4)\right].$$

Since $\pi^U \leq 1$ and both weights decrease strictly in θ^i, the bracketed term increases strictly in θ^i. For individual L, $\pi^U \geq \lambda^L(4)$ implies

$$\left(1 + \frac{h\sigma_q^2}{\rho^2}(1 - \pi^U)\right) w^L(2)w^L(4) \leq w^L(2) < 1.$$

Thus the bracketed term is positive for L and strictly larger for H. Under $B^H(4, \tau) \leq 1/(2\rho)$, Proposition 2(ii) also gives $\beta^H_{\text{Baseline}} > \beta^L_{\text{Baseline}} > 0$. Both factors are therefore positive and larger for H, yielding $\Delta\beta^H < \Delta\beta^L < 0$. ■

E Pre-Registered Hypotheses

We pre-registered the design, primary outcomes, and three hypotheses for Stage 1 in the AEA RCT Registry (AEARCTR-0016214) before data collection (Choi et al., 2025).

The registry was written before the model in Sections 3 and 6 was developed, so the model's predictions and the registered hypotheses do not coincide one for one. This appendix records the correspondence so that readers can distinguish pre-registered tests from theory-guided ones.

E.1 Stage 1

Table E.1 distinguishes the pre-registered Stage 1 hypotheses from additional model predictions and gives their references in the paper.

Table E.1: Registered Hypotheses and Model Predictions, Stage 1

Registered hypothesis	Counterpart in the paper	Status
H1. Measured risk aversion rises when redundant assets are introduced.	Attenuation of relative demand with respect to the log price ratio, Proposition 1(i).	Pre-registered.
H2. A substantial fraction of individuals exhibit attenuation, while others show no change or amplification.	Individual-level heterogeneity in attenuation, Section 4.	Pre-registered.
H3. Individuals with higher cognitive uncertainty attenuate more.	Corollary 1.	Pre-registered.
Persistence of attenuation under SP indicates difficulty in optimizing rather than in computing payoffs.	Proposition 1(i) in the SP condition.	Pre-registered (stated as an interpretation).
Model implications not registered		
Attenuation operates on the slope of demand, not on its level.	Proposition 1(ii).	Theory-guided.
Price sensitivity is equal across SP and NSP in Simple rounds and lower under NSP in Complex rounds, so attenuation is larger under NSP.		
Cognitive uncertainty measured in the Simple environment alone predicts attenuation.	Corollary 1.	Theory-guided.
Cognitive uncertainty is higher in Complex than in Simple rounds within subject.	Discussion following Corollary 1.	Theory-guided.

Two further points concern the registered outcomes. First, the registry describes the primary outcome as measured risk aversion, whereas the paper works with the slope of relative demand with respect to the log price ratio. The two are monotonically related under expected utility, and Section 4 reports the implied change in the coefficient of relative risk aversion alongside the slope estimates. Second, cognitive ability and implementation error were registered as secondary outcomes for exploratory analysis, and the results on these measures in Section 4 should be read as such. The prediction that attenuation is larger under NSP than under SP was not pre-registered but follows from Proposition 1(iii), so this comparison is a theory-guided test.

E.2 Stage 2

The registry anticipated the structure of Stage 2 but not its directional predictions. It specifies the two arms, with displays constructed separately from previous participants who did and did not exhibit attenuation, and states that the effect of social information should differ across arms. It frames the outcome as a reduction in cognitive uncertainty rather than in attenuation. It does not state which arm should reduce attenuation, that Unattenuated Information should produce a larger reduction than Attenuated Information, or that the correction should be larger among subjects with high cognitive uncertainty. These predictions, Proposition 3(i) and (ii) and Proposition 4, are derived from the model in Section 6 and should be regarded as theory-guided rather than pre-registered tests. The registered outcome, cognitive uncertainty in Stage 2, is reported in Section 7 alongside the attenuation results.

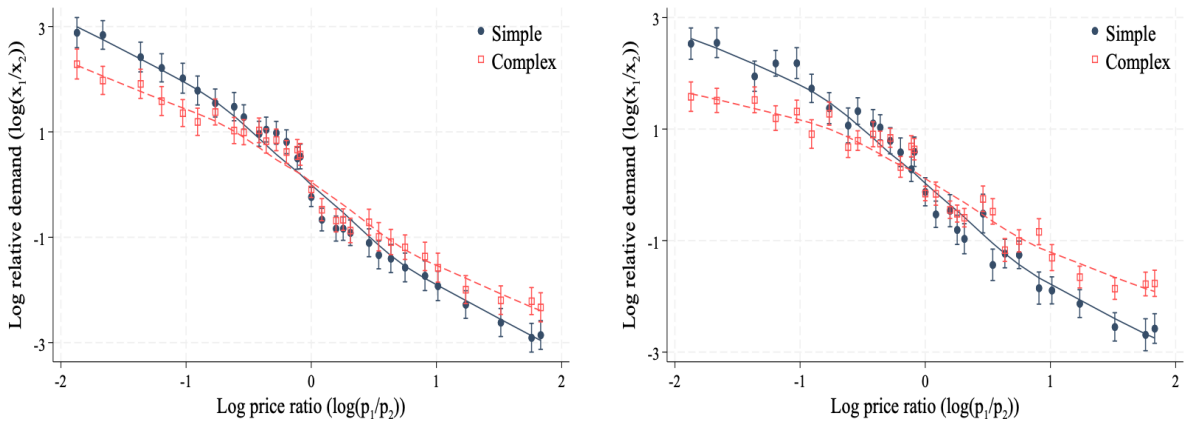
F Robustness Check

F.1 Robustness Using the Log Demand Ratio

In this subsection, we show that our main results are robust to using $\log(x_1/x_2)$ as the dependent variable instead of $x_1/(x_1 + x_2)$. To accommodate boundary solutions, we replace x_1 with 1 when $x_1 < 1$ and replace x_2 with 1 when $x_2 < 1$. Because this adjustment may violate the budget constraint, $p_1x_1 + p_2x_2 = 100$, we rescale both x_1 and x_2 by multiplying them by $100/(p_1x_1 + p_2x_2)$.

Table F.1: Redundancy and Price Sensitivity: Average Effect (Table 1 in the main text)

	Dependent Variable: $\log(x_1/x_2)$			
	(1) Pooled	(2) SP	(3) NSP	(4) Pooled
$\mathbf{1}\{\text{Complex}\} \times \log(p_1/p_2)$	0.476^{***}	0.398^{***}	0.556^{***}	0.398^{***}
	(0.032)	(0.042)	(0.047)	(0.042)
$\mathbf{1}\{\text{Complex}\}$	0.006	-0.010	0.022	-0.010
	(0.016)	(0.023)	(0.023)	(0.023)
$\log(p_1/p_2)$	-1.731^{***}	-1.802^{***}	-1.658^{***}	-1.802^{***}
	(0.060)	(0.092)	(0.075)	(0.092)
$\mathbf{1}\{\text{Complex}\} \times \log(p_1/p_2) \times$ NSP				0.159^{**}
				(0.063)
$\mathbf{1}\{\text{Complex}\} \times$ NSP				0.032
				(0.032)
$\log(p_1/p_2) \times$ NSP				0.144
				(0.119)
Constant	0.011	0.008	0.013	0.011
	(0.008)	(0.011)	(0.011)	(0.008)
Individual Fixed Effects	Yes	Yes	Yes	Yes
Observations	18,840	9,540	9,300	18,840
Individuals	314	159	155	314
R^2	0.452	0.472	0.434	0.455

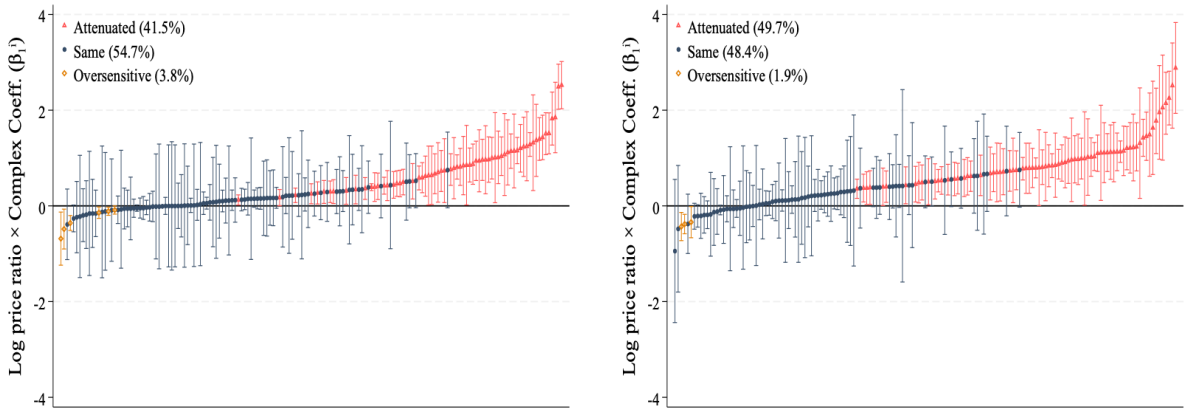


(a) State Payoff (SP) (b) No State Payoff (NSP)

Figure F.1: Aggregate Demand across Log Price Ratio (Figure 2 in the main text)

Table F.2: Cognitive Uncertainty and Behavioral Attenuation (Table 2 in the main text)

	Dependent Variable: $\log(x_1/x_2)$		
	(1) Pooled	(2) SP	(3) NSP
CU Simple $\times \mathbf{1}\{\text{Complex}\} \times \log(p_1/p_2)$	0.623***	0.786***	0.464*
	(0.173)	(0.245)	(0.241)
CU Simple $\times \mathbf{1}\{\text{Complex}\}$	0.017	−0.055	0.083
	(0.080)	(0.107)	(0.117)
CU Simple $\times \log(p_1/p_2)$	1.470***	1.860***	1.099***
	(0.314)	(0.494)	(0.399)
$\mathbf{1}\{\text{Complex}\} \times \log(p_1/p_2)$	0.270***	0.140*	0.402***
	(0.062)	(0.078)	(0.094)
$\mathbf{1}\{\text{Complex}\}$	0.000	0.008	−0.006
	(0.035)	(0.046)	(0.053)
$\log(p_1/p_2)$	−2.216***	−2.412***	−2.022***
	(0.125)	(0.192)	(0.162)
Constant	0.011	0.008	0.013
	(0.008)	(0.011)	(0.011)
Individual Fixed Effects	Yes	Yes	Yes
Observations	18,840	9,540	9,300
Individuals	314	159	155
R^2	0.476	0.505	0.449



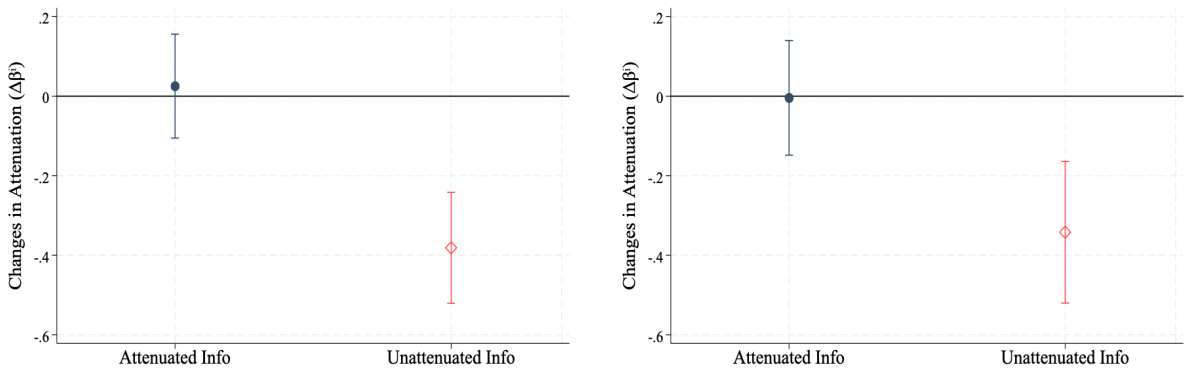
(a) State Payoff (SP)

(b) No State Payoff (NSP)

Figure F.2: Individual Heterogeneity in Attenuation (Figure 3 in the main text)

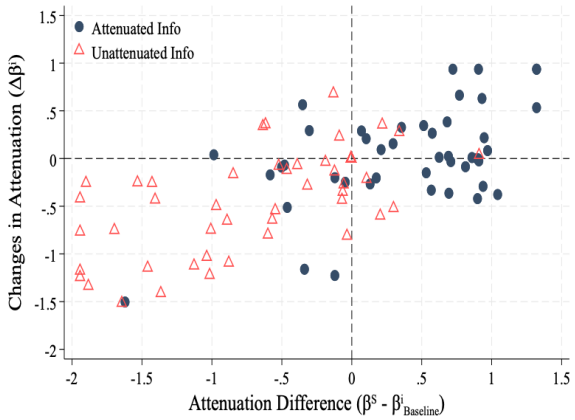
Table F.3: Factors Explaining Heterogeneity in Attenuation (Table 3 in the main text)

	Dependent variable: $\hat{\beta}_i$							
	SP		NSP		SP		NSP	
	(1)		(2)		(3)		(4)	
	Coef.	Shapley	Coef.	Shapley	Coef.	Shapley	Coef.	Shapley
CU Simple	0.161***	55.6	0.098*	29.3	0.206***	35.9	0.135**	15.8
	(0.055)		(0.054)		(0.055)		(0.054)	
CU Diff	0.083**	14.1	−0.028	11.0	0.117***	10.7	−0.024	3.9
	(0.039)		(0.050)		(0.035)		(0.051)	
CA	−0.203	5.2	0.146	2.3	−0.306	3.4	−0.075	0.5
	(0.247)		(0.295)		(0.238)		(0.275)	
IE Simple	0.009	3.1	0.130	8.6	−0.026	1.5	0.143	3.6
	(0.050)		(0.101)		(0.044)		(0.091)	
IE Diff	−0.061	9.6	0.162*	17.5	−0.076*	5.1	0.165**	6.4
	(0.049)		(0.087)		(0.041)		(0.082)	
RT Simple					1.533***	31.0	2.118***	52.3
					(0.328)		(0.541)	
SD Mirror Simple					−0.693*	3.8	0.471	2.1
					(0.410)		(0.313)	
CCEI Simple					0.461	1.1	−0.757*	2.4
					(0.615)		(0.390)	
Demographics	Yes	12.4	Yes	31.2	Yes	7.7	Yes	13.0
Constant	0.945**		0.500		0.059		−0.432	
	(0.404)		(0.491)		(0.548)		(0.580)	
Observations	159		155		159		155	
R-squared	0.138		0.082		0.273		0.221	

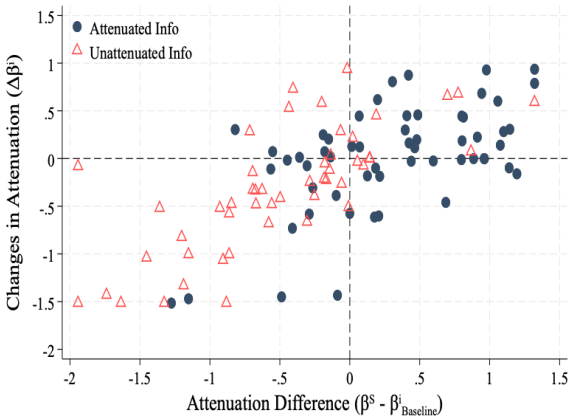


(a) State Payoff (SP) (b) No State Payoff (NSP)

Figure F.3: Average Treatment Effect of Social Information (Fig 5 in the main text)

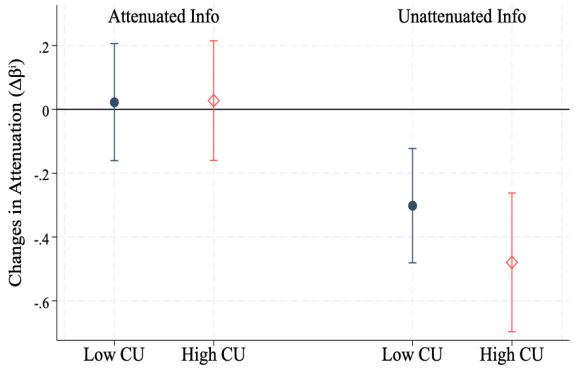


(a) State Payoff (SP)

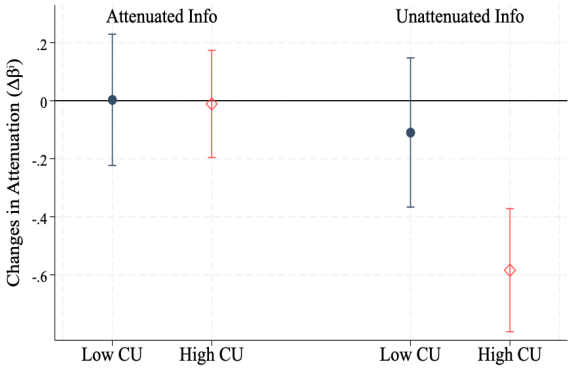


(b) No State Payoff (NSP)

Figure F.4: Individual-level Effect of Social Information (Fig 6 in the main text)



(a) State Payoff (SP)



(b) No State Payoff (NSP)

Figure F.5: Heterogeneous Treatment Effect across Cognitive Uncertainty (Fig 7)

F.2 Robustness Check Table 2: Alternative Measures of Cognitive Uncertainty

In this subsection, we assess the robustness of Table 2 to alternative measures of cognitive uncertainty. CU Complex is the individual average across six Complex rounds, while CU Pooled is the individual average across six Simple and six Complex rounds. Table F.4 uses CU Complex in columns (1)–(3) and CU Pooled in columns (4)–(6). We find overall robust results across all columns that CU $\times$ Complex $\times \log(p_1/p_2)$ are positive and significant except for column (3).

Table F.4: Cognitive Uncertainty and Behavioral Attenuation: Alternative CU Measures

	Dependent Variable: $x_1/(x_1+x_2)$					
	CU Complex			CU Pooled		
	(1) Pooled	(2) SP	(3) NSP	(4) Pooled	(5) SP	(6) NSP
CU $\times$**1**{Complex} $\times \log(p_1/p_2)$	0.065***	0.088***	0.042	0.081***	0.099***	0.064**
	(0.018)	(0.022)	(0.027)	(0.019)	(0.025)	(0.028)
CU $\times$**1**{Complex}	0.007	−0.004	0.021	0.007	−0.007	0.022
	(0.011)	(0.016)	(0.016)	(0.012)	(0.016)	(0.017)
CU $\times \log(p_1/p_2)$	0.126***	0.157***	0.093**	0.130***	0.167***	0.092**
	(0.031)	(0.045)	(0.040)	(0.033)	(0.051)	(0.043)
1{Complex} $\times \log(p_1/p_2)$	0.026***	0.009	0.042***	0.022***	0.008	0.035***
	(0.007)	(0.008)	(0.012)	(0.007)	(0.008)	(0.012)
1{Complex}	−0.002	0.000	−0.004	−0.001	0.001	−0.004
	(0.005)	(0.008)	(0.007)	(0.005)	(0.007)	(0.008)
$\log(p_1/p_2)$	−0.291***	−0.307***	−0.275***	−0.289***	−0.306***	−0.273***
	(0.013)	(0.020)	(0.017)	(0.014)	(0.020)	(0.018)
Constant	0.503***	0.503***	0.503***	0.503***	0.503***	0.503***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,840	9,540	9,300	18,840	9,540	9,300
Individuals	314	159	155	314	159	155
R^2	0.525	0.555	0.496	0.525	0.555	0.497

G Discussion

G.1 Interpretation of Cognitive Uncertainty

In this section, we examine whether the within-subject increase in CU under redundancy can be explained solely by the outcome uncertainty of the chosen portfolio, as discussed by Bernheim et al. (2026). Each subject reports CU in six Simple rounds and six Complex rounds, with the budget sets matched exactly across the two environments.

For subject i and round t, we estimate variants of the following specification separately

for SP and NSP:

$$\begin{aligned} \text{CU}_t^i = \alpha_1 \, \mathbf{1}\{\text{Complex}\}_t^i + \alpha_2 \, \text{Ex-post Riskiness}_t^i + \alpha_3 \left(\text{Ex-post Riskiness}_t^i\right)^2 \\ + \alpha_4 \, \text{Boundary}_t^i + \delta^i + q_t^i + \epsilon_t^i. \end{aligned} \tag{23}$$

Here, $\text{Ex-post Riskiness}_t^i = [|x_1 - x_2|/(x_1 + x_2)]_t^i$ measures the riskiness of the chosen portfolio, and Boundary_t^i equals one if either state payoff is zero. The term δ^i is an individual fixed effect, and q_t^i is a fixed effect for the log price. All specifications include both sets of fixed effects, and standard errors are clustered at the individual level.

Table G.1: Redundancy and Cognitive Uncertainty: Log Price Ratio Fixed Effects

	Dependent Variable: Cognitive Uncertainty (CU)							
	SP				NSP			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Complex	0.059***	0.060***	0.043***	0.055***	0.035***	0.045***	0.031***	0.041***
	(0.010)	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Ex-post Riskiness		0.015	0.624***	0.112***		0.057***	0.422***	0.080***
		(0.029)	(0.080)	(0.029)		(0.021)	(0.064)	(0.021)
Ex-post Riskiness^2			−0.621***				−0.371***	
			(0.078)				(0.068)	
Boundary				−0.158***				−0.059**
				(0.029)				(0.028)
Constant	0.267***	0.263***	0.228***	0.259***	0.268***	0.254***	0.239***	0.255***
	(0.033)	(0.034)	(0.032)	(0.033)	(0.026)	(0.027)	(0.027)	(0.028)
Individual FE	Y	Y	Y	Y	Y	Y	Y	Y
Log Price FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	1,908	1,908	1,908	1,908	1,860	1,860	1,860	1,860
Individuals	159	159	159	159	155	155	155	155
R^2	0.612	0.613	0.646	0.631	0.621	0.623	0.636	0.626

Notes: Each observation is a CU report matched to the choice in the same round, with 12 observations per individual. CU is divided by 100 and ranges from 0 to 1. Columns (1)–(4) report SP results; columns (5)–(8) report NSP results. All specifications include individual fixed effects and fixed effects for the 30 distinct log price ratios. Expost Risk is $|x_1 - x_2|/(x_1 + x_2)$ and Boundary is an indicator equal to one if $x_1 = 0$ or $x_2 = 0$. Standard errors clustered at the individual level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table G.1 reports the results for SP in columns (1)–(4) and NSP in columns (5)–(8). The coefficient on the Complex indicator is positive and significant at the 1% level in every specification, including those controlling for ex post portfolio riskiness. Columns (3) and (7) include both linear and quadratic riskiness terms. The linear coefficient is positive and the quadratic coefficient is negative, both significant at the 1% level, indicating an inverted-U-shaped relationship between portfolio riskiness and CU. Columns (4) and (8) additionally include a boundary-choice indicator. Conditional on portfolio riskiness and the fixed effects, boundary choices are associated with lower CU by 0.158 under SP and 0.059 under NSP.

In Fig G.1, we illustrate the inverted-U-shaped relationship between CU and ex-post riskiness using a binned scatter plot. Within each condition (SP or NSP) and environment (Simple or Complex), we divide observations into five equal-sized bins based on ex-post riskiness and plot mean CU with 95% confidence intervals. The figure shows a clear pattern: CU is lower when ex-post riskiness is close to zero or one and higher at intermediate levels.

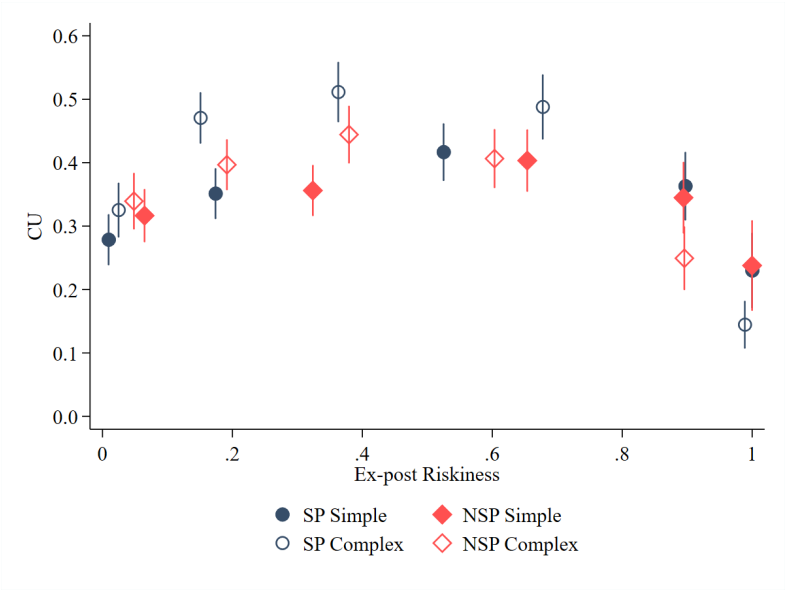


Figure G.1: Cognitive Uncertainty and Ex-post Riskiness

Notes: The figure plots mean cognitive uncertainty against mean ex-post portfolio risk, $|x_1 - x_2|/(x_1 + x_2)$, using five equal-sized bins within each condition (SP or NSP) and environment (Simple or Complex). Vertical bars indicate pointwise 95% confidence intervals.

G.2 Correlation Neglect: Calibration and Predictions

This section describes how we calibrate a mean–variance model in Eyster and Weizsäcker (2011) with full correlation neglect to Simple-round choices and use it to predict Complex-round choices.

G.3 Model

Let R^j denote the payoff per ECU invested in asset j. Each asset pays R_1^j or R_2^j with equal probability, so

$$\mu^j = \frac{R_1^j + R_2^j}{2}, \qquad v^j = \frac{(R_1^j - R_2^j)^2}{4}.$$

An investor with full correlation neglect perceives all asset covariances as zero. Given a budget $M = 100$, she chooses expenditure shares w^j to solve

$$\max_{\substack{w^j \geq 0 \\ \sum_j w^j = 1}} M \sum_j w^j \mu^j - \gamma^{\text{EW}} \frac{M^2}{2} \sum_j (w^j)^2 v^j, \tag{24}$$

where $\gamma^{\text{EW}} > 0$ is the risk-aversion parameter. The model preserves each asset's marginal mean and variance but omits the covariance terms in portfolio variance.

For each experimental menu, we solve this problem using the actual asset prices and returns. We convert the resulting expenditure shares into state payoffs,

$$x_s = M \sum_j w^j R_s^j,$$

and define the predicted demand share as

$$\widehat{s} = \frac{x_1}{x_1 + x_2}.$$

G.4 Calibration and Predictions

We calibrate γ^{EW} separately for SP and NSP using only Simple-round choices. Let $\bar{s}^S_{\tau t}$ denote the average observed demand share in condition τ at budget set t, and let $\widehat{s}^S_t(\gamma^{\text{EW}})$ denote the corresponding model prediction. We choose

$$\widehat{\gamma}^{\text{EW}}_\tau = \arg \min_{\gamma^{\text{EW}} > 0} \frac{1}{30} \sum_{t=1}^{30} \left[\bar{s}^S_{\tau t} - \widehat{s}^S_t(\gamma^{\text{EW}}) \right]^2. \tag{25}$$

The fitted parameters are 0.0291 under SP and 0.0298 under NSP. Each condition has a single fitted parameter.

Holding $\widehat{\gamma}^{\text{EW}}_\tau$ fixed, we then solve equation (24) for each corresponding Complex price variations.

The fitted model predicts Complex-round demand slopes of -0.2875 under SP and -0.2849 under NSP, compared with predicted Simple-round slopes of -0.2558 and -0.2506, respectively. Thus, the model predicts a steeper demand response in Complex rounds in both conditions, opposite to the attenuation observed in our data.

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