Caution in the Face of Complexity*

Geoffroy de Clippel† Paola Moscariello‡ Pietro Ortoleva§ Kareen Rozen¶

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Abstract

We show experimentally that people undervalue options they find complex. We document this phenomenon for tasks as diverse as belief updating, visual perception, and compound risk. This behavior is incompatible with Expected Utility, even when accounting for risk aversion and incorrect beliefs. Instead, it suggests that complexity generates a form of "internal ambiguity" to which many subjects react with caution. Our data supports this explanation: our effects increase when both ambiguity aversion (measured as in Ellsberg) and self-perception of complexity (measured as cognitive uncertainty) increase. We also find corroborating evidence in the data of Enke and Graeber (2023), where cognitive uncertainty, in addition to attenuating responses, also substantially lowers the value of lotteries. At a broad level, our results suggest that individual preferences in the face of complexity play an important role in valuation. At a narrower level, our paper informs the literature on non-Bayesian updating, which does not discuss complexity aversion, and the connection between compound lottery and ambiguity aversion, which, we show, holds primarily for subjects who find compound lotteries complex.

Keywords: cognitive uncertainty, ambiguity aversion, caution, Bayesian updating, compound lotteries, perception

JEL codes: C91, D91, G0

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†de Clippel: Economics Department, Brown University, declippel@brown.edu.
‡Moscariello: Department of Economics, Princeton University, pm27@princeton.edu.
§Ortoleva: Department of Economics and SPIA, Princeton University, pietro.ortoleva@princeton.edu.
¶Rozen: Economics Department, Brown University, kareen_rozen@brown.edu.

1 Introduction

We show experimentally that most people undervalue options they find complex. We document this phenomenon in three large-scale experiments for diverse tasks: belief updating, visual perception, and compound risk. The behavior we document is incompatible with Expected Utility, even when accounting for risk aversion, incorrect beliefs, or inattention. Instead, it suggests that complexity generates a form of "internal ambiguity" to which individuals react with caution. In line with this interpretation, we show that aversion to complexity increases when ambiguity aversion—measured in a separate Ellsberg task—and the subject's individual perception of complexity—measured as cognitive uncertainty—are both higher.

At a broad level, our results demonstrate how most individuals react with *caution in the face of complexity*, giving lower values to complex options. Because our effects are substantial in magnitude, they suggest this may be an important aspect of individual choices. More narrowly, our results inform the literature on non-Bayesian updating, which in most cases does not consider the role of complexity, and the connection between compound-risk and ambiguity aversion.

Complexity has long been recognized as an important factor in decision-making by several literatures. Our results relate to and connect many of these strands. A large literature in cognitive sciences and economics focuses on how complexity may generate attenuation towards the prior, while many papers study information acquisition and rational (in)attention. Yet, virtually all these approaches assume Expected Utility and that individuals are not averse to complexity *per se*. Instead, we show that attitudes toward complexity substantially affect values in ways incompatible with Expected Utility. Other papers study aversion to complexity for preferences under risk. We demonstrate complexity aversion in novel environments (updating and perception), introduce new experimental methods, and provide evidence of the mechanism connecting complexity aversion with caution and cognitive uncertainty. Lastly, a long tradition studies ambiguity aversion, caution, and their implications. We show how behavior reminiscent of ambiguity aversion and caution applies widely, from high-level tasks like updating to low-level ones like visual perception, where ambiguity's role has not been studied. We also show how this is connected to the perception of complexity and confidence. We discuss the vast literature in the next section.

Understanding attitudes toward complexity is central to modeling decision-making and policy design. If, as we demonstrate, individuals are averse to complexity, this may explain preferences for simpler options or why people might avoid making choices altogether. This aversion may also explain why companies often highlight the simplicity of their offerings. Policymakers who overlook complexity aversion risk designing overly complicated options, discouraging engagement. Instead, our findings support a well-established principle in policy design: simpler options can be more effective than complex alternatives, even at the expense of limiting choice.

Experiments. We conduct three preregistered experiments on Prolific, totaling 2245 subjects. All experiments follow the same basic structure. In typical questions, there is a binary state of the world, and participants are asked to assign a dollar value to two bets—one for each state—or to their preferred bet. For example, in Experiment A, subjects are presented with an updating task and asked the value of bets that pay \$30 under each of the two states. Separately, participants report their beliefs (as in typical experiments), their uncertainty in these beliefs (measured as cognitive uncertainty), and the dollar value they assign to 50/50 lotteries and bets on an Ellsberg urn.

Our main test in this experiment compares the value of bets in the updating task with that of 50/50 lotteries. Under Expected Utility, at least one of the two bets must be as valuable as the 50/50 lottery since the probability of at least one of the two states must be at least 50%. If the observed values are lower, another force must be at play. This design mirrors the Ellsberg paradox but applies to tasks without typical ambiguity.

The three experiments differ in how the state is determined. In Experiment A (updating), the state corresponds to the color of a drawn ball, where participants must perform a simple updating task to assess the chances. In Experiment B (visual perception), participants are shown two circles with dots, and the state identifies the circle with more dots. In Experiment C, the state results from a compound lottery. Despite these variations, the experiments follow a very similar structure, including measures of uncertainty and assessments of lottery values and Ellsberg bets.

To further investigate the underlying mechanism, we include variants designed to "switch off" complexity while keeping all other elements constant. For example, in Experiment A, a "mirror" treatment involved a task computationally identical to updating but conceptually much simpler.

Complex Options Receive Lower Values. Our main finding is that individuals significantly undervalue options they perceive as complex. In Experiment A (updating), subjects valued updating bets on average \$12.7 against \$14.3 for 50/50 lotteries. In Experiment B (perception), participants with below-median confidence valued their preferred bet about \$1 less than a 50/50 lottery. In Experiment C (compound risk), participants valued a non-trivial compound lottery with a 50% chance of payout \$2.6 less than a 50/50 lottery. (The latter is the standard aversion to compound lotteries.) These effects are not only statistically significant and robust but also economically meaningful.

Relation with Ambiguity Aversion and Cognitive Uncertainty. Next, we explore the mechanism. We propose that complexity generates a form of "internal ambiguity," to which subjects who are ambiguity averse react with caution, lowering bet values. Consistent with this mechanism, we find that undervaluation is strongly linked to the *interaction* between ambiguity aversion—measured in a separate Ellsberg task—and subjects' uncertainty in their ability to make predictions—measured as cognitive uncertainty of their beliefs (or lack of confidence in the case of perception):

participants who both are ambiguity averse *and* report high uncertainty exhibit significantly greater undervaluation. This holds robustly across all experiments and regression models.

To further validate this mechanism, we demonstrate that undervaluation nearly disappears when participants do not perceive the tasks as complex. Within experiments, the effect vanishes for tasks perceived as easier (when available). Additionally, our effects completely disappear in the mirror treatment in Experiment A, where the computational demands are identical, but conceptual complexity is removed. This confirms that the results are not artifacts of the design but appear to reflect complexity aversion.

In sum, we provide three different types of evidence across our three settings (belief updating, perception, compound lotteries): 1) individuals value bets on both states less than 50-50 bets; 2) this effect is stronger among subjects who have higher uncertainty about their beliefs and act in a more ambiguity averse fashion in a separate Ellsberg task; 3) the effect goes away when the complexity of the decision task is experimentally reduced.

Implications for Updating and Compound Aversion. Beyond their broader implications for how complexity affects valuations, our results provide insights into the specific tasks we examine, which have long traditions in economics. In Experiment A, participants assign significantly lower values to bets that require updating, with a behavior incompatible with Expected Utility. This aversion to the complexity of updating is largely ignored in the extensive literature on non-Bayesian behavior, which often allows for non-Bayesian posteriors but assumes that participants still hold well-defined posteriors and follow Expected Utility. Our findings challenge this assumption, suggesting that people dislike bets that rely on updating for their inherent complexity.

Similarly, many papers find a correlation between ambiguity and compound lotteries aversion, interpreted as ambiguous bets perceived as compound or compound ones perceived as ambiguous. Our results point towards the latter interpretation, as we find that the relationship is modulated by cognitive uncertainty and diminishes when participants do not perceive compound bets as complex.

In the Data of Enke and Graeber (2023). To further test our mechanism, we reanalyze the data of Enke and Graeber (2023), which measures the certainty equivalents of lotteries and cognitive uncertainty. According to our mechanism, higher cognitive uncertainty should correspond to lower valuations. We find strong evidence for this effect in addition to the attenuation already documented in that paper: going from 0 to 1 in cognitive uncertainty lowers the certainty equivalents by about 27%. This holds even when attenuation should have no effect. This not only validates our findings in an existing dataset but also shows our mechanism at play in the domain of lottery evaluation, with sizable effects.

2 Related Literature

An immense literature in several disciplines studies complexity and its implications. As it is too large to discuss here, we focus on recent contributions, particularly in economics. While studying complexity often requires defining it, this is, however, tangential to our goals, as we will focus on subjects' perception of complexity in our specific tasks.

Implications of Complexity: Rational Attention and Cognitive Models. Many papers study the implications of complexity theoretically and empirically, showing how it can lead to mistakes and stochasticity, impact attention and salience, increase the use of heuristics, yield choice avoidance and a preference for simpler options. Recent contributions in economics include Agranov and Ortoleva (2015); Halevy and Mayraz (2022); Lacetera et al. (2012); Bordalo et al. (2023); Molavi et al. (2023); Kendall and Oprea (2024); Arrieta and Nielsen (2024). Lipman (1995); Oprea (2024); de Clippel and Rozen (2024) provide overviews. The literature in cognitive sciences has long studied the role of complexity and, importantly for our work, confidence and metacognition, that is, subjects' ability to assess their own difficulty. Among many, see Koriat and Goldsmith (1996); Pleskac and Busemeyer (2010); Kepecs et al. (2008); Kiani and Shadlen (2009); Fleming et al. (2010); De Martino et al. (2013); Pouget et al. (2016); Desender et al. (2018); Boldt et al. (2019). Fleming and Daw (2017) presents a theoretical framework, while Yeung and Summerfield (2012) and Fleming (2024) give comprehensive reviews.

Two approaches to complexity have been extensively studied in economics in recent years. First, an expanding literature studies Bayesian models of limited cognition, where individuals receive noisy signals about features of the environments and follow Bayes' rule to construct their beliefs; once these are formed, they maximize Expected Utility. These models typically display *attenuation*, that is, shrinkage of beliefs towards the prior. Woodford (2020) and Enke (2024) provide extensive reviews. Second, models of *inattention*, especially rational inattention, where individuals, when faced with a complex environment, endogenously decide what information to acquire to maximize Expected Utility. These models have been widely applied: Gabaix (2019) and Woodford (2020) provide extensive surveys; Fabbri (2024) considers the case of ambiguity aversion.

A common feature of these two popular approaches—inattention and cognitive models—is that complexity affects how beliefs are formed, but individuals continue to form beliefs and follow Expected Utility given these beliefs. Once beliefs are defined, there is no aversion to complexity beyond Expected Utility. In rational inattention, individuals are averse to the cost that complexity entails to gather information, but once information is obtained, they do not lower the value of an option because it is complex. In cognitive models, complexity entails uncertainty, which increases the attenuation of beliefs, but once these are formed, there is no aversion to complexity *per se*.

Contrary to this assumption, our results show that individuals are averse to complexity even after information is gathered and a decision is made. In general, we show that Expected Utility fails to capture how values are given in complex environments. This suggests that models of inattention and cognition are currently disregarding an important aspect—aversion to complexity or caution—that may have substantial implications for behavior.

Aversion to Complexity. A much smaller but growing literature focuses instead on aversion to complexity. Empirically, several papers document that the complexity of lotteries—most often understood as the number of possible outcomes—lowers their values. Among recent contributions, Huck and Weizsäcker (1999), Sonsino et al. (2002), Moffatt et al. (2015), Bernheim and Sprenger (2020), Fudenberg and Puri (2022a,b), and Puri (forthcoming) highlight the role of such complexity as a significant driver of behavior in lottery choices. Similarly, empirical work in real-world data in finance demonstrates the negative effect of complexity on prices (Carlin, 2009; Célérier and Vallée, 2017); Goodman and Puri (2024) shows that many retail investors in option markets prefer binary options against strictly dominant but more complex alternatives.

On the theoretical front, Puri (forthcoming) characterizes a model in which lotteries are evaluated by subtracting from the Expected Utility a cost of complexity that depends on the support size of a lottery (or coherent extensions beyond risk). The model in Mononen (2023) is similar, except that the cost depends on the lottery's entropy, while in Hu (2022) it depends on the size of a partition of outcomes. Gabaix and Graeber (2023) propose a tractable model in which complexity is defined as the inverse of the total factor productivity of thinking about a task and optimally allocating attention; an extension of their model allows subjects to have a form of first-order complexity aversion. In Ortoleva (2013), individuals lower the value of choice sets that require a thinking cost to determine the optimal choice to the point that they may prefer fewer options.

Our paper contributes to this literature by providing new evidence of aversion to complexity in novel environments, such as updating and perception, where complexity matters in ways beyond support size—indeed, the 50/50 lottery has the same number of possible prizes as the updating bet and the perception bet, yet values are all different. We also introduce new methods to measure attitudes towards complexity. Importantly, we also connect this aversion to cognitive uncertainty and ambiguity aversion, which provides novel insight into the mechanism at play.

Additionally, several papers documented how individuals often avoid choosing (or revert to the default choice) when the number of options or the complexity of the problem increases—a phenomenon dubbed *choice overload*: see Iyengar and Lepper (2000); Iyengar et al. (2004); Iyengar and Kamenica (2010); Dean et al. (2023) and the reviews in Scheibehenne et al. (2010); Chernev et al. (2015). Choice avoidance in the face of complexity is a natural implication of the aversion to complexity we document.

Ambiguity Aversion and Caution. A separate strand of the literature studies ambiguity aversion, the aversion to alternatives whose value depends on states the likelihood of which is not exogenously given or is comparably less clear; see the review in Gilboa and Marinacci (2013). Our results are naturally related. We document aversion to complexity using a method that mirrors the Ellsberg paradox, and we find that this is correlated with regular ambiguity aversion. From this vantage point, our results can be seen as showing how a cautious behavior correlated with ambiguity aversion is also present in tasks where the latter is typically not applied—such as simple updating—or where it is not obvious it should even apply—such as visual perception tasks where the prior is given. Moreover, our results show how the effect of ambiguity aversion is modulated by the subjective perception of uncertainty (cognitive uncertainty). As we discuss below, the relation between complexity and ambiguity aversion can have many interpretations: it may be that complexity generates ambiguity, that ambiguous choices are complex, or that both are instances of a general dislike towards poorly understood options akin to caution.

More broadly, our results that individuals give lower values to complex alternatives relate to the broader notion of *caution* of Cerreia-Vioglio et al. (2015a, forthcoming). In these models, individuals act cautiously, in the sense of lowering values, when faced with the difficulty of evaluating lotteries or determining preferences; these papers show how such an approach can generate typical patterns of behavioral economics like the certainty effect, the endowment effect, or loss aversion. In line with this broad perspective, our results show experimentally that individuals generally adopt a cautious approach when faced with difficult decisions.

Additionally, our results on how complexity lowers values relate to the recent literatures on information gaps (Golman and Loewenstein, 2018; Golman et al., 2021) and on "ambiguous information," because one can model it as if complexity generated hard-to-interpret signals, as in the model of Epstein and Halevy (2024, Sect. 4 and A.1), where individuals are unsure of the joint distribution between signals and states; see also Shishkin and Ortoleva (2023); Liang (forthcoming). We elaborate on this point in Section 7.

Incomplete Preferences and Deliberate Randomization. Decision difficulty may also induce preferences to be incomplete. Recently, Halevy et al. (2023) demonstrated how this is likely the case in difficult decisions based on perceptual tasks using a richer notion of probability equivalents. These findings complement ours and can be read jointly: complexity may induce incompleteness, and subjects may complete preferences using caution; this reflects, once again, the approach in Cerreia-Vioglio et al. (2015a) as well as Gilboa et al. (2010), which shows that non-Expected Utility models compatible with our results can be derived from cautious completions of incomplete preferences ("when in doubt, go with certainty;" see Section 4 in Cerreia-Vioglio et al. 2015a).

Recent evidence also shows how decision difficulty may induce people to randomize (Agranov and Ortoleva, 2015; Dwenger et al., 2018). Arts et al. (2024) shows that decision confidence and preference for randomization are strongly (negatively) correlated. This is again in line with our results and interpretations: we show that complexity generates difficulty in understanding to which individuals react with caution, lowering values and violating Expected Utility; the same cautious preferences can lead to a preference for randomization, as in the models of Cerreia-Vioglio et al. (2015b) and Fudenberg et al. (2015).

Non-Bayesian Updating. Our results also relate more specifically to the literature on non-Bayesian behavior. A vast literature documents violations of Bayes' rule and proposes alternative models; see the surveys of Benjamin (2019) and Ortoleva (2024). In virtually all of these models, individuals may deviate from Bayes' rule but do nonetheless form a well-defined posterior—a probability distribution over the states of the world—and use it following Expected Utility. Several papers suggest that the complexity of the task affects how the posterior is computed and the role of cognitive uncertainty, either by guiding attention or leading to attenuation in various directions; for recent examples, Enke and Graeber 2023; Augenblick et al. 2023; Ba et al. 2023. The complexity of the task may also affect the representativeness of various states (Bordalo et al., 2016) and the complexity of the models may affect updating (Ortoleva, 2012). However, even in these cases, a posterior is computed, and complexity plays no further role once it is computed.

Our results show that this literature may be overlooking an important aspect: the undervaluation of bets because updating is complex. We show how this may lead individuals to evaluate bets after updating in a way incompatible with having a well-formed posterior and following Expected Utility, contrary to *all* typical models of non-Bayesian behavior. Overall, our results suggest that the literature on non-Bayesian behavior may be ignoring an important component.

Ambiguity and Compound Lotteries. Finally, our results speak to the large literature on the relationship between ambiguous and compound lotteries. Starting with Halevy (2007), several papers documented a strong relationship between ambiguity and compound aversion (e.g., Abdellaoui et al. 2015; Dean and Ortoleva 2019; Gillen et al. 2019; Chapman et al. 2023; Wu et al. 2024). Two interpretations have been offered: either ambiguous bets are perceived as compound for the uncertainty on the urn composition, as suggested by Segal (1987) and Halevy (2007); or compound lotteries, being complex, are perceived as ambiguous, as explicitly suggested, for example, in Dean and Ortoleva (2019) and Gillen et al. (2019). Recently, in independent and preceding work, Wu et al. (2024) provides evidence supporting the latter by showing that teaching individuals how to reduce compound lotteries eliminates compound but not ambiguity aversion.

Our results provide further evidence that it may be the complexity of compound lotteries that makes them ambiguous and generates the aversion. First, we show that the correlation between the two attitudes is stronger for subjects with high cognitive uncertainty about the compound lottery's payment probabilities. Second, we show that some aversion remains when lotteries are transformed into one-stage, maintaining some complexity.

3 Experiment A: Updating

Although Bayes' rule may be intuitive to some, updating beliefs remains nonetheless a non-trivial task, even for those familiar with the formula. Indeed, it is widely established that most people tend to make systematic errors and are prone to various biases in belief updating (Benjamin, 2019), an undertaking which often requires deliberate effort to be accurate—including for the authors of this article. At the same time, choices that require updating are commonplace—from medical decisions (doctors and patients) to financial or political news to strategic interactions. Our first experiment investigates whether people might undervalue prospects that depend on updating due to the inherent complexity of forming posterior beliefs.

3.1 Design

The idea of our design is to present subjects with updating tasks and measure not only their posterior beliefs but also the *dollar value* they assign to bets that depend on updating and compare it to the dollar value of 50/50 bets. In each bet, the computer simulates the draw of a ball from a bag with green or purple balls, and the bet pays $30 if the drawn ball is purple ($0 otherwise). We elicit bet values through standard multiple-price lists (MPL).[1] Participants face multiple scenarios that differ in the information provided about the bag composition:

- **50/50 Lottery**: The bag contains an equal number of purple and green balls, making it easy to see that the probability of winning is 50%. Subjects face two versions of this lottery at different points, once with a bag containing 25 purple balls and 25 green balls and once with a bag containing 50 purple balls and 50 green balls.

- **Updating Bet**: The information for this bet is presented in Figure 1. Correctly applying Bayes' rule shows that the winning probability of purple is 50%. However, some subjects may hold different beliefs or find it challenging to figure out the odds of winning.

[1] The MPL works as follows. For each amount $m \in \{\$1, \dots, \$30\}$, subjects choose between $m for sure or $30 if the drawn ball is purple ($0 otherwise), with only one switching point permitted. Subjects are trained on the use of MPLs and their understanding is tested in a quiz that checks if they fill out the MPL correctly when valuing the sure amount of $5.50. Subjects cannot proceed until they pass the quiz, and, as we discuss below, the main analysis focuses on subjects who pass the quiz on the first try. The Online Appendix includes screenshots of the interface, including the instructions and quiz. To define a value from the discrete grid, we follow the standard practice of taking the average of the two values where switching occurs (except at the extreme, where we use boundary values).

- **20 Green** balls and **30 Purple** balls.
- **1/2** of the **Green** balls are marked with an **X**
- **1/3** of the **Purple** balls are marked with an **X**

A ball has been drawn from the bag. The computer informs you that this ball is **marked with an X**.

Figure 1: The Scenario of the Updating Bet.

- **Complement Updating Bet**: The information is the same as the previous bet except that the numbers of purple and green are inverted. This is equivalent to betting on the green in the same environment of Figure 1 while keeping all bets on purple, which is easier for subjects, and making clear that these are different draws from different bags.
- **Ellsberg Bet**: Subjects are only told that the bag contains 100 purple or green balls, but not the exact composition, and that "they could be all Purple, all Green, or any combination."

In addition to measuring the dollar value, for the Updating Bet and its Complement we elicit on separate screens both *i*) the belief of the "exact" chance that the drawn ball is purple (incentivized with binarized-scoring, $5 prize) and *ii*) the subject's self-perception of their own ability to compute this chance—their *cognitive uncertainty* (CU). For the latter, following Enke and Graeber (2023), subjects indicate how confident they are about their answer about the exact chance, from 0% ("*very uncertain*") to 100% ("*completely certain*") in steps of 10%; their cognitive uncertainty is then 100% minus their confidence.

A vast literature used similar scenarios to test Bayes' rule, measuring beliefs after information. We depart from this literature in that we measure the dollar value of bets after updating, in addition to beliefs, and also because we measure the value for (the equivalent of) bets on *both* colors.[2]

Our design is motivated by the following observation. Most economic models assume agents apply Bayes' rule; in that case, the Updating and Complement bets are both equivalent to the 50/50 Lottery. Models from psychology and behavioral economics generalize this and permit posterior beliefs to be distorted due to a variety of possible biases (e.g., base-rate neglect or over- or under-inference). Even then, virtually all models assume that subjects do hold a belief and follow Expected Utility. But if they hold a belief about the chances of Purple vs. Green—*any* belief, Bayesian or not—

[2]We also deviated from the classic "bookbag-and-poker-chip" experimental design (see Benjamin 2019 for a survey) by using "marked balls" instead. We did so for two reasons. First, our design easily lends itself to simple Mirror treatments described below. Second, and more importantly, the classic design involves two stages of uncertainty, which may induce subjects to dislike the bets for other reasons (see Experiment C below).

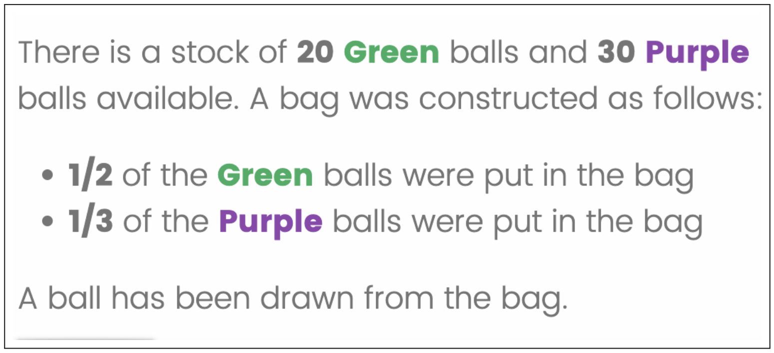


Figure 2: The Mirror counterpart of the scenario from Figure 1.

they should assign to at least one of the two bets a probability of winning of at least 50%. This means that they cannot assign to both bets a value below that of the 50/50 lottery. Therefore, our first test will compare the value of the updating bets with that of 50/50 lotteries, and we will measure complexity aversion as the difference in values. In addition, we conjecture that such differences may occur because the complexity of updating may generate subjective uncertainty. For this reason, we include a measure of subjective uncertainty (cognitive uncertainty) and we measure ambiguity aversion as the difference in value for the 50/50 lottery and the Ellsberg bet. Our second test will be to study the relationship between complexity aversion, on the one hand, and ambiguity aversion and cognitive uncertainty, on the other hand.

The experiment proceeds as follows. After training about scenarios and MPLs, and after comprehension quizzes, subjects face a 50/50 lottery; the Updating and Complement bets (in random order) with associated belief and cognitive uncertainty elicitation; another 50/50 lottery; and, finally, the Ellsberg bet.[3]

Mirror Treatment. One may conjecture that complexity aversion should be mitigated when complexity is reduced. To test this, we devised a treatment computationally identical but conceptually much simpler because the sequence of steps becomes self-evident. Figure 2 shows the Mirror counterpart of the scenario in Figure 1. We conjecture that cognitive uncertainty is much lower in this treatment and that complexity aversion disappears.

Implementation. A total of 493 and 254 subjects participated in treatments the Main and Mirror treatments, respectively, through the Prolific platform in April 2024 and the experiment was

[3]The experiment, like all our experiments in this paper, ends with unincentivized questions to measure overconfidence (overprecision): subjects are asked when the telephone was invented and their confidence. Following Ortoleva and Snowberg (2015), overconfidence is defined as the residual of a regression of confidence on a fourth-degree polynomial of accuracy.

pre-registered on AsPredicted.org.[4] As required by our pre-registration, the main body of the paper focuses only on the subjects who pass our comprehension quiz on the first attempt (69% in either treatment); this selects the most attentive part of the sample, reducing concerns about noise. Appendix C replicates our figures and tables for the entire sample, obtaining very similar results.

Safeguarding Against Spurious Correlation. Before discussing our results, we address a technical point. One difficulty in studying the relationship between complexity aversion and ambiguity aversion is that the value of 50/50 lotteries is used to define both, which may lead to a spurious correlation in the case of measurement noise. One way to circumvent this issue is to define complexity aversion and ambiguity aversion using the answers to different lottery questions. However, this means that each variable is constructed with fewer measurements and is more noisy. Instead, we adopt an approach that uses all measurements for each variable while avoiding spurious correlation via constrained regression, a standard econometric tool that, to our knowledge, finds novel application in this literature.

To illustrate, denote by U, E and L the value of the Updating Bet (or its Complement), of the Ellsberg Bet, and the average of the two 50/50 lotteries, respectively; and denote by CA and AA complexity and ambiguity aversion, where $\mathrm{CA} = \mathrm{L} - \mathrm{U}$ and $\mathrm{AA} = \mathrm{L} - \mathrm{E}$. Imagine we want to regress CA on AA, possibly with controls, that is

$$\mathrm{CA} = \alpha + \beta \mathrm{AA} + \vec{\gamma} \cdot \textit{controls} + \textit{error}.$$

A spurious correlation may emerge between CA and AA if L is measured with error. However, note that the regression above is equivalent to $\mathrm{L} - \mathrm{U} = \alpha + \beta(\mathrm{L} - \mathrm{E}) + \vec{\gamma} \cdot \textit{controls} + \textit{error}$, and thus to $-\mathrm{U} = \alpha + (\beta - 1)\mathrm{L} - \beta \mathrm{E} + \vec{\gamma} \cdot \textit{controls} + \textit{error}$. But then, we can simply run the constrained regression

$$\mathrm{U} = \alpha' + \beta_1' \mathrm{L} + \beta_2' \mathrm{E} + \vec{\gamma}' \cdot \textit{controls} + \textit{error}, \qquad \text{with constraint} \quad \beta_1' = 1 - \beta_2'.$$

This yields the estimates $\alpha = -\alpha'$, $\beta = \beta_2'$, and $\vec{\gamma} = -\vec{\gamma}'$. This regression is not subject to spurious correlation while using all available information. The same approach can be used when considering discrete or continuous models of how CU may interact with ambiguity aversion; Appendix A provides full details for both types of models.

In the remainder of the paper, we use the constrained regression approach to estimate the impact of ambiguity aversion (and its interactions) on complexity aversion. That is, we report the

[4] We restricted our pool to subjects in the US, between 21 and 65 years of age, with at least an undergraduate degree and a Prolific approval rate above 98%. Median completion time was about 10 minutes. Subjects received $3 for participation, and 10% of subjects were eligible for a bonus payment based on their answer to one of the main tasks (drawn at random). The average bonus was $11.90. One subject somehow completed both treatments, and it was dropped. The protocol can be found at https://aspredicted.org/fzds-2r8d.pdf.

imputed coefficients $\alpha, \beta, \vec{\gamma}$, etc. from the original model, not $\alpha', \beta', \vec{\gamma}'$ from the auxiliary, constrained regression. Unfortunately, we are not aware of a natural counterpart of this method to draw figures that depend on both complexity and ambiguity aversion (e.g., in Figure 4 below); for those, we use different lottery values to construct the two measures, using adjacent elicitations when possible.

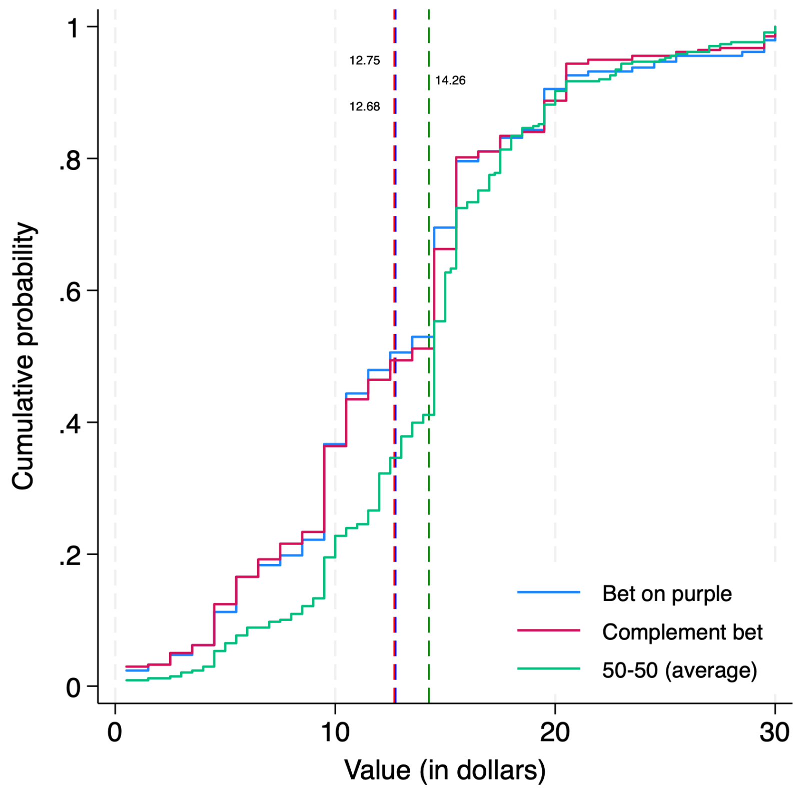
3.2 Results

Caution. We begin by analyzing the Main treatment. Our core question is assessing the presence of complexity aversion and the role of cognitive uncertainty and ambiguity aversion in mediating this. We approach the data from two angles. We first provide summary statistics, comparing the values for our updating bets with the (average) values of the 50/50 lotteries. We then further investigate the mechanism through regression analysis.

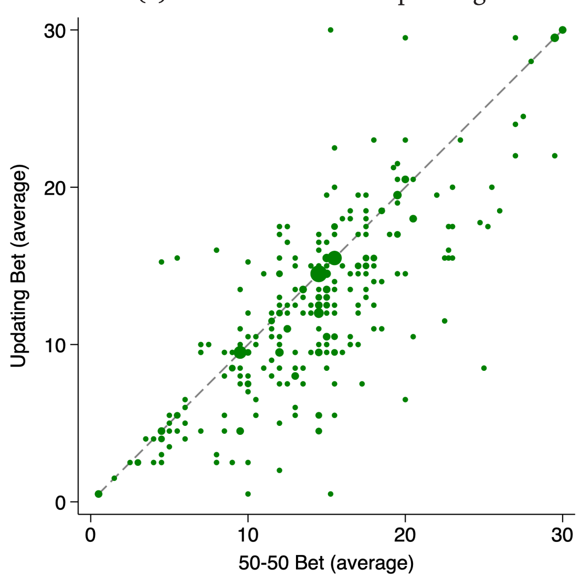
The blue and red curves in Figure 3(a) depict the CDF of dollar values of the Updating and Complement bets next to the CDF of the average value of 50/50 Lotteries. Our first main result is that, while the distributions of values of updating bets are nearly identical, they are both *first-order stochastically dominated* by that of 50/50 lottery values (both sign-rank tests $p < 0.0001$). Figure 3(b) shows this at the individual level: for most subjects, the average value of the two updating bets is lower than that of the 50/50 lottery (below the 45° line). For each subject, we can define *average complexity aversion* as the average 50/50-lottery value minus the average value of the two updating bets: Figure 3(c) depicts the resulting histogram, showing that 19% of subjects exhibit a strictly negative value, 27% zero, while the remaining 54% exhibit a strictly positive value. Overall, average complexity aversion is \$1.54, with a large variance; it is \$3 or more for subjects in the top quartile. Among complexity-averse subjects, the mean is \$3.8. Average complexity aversion can thus be high—at least 10%, but easily 20%, of the expected value of the lottery.

Robustness. In Figure 3(a), we compared the value of each of the two updating bets with that of 50/50 lotteries at the population level, while in Figure 3(b)-(c) we compare the average value of the two updating bets with that of 50/50 lotteries. Are these the right tests? What if subjects hold incorrect and thus asymmetric beliefs, making the values of the two bets very different? First, note that under expected utility, as long as the Bernoulli utility is not strictly risk-seeking in any range of prizes, the average value of the two bets must still be above that of the 50/50 lottery even with very different beliefs; hence, comparing averages is, under typical assumptions, a conservative test.[5]

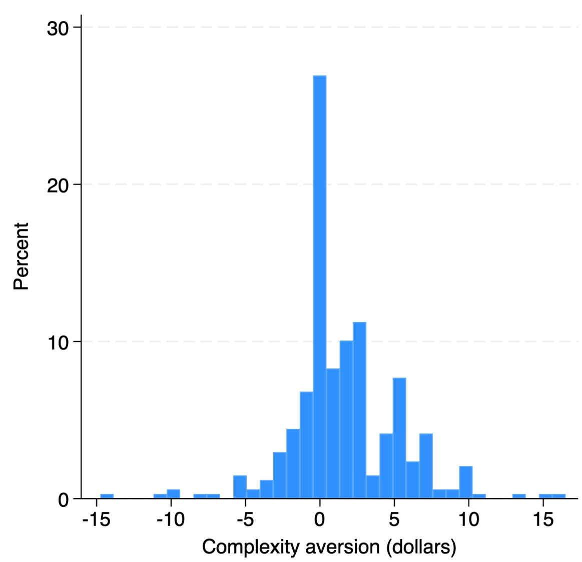
[5]If u is the Bernoulli utility and π the chances of purple, the values of bets of purple and green are $u^{-1}(\pi u(30))$ and $u^{-1}(((1-\pi)u(30))$. As long as u is nowhere strictly convex, by Jensens' inequality, the average of these two values is above that of the 50/50 lottery, $u^{-1}((0.5u(30))$. The same also holds if we allow probability weighting of high prizes (Cumulative Prospect Theory, Rank-Dependent preferences), as long as the average weight given to π and $(1-\pi)$ is above that of 0.5; this is the case in all typical specifications when π is not too small, or with any convex weighting function. The same holds with disappointment-averse preferences (Gul, 1991, $\beta > 0$).



(a) CDFs of values of updating bets and 50/50 lottery, with sample means marked.



(b) Frequency-weighted scatterplot of the average values of updating bets versus the 50/50 lottery.



(c) Histogram of average complexity aversion (avg. values of updating bets minus avg. value of 50/50 lottery)

Figure 3: Three graphs on the value of updating bets and 50/50 lotteries in the Main treatment.

Second, we can focus on subjects with 50/50 beliefs on both bets, as measured by the reported beliefs; this is the correct Bayesian posterior, computed by about 35% of our subjects.[6] While 42% of them are neutral to complexity, another 40% continue to exhibit complexity aversion: the total average is \$.79, significantly different from zero (t-test p-value $< .0001$). This could be of interest *per se*: even some of the subjects who correctly compute the Bayesian posterior may continue to exhibit complexity aversion—because, as we will later argue, many of them remain unsure.[7]

Third, we can compare the max of the values of the two updating bets with the values of 50/50 lotteries; more precisely, to reduce bias due to measurement error, we can compare it with the max of the two 50/50 lotteries.[8] This is too stringent of a test: when beliefs are very asymmetric, we should expect at least one of the two lotteries to be valued more, even if complexity aversion is at play.[9] But we continue to see complexity aversion: the average difference is very similar, at \$1.59 (significantly different from zero, paired t-test $p < .0001$). As can be seen from Figure B.11 in Appendix B, the CDF of maximum values for the 50/50 lotteries first-order dominates that of the maximum value of bets (and these are significantly different; sign-rank test $p < .0001$).

Overall, these findings are incompatible with virtually all existing theories of non-Bayesian updating, according to which individuals have a (possibly non-Bayesian) posterior that they use following Expected Utility: instead, we show that they reduce the value of bets depending on updating in a way *incompatible* with having a posterior and following Expected Utility.

Relation with Ambiguity and Cognitive Uncertainty. Next, we explore the mechanism. We propose that complexity generates a form of "internal ambiguity," to which subjects who are ambiguity averse react with caution, lowering bet values. If this is correct, complexity aversion should increase with cognitive uncertainty, ambiguity aversion, and, most importantly, their interaction: We should observe high complexity aversion when both are high.

First, we can depict this graphically. Figure 4 shows the CDF of complexity aversion for subjects in the top and bottom quartiles of cognitive uncertainty, sub-divided by whether or not they are ambiguity averse.[10] It is evident that one group has higher complexity aversion than the others:

[6]This value is relatively high and shows how comparably easy our updating task is. The remaining subjects exhibit classical patterns, with clusters around the base rate, ignoring the base rate, or other known fallacies.

[7]Only 40% of subjects with the correct posterior report no cognitive uncertainty; the average cognitive uncertainty is 17%. This is, however, much lower than that of everyone else (45% on average).

[8]To see why this is needed, suppose we didn't, and we compared the max of the two bets with the average of the 50/50 lotteries. If all four values are drawn from the same distribution, by construction, the max of two values will typically be strictly above the average of the other two.

[9]For example, suppose that complex options are valued by Expected Utility minus a penalty c. If one of the beliefs is very high, one of the bets will have value close to \$30, higher than the 50/50 lottery even if c is large.

[10]It is worth mentioning that cognitive uncertainty and ambiguity aversion are not correlated (and remain uncorrelated in Experiments B and C). As mentioned above, to avoid spurious correlation, this picture uses the 50/50 lottery evaluation adjacent to the ambiguous bet to define ambiguity aversion, using the other 50/50 lottery evaluation to define complexity aversion. Ambiguity aversion is defined as assigning a value to the ambiguous bet which is strictly

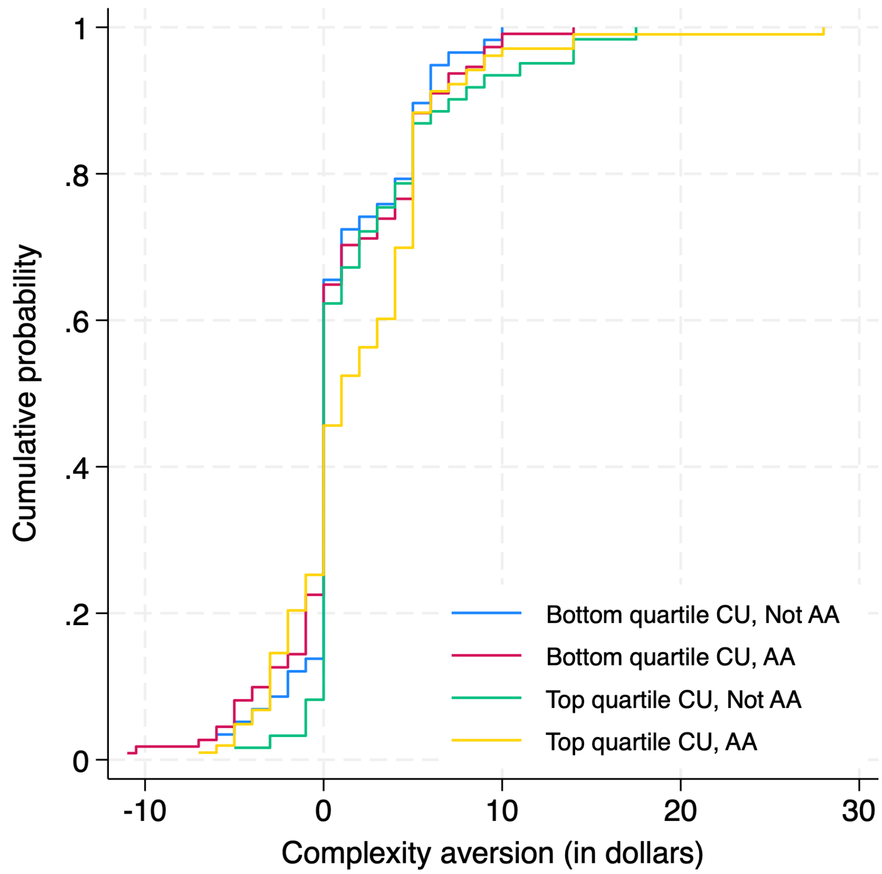


Figure 4: Complexity aversion in 4 subgroups: top and bottom quartiles of Cognitive Uncertainty, divided based on (strict) Ambiguity Aversion vs. Ambiguity Neutrality/Seeking

subjects in the top quartile of cognitive uncertainty who are *also* ambiguity averse. Even within the same top quartile of CU, the difference is significant when comparing to non-ambiguity averse subjects (Wilcoxon rank-sum test, p-value .0236).

Table 1 corroborates this result in regressions. We say a subject has high cognitive uncertainty in an observation if they express a CU in the top half of the overall distribution of cognitive uncertainties. Column (1) considers a discrete interaction, contrasting the role of ambiguity aversion when subjects express high versus low cognitive uncertainty. Column (2) models a continuous interaction instead (allowing for the possibility that CU and ambiguity aversion may also impact complexity aversion separately). Once again, the results are clear. In the first regression, we have a strong and highly significant effect of ambiguity aversion for subjects with high cognitive uncertainty; for those with low cognitive uncertainty, the effect of ambiguity aversion is much smaller and only marginally significant (the two coefficients are indeed statistically different, p-value 0.0022). To interpret the coefficient on those with high CU, 38 cents per dollar of ambiguity aversion goes towards complex-

below that of the 50/50 lottery.

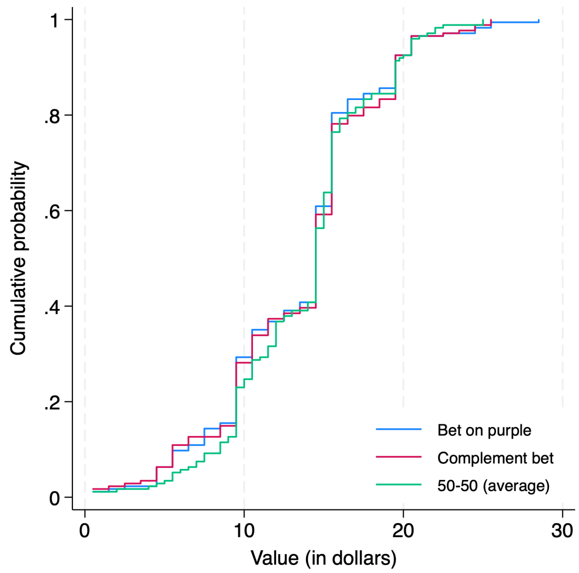
Table 1: Experiment A: The Role of Ambiguity and Cognitive Uncertainty

	Complexity Aversion (1)	(2)
High Cognitive Uncertainty:		
Ambiguity Aversion	.38***	
	(.06)	
Low Cognitive Uncertainty:		
Ambiguity Aversion	.11*	
	(.06)	
Ambiguity Aversion		.09
		(.06)
CU		-.76
		(.60)
Ambiguity Aversion × CU		.43***
		(.11)
Constant	2.64***	2.65***
	(.61)	(.63)
Observations	676	676
Controls	Y	Y

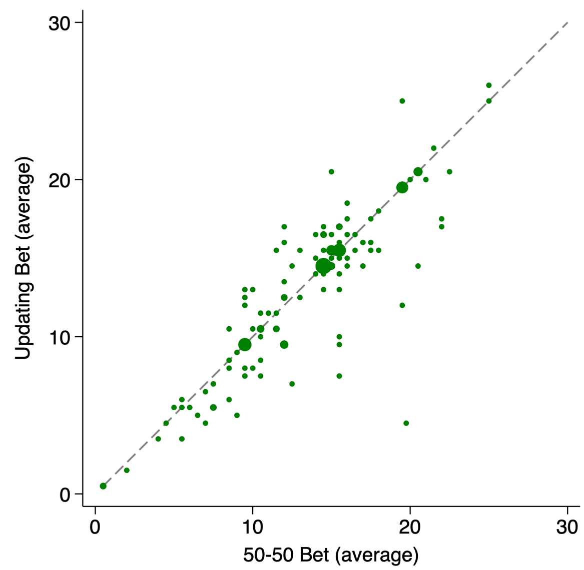
Notes: Each updating bet is an observation, with robust standard errors clustered by subject in parentheses. * $p < .1$,*** $p < .01$. Both (1) and (2) are obtained from constrained regressions following the method explained above. Controls include beliefs about probabilities and a dummy for each updating task and, in model (1), a dummy for high CU.

ity aversion. The same conclusions also hold in the second regression, which shows *i*) a strongly significant continuous interaction between ambiguity aversion and cognitive uncertainty and *ii*) that neither CU nor ambiguity aversion is significant beyond that interaction. In particular, $43 \times \text{CU}$ cents per dollar of ambiguity aversion go towards complexity aversion.

Mirror. If complexity aversion is the reason that updating bets are undervalued, these effects should be mitigated if complexity is reduced—the goal of our Mirror treatment. Our measure of cognitive uncertainty confirms that this treatment was effective: the average cognitive uncertainty went down to 15% in the Mirror treatment (from 35% in the Main treatment), with 55% of subjects expressing zero cognitive uncertainty in the Mirror (versus 25% in the Main treatment). If our hypothesis is correct, complexity aversion should disappear. Figure 5 shows that it does: Panel (a) shows the CDFs of values for the updating bets are nearly the same as 50/50 lotteries, while Panel (b) shows that most people indeed report nearly identical values. That is, our Mirror treatment was



(a) Mirror Treatment: CDFs of dollar values of updating bets and average value of 50/50 lotteries.



(b) Mirror Treatment: Scatter Plot of average dollar value of updating bets and 50/50 lotteries.

Figure 5: The value of updating bets and 50/50 lotteries in the Mirror treatment.

effective in sharply reducing complexity, and complexity aversion disappeared.

Aside from further supporting our hypothesis and reassuring that our earlier results are not an artifact of the design, the results of the Mirror treatment also shed light on which aspect of updating is mostly responsible for complexity. Recall that the Mirror treatment involves the same algebraic operations but with very little conceptual difficulty in identifying those steps. The fact that both cognitive uncertainty and complexity aversion go down sharply suggests that it is indeed the *conceptual* rather than the algebraic difficulty of updating that mostly determines the complexity of the task—and subjects' aversion to it.

Demographics and Overconfidence. We have data on participants' gender, age, and overconfidence (measured as overprecision). Do these relate to our findings? In general, they do not. Participants identifying as female report higher cognitive uncertainty, and overconfidence is negatively related to both cognitive uncertainty and ambiguity aversion; however, neither gender, age, nor overconfidence relates to complexity aversion. Including these variables as controls in our regressions does not affect the results (and these controls are almost always non-significant). The lack of effect from overconfidence suggests that complexity aversion is driven by participants' introspective perception of confidence rather than a "normalized" version that removes the overconfidence component. Similar findings hold across all experiments, so we will not repeat them.

Summary of the Results. We have shown that 1) the majority of subjects value two complementary updating bets less than 50/50 lotteries, a result incompatible with typical preference models, suggesting that another force is at play; 2) this difference in value, which we call complexity aversion, can be substantial; 3) complexity aversion is significantly higher for subjects who *jointly* have high ambiguity aversion and cognitive uncertainty; 4) this effect disappears in the mirror treatment, showing that complexity in updating arises from the conceptual difficulty of identifying the correct updating rule rather than algebraic difficulty.

4 Experiment B: Perception

The experiment above required subjects to perform a relatively high-level information-processing task, which included the conceptual process of updating probabilities and the need to manipulate numbers to determine the likelihood of winning. Are our results limited to high-level tasks, or do they also occur in low-level tasks?

This motivates our second experiment, which relies on tasks based on *visual perception*. Standard in cognitive science, such tasks may be more natural to humans, as the skills they require have been honed through evolutionary adaptation. Nonetheless, visual perception remains imperfect, ensuring that complexity does not disappear altogether, at least in more difficult tasks. Below, we present evidence that complexity aversion is also found in this new context, along with the mediating role of the interaction of ambiguous attitudes and perceived success.

4.1 Design

The main task of this section builds on a standard design in cognitive science (we use figures and design principles from Kaanders et al. 2022). Two circles containing some dots sequentially and briefly appear on the screen on the left and the right. One of these two circles, randomly determined, contains more dots. In typical experiments, subjects are asked *i*) which circle has more dots? and, sometimes, *ii*) their confidence in having made the right choice. By contrast, in the valuation phase of our experiment, we ask *i*) which circle has more dots?, and *ii*') we elicit the value, using a MPL, of the bet that pays $30 if the answer is correct.

The idea of our design is similar to that of Experiment A. As the location of the circle with more dots is determined randomly, all standard economic models of perception and information acquisition agree that the bet value cannot fall below that of 50/50 lotteries. Indeed, the literature typically models perception and information acquisition as receiving data from a Blackwell experiment or choosing an experiment or a distribution of posteriors subject to a cost. Either way, the decision maker ends up holding a posterior probability regarding the location of the circle with more dots. Being free to choose which circle to bet on, she must view the bet as a lottery with a winning chance above 1/2. By contrast, we conjecture that subjects may feel unsure about their winning chance when selecting the bet, treat it as akin to an ambiguous prospect, and consequently *undervalue* it.

After training about MPLs and a comprehension quiz, the experiment unfolds in four parts. In Part 1, subjects complete valuation tasks for a 50/50 lottery, 70/30 and 30/70 lotteries (in random order), another 50/50 lottery, and an ambiguous bet; these lotteries are based on the color of the ball drawn, similar to Experiment A. Part 2 introduces the perceptual task described above. After a practice question, subjects are asked the value of 4 perceptual bets with varying difficulty: one easy, one intermediate, and two hard (the easy one is always first, and one of the hard ones is always last). Part 3 repeats the perceptual tasks, but, instead of asking the value of the bet, has subjects use a slider to report the percent chance they think their answer is correct (unincentivized). Finally, Part 4 has subjects again value a 50/50 lottery and an ambiguous bet.

While the design is broadly similar to Experiment A, we should highlight two differences. First, subjects now choose which circle to bet on before reporting values instead of evaluating both bets. Second, our measure of uncertainty here—the reported chance of being wrong (i.e., one minus confidence)—is not the same as cognitive uncertainty in Experiment A: the latter captured the subject's confidence in their stated posterior, not the chance of winning the prize as measured here. But we expect that reporting a higher chance of winning, meaning that one views the task as easier, is on average associated with lower cognitive uncertainty.

Implementation. 498 subjects participated through Prolific in April 2024, and the experiment was pre-registered.[11] As before, following our pre-registration, the main body of the paper focuses only on the subjects who pass our comprehension quiz on the first attempt (69% of subjects), while Appendix C replicates our figures and tables for the entire sample; once again, results are very similar.

4.2 Results

Preliminaries. We begin with two sanity checks regarding the perceptual bets. First, as expected, the values of bets on the perceptual task vary with difficulty. The average values for easy, intermediate, and hard bets were \$27.56, \$18.28, and \$14.47, with the distributions of values first-order

[11] Median completion time was about a bit over 10 minutes. As in Experiment A, subjects received \$3 for participation, and 10% of subjects were eligible for a bonus payment based on their answer to one of the main tasks (drawn at random). The average bonus paid was \$17.60, with a maximum potential bonus of \$30. The protocol can be found at https://aspredicted.org/9vrx-6mm7.pdf.

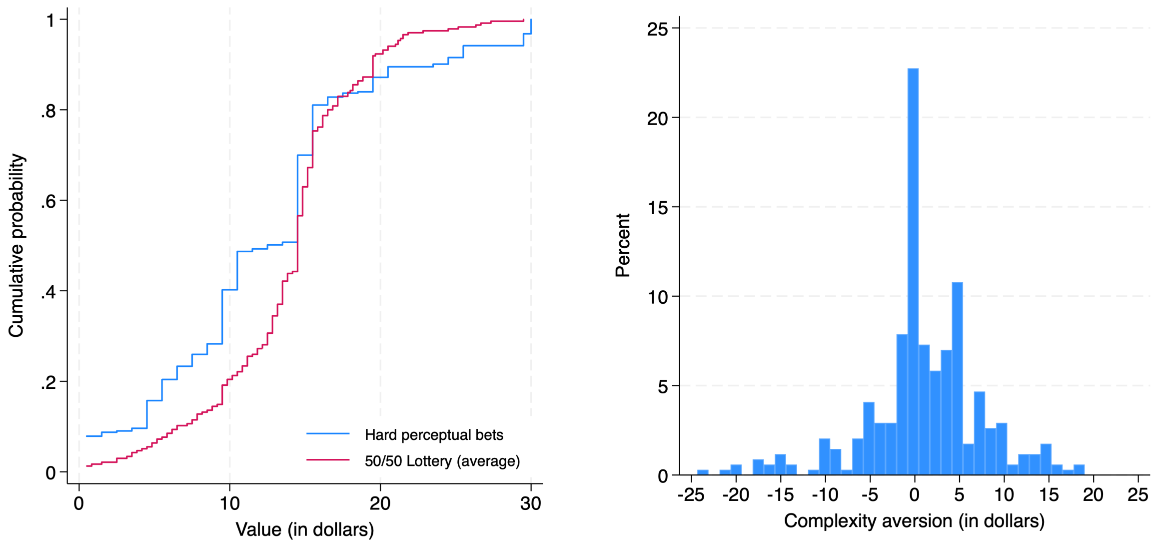


Figure 6: Two graphs on the values of hard perceptual bets for observations with uncertainty above the median. Left panel: CDFs of dollar value of hard perception bets and average value of 50/50 lottery for those subjects. Right panel: histogram of complexity aversion (difference between value of hard perceptual bets and average value of 50/50 lotteries).

stochastically ranked in the natural direction (see Figure B.12b of Appendix B).[12] Second, for each type of perceptual bet, the value of the bet varies significantly with the subject's uncertainty about that perceptual question (all p-values $< .001$; this is also significantly correlated with accuracy, with overall p-values $< .001$). Given our interest in complexity, we focus on the hard bets, for which 50/50 lotteries serve as a natural benchmark. As explained above, for any of the perceptual bets, the value should theoretically exceed that of the 50/50 lottery, and this constraint is most likely to bind when the perceptual task is most difficult.

Caution. Like in Experiment A, we are interested in comparing the value of the hard perceptual bets with the average value of 50/50 lotteries, particularly for subjects who are relatively uncertain. We say a subject has high uncertainty in an observation if their uncertainty is in the top half expressed among all hard bets. Once again we find that, for each of the two hard perceptual bets, subjects who express high uncertainty undervalue the bet relative to how they value the 50/50 lotteries. The left panel in Figure 6 plots the CDF of hard-bet values for observations with high uncertainty alongside the average values of the 50/50 lotteries. This shows, once again, that complex options have a lower value (sign-rank p-values 0.0015 and 0.0113 for each of the hard bets

[12]Similarly, Figure B.12a of Appendix B shows that the distributions of values for the lotteries are also first-order stochastically ranked in the natural direction. This is reflected in accuracy: 98.2%, 92.6%, 47%, and 56.8% give the correct answer in easy, intermediate, and each of the hard questions, respectively.

Table 2: Experiment B: The Role of Ambiguity

	Complexity Aversion (1)	(2)
High Uncertainty:		
Ambiguity Aversion	.58*** (.09)	
Low Uncertainty:		
Ambiguity Aversion	.22* (.13)	
Ambiguity Aversion		.09 (.20)
Uncertainty	9.01*** (2.51)	6.66*** (2.26)
Ambiguity Aversion × Uncertainty		.77** (.38)
Constant	-5.23*** (1.01)	-4.89*** (1.09)
Observations	684	684
Controls	Y	Y

Notes: Each perceptual bet is an observation, with robust standard errors clustered by subject in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$. Both (1) and (2) are obtained from constrained regressions, as explained earlier. Controls include a dummy for which hard perceptual task the observation corresponds to, and in model (1), a dummy for high uncertainty.

separately). If we define, like before, complexity aversion as the value difference between 50/50 lotteries and the perceptual bet, the right panel of Figure 6 depicts the histogram of complexity aversion for perceptual bets where the subject expresses high uncertainty. It shows that it is negative for 33.2%, zero for 14.3%, and strictly positive for 52.5%. Average complexity aversion among these observations is $1.02 (significantly different from zero, p-value 0.01), with large variation; among those who are strictly complexity-averse, average complexity aversion is $5.36 (with a median of $4.67). Once again, complexity aversion can be high.

Relation with Ambiguity. We can test the relationship with ambiguity as mediated by uncertainty—noting, however, how uncertainty here relates to the chance of having incorrectly guessed which circle has more dots. Table 2 shows the same regressions we computed for Experiment A for hard perceptual tasks for all subjects (who pass our comprehension tests); we use the same constrained-regression approach, with perceptual bets instead of updating bets. Regression (1) shows how ambiguity aversion is positively and very strongly related to complexity aversion for subjects with high uncertainty, while it is much smaller and barely significant (p-value 0.099) for subjects with low uncertainty (the coefficients on ambiguity aversion for high/low uncertainty are statistically different, $p = .0266$). Regression (2) shows that while ambiguity aversion alone does not affect complexity aversion, the interaction term with uncertainty is significant. Uncertainty alone is also significant. This is to be expected: aside from being likely correlated to cognitive uncertainty, it also directly reflects the probability of (not) getting the prize. Overall, our results mirror those of Experiment A despite the substantial differences in the tasks.

Experiment B corroborates our main takeaways from Experiment A: complex options are undervalued in a way incompatible with standard models and this phenomenon is related to ambiguity aversion but mediated by how uncertain a subject is. Importantly, these takeaways are confirmed in a task on the opposite end of the cognitive spectrum with a different design.

5 Experiment C: Compound Risks

5.1 Design

Our third experiment studies the role of complexity and caution in a classical task in decision-making under risk: compound lotteries. It is well established that individuals are averse to compound lotteries and that this aversion is associated with ambiguity aversion (Halevy, 2007). Is this relationship mediated by the subject's perception of complexity?

The experiment design shares many features with previous ones, including interfaces, order of questions, training, and comprehension quizzes. Subjects face several scenarios in which the computer draws a card from a deck (decks were chosen for reasons that will become clear). Like before, in valuation tasks, subjects receive either \$0 or \$30 based on the color of the drawn card.

In our main treatment, the experiment begins with subjects valuing a 50/50 lottery, 70/30 and 30/70 lotteries (in random order), another 50/50 lottery, and an ambiguous bet. Subjects then evaluate compound bets (in random order). The main ones appear in Figure 7. Both are non-degenerate compound lotteries that reduce to a 50/50 probability of winning. However, this equivalence is much less transparent for the scenario on the left than the one on the right: we refer to the former as the *non-trivial compound lottery* and to the latter as the *trivial compound lottery*.[13] Following these valuations, for each compound scenario, we elicit the subject's belief of the "exact" chance that the drawn card is purple (incentivized with binarized scoring, \$5 prize) and

[13]The experiment also included a third compound risk, which also reduces to a 50/50 lottery but is unusual as the presence of a second stage is contingent on the initial draw; we call it the *draw-again* compound lottery. As we discuss below, this was misunderstood by several subjects and is discussed separately.

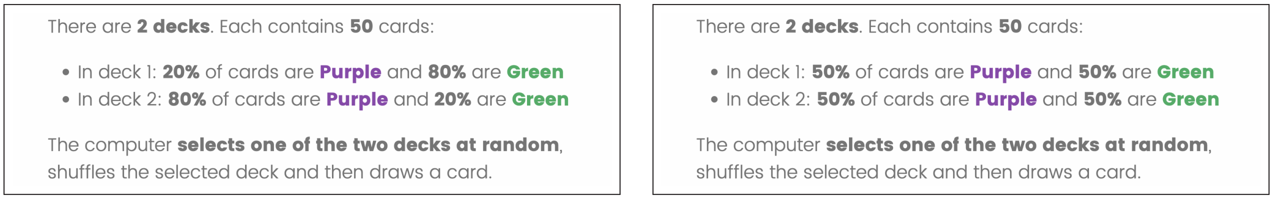


Figure 7: Compound risks, as phrased in the Main (percents) treatment. Both scenarios yield a 50/50 distribution over the card color, though this is less obvious in the left panel than the right.

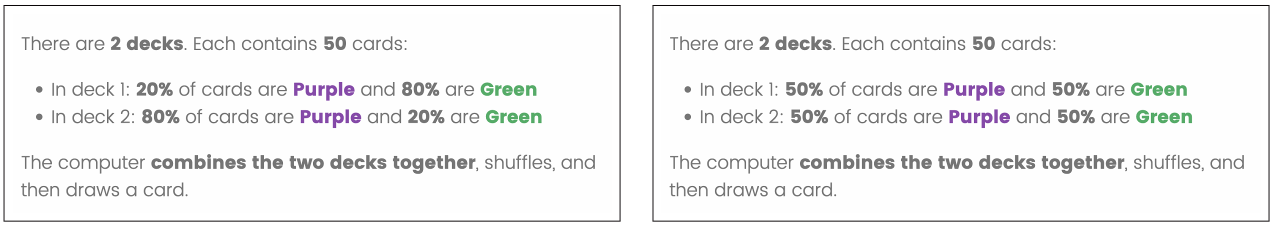


Figure 8: The One-Stage Mirror treatment counterparts of the compound risks in Figure 7.

the cognitive uncertainty about this belief. Subjects then complete two final valuation tasks—for another 50/50 lottery and another ambiguous bet.

The compound bets in Figure 7 correspond to our "Percents" framing. For robustness, an equal number of subjects take an otherwise identical "Graphical" framing, which defines the compound scenarios using smaller numbers with visual aids (5 cards instead of 50, and instead of percentages, the screen displays 1 purple card and 4 green cards; see Figure Online-A.58 in the Online Appendix).

One-stage Mirror. Is the source of complexity in compound lotteries the computation needed to reduce the lottery or the presence of multiple stages? To test this, we introduce a One-Stage Mirror treatment that aims to preserve the computational structure with only one stage of risk. Figure 8 shows the mirror counterparts of our main compound lotteries: instead of randomly choosing a deck, decks are now combined, making it a one-stage lottery. Aside from this adjustment, the one-stage treatment is identical to the Percent framing of the Main treatment. Testing how cognitive uncertainty and complexity aversion vary in this treatment is informative of whether the source of complexity is the computation or the conceptual difficulty of dealing with multiple stages.

Implementation. 994 subjects participated through Prolific in May 2024, with 397 subjects in each version of the Main treatments and 200 subjects in the One-Stage Mirror, and was pre-registered.[14] As before, following our pre-registration, the main body of the paper focuses only

[14]Median completion time was slightly over 12 minutes. As in Experiment A, subjects received $3 for participation, and 10% of subjects were eligible for a bonus payment based on their answer to one of the main tasks (drawn at random). The average bonus paid was $10.57, with a maximum potential bonus of $30. The protocol can be found at

on the subjects who pass our comprehension quiz on the first attempt (approximately 70% of subjects across treatments), while Appendix C replicates our figures and tables for the entire sample; like before, results are very similar.

5.2 Results

Because behavior in the Percent and Graphical framing of the Main treatment was very similar, we analyze them jointly.[15] Moreover, we focus on the two traditional compound lotteries and discuss the behavior with the third one (draw-again) in Appendix D.2; this is because a substantial fraction of subjects appear to have misunderstood the question (in the direction of our desired results, but possibly spuriously), making interpretation more difficult.

Compound Aversion, Cognitive Uncertainty, and Ambiguity. As we did with the other experiments, we begin with the raw data: The left panel of Figure 9 depicts the CDFs of the values of the trivial and non-trivial compound lotteries and the average value of 50/50 lotteries. Unsurprisingly, given the extensive evidence on compound aversion, the non-trivial compound lottery is significantly undervalued: on average, by $2.56 (complexity aversion is strictly negative for 16%, zero for 21%, and strictly positive for 63%). The trivial compound lottery shows no sign of such aversion (compound aversion is 19 cents on average; it is strictly negative for 31%, zero for 33%, and strictly positive for 36%). This is intuitive, as it is easier to see that the trivial compound lottery gives a 50% chance of winning. At the individual level, most subjects express at least as much cognitive uncertainty for the non-trivial compound lottery than the trivial one (see the scatterplot in Figure B.13b of Appendix B). Even so, there remains some cognitive uncertainty for the trivial compound lottery: an average CU of 26%, compared to 42% for the non-trivial compound. Broadly, we say a subject expresses high cognitive uncertainty for a bet if their CU is in the bottom half of the distribution over the two compound lotteries.[16] Among low (high) CU observations, about 61% (40%) correspond to the trivial compound lottery.

As in previous experiments, we can define complexity aversion as the difference between the average value of 50/50 lotteries and the value of the complex object, the compound lottery; here,

https://aspredicted.org/n7p4-6m3y.pdf.

[15]We don't find evidence of cross-frame differences in the value of trivial or non-trivial compound bets (p-values > 0.52 for Kolmogorov-Smirnov, or Wilcoxon ranksum, or t-tests), confidence for either question (p-values > 0.34 in all cases), subject-level-average value of the 50/50 lottery (p-values > 0.41 in all cases), or of the Ellsberg bet (p-values > 0.28 in all cases). Similarly, we cannot reject the hypothesis that, for each column in our regression table discussed below (Table 3), the estimated regression coefficients are equal across the two framings ($p > 0.24$ in all columns, robust Chow test). For completeness, the results per framing are provided in Appendix D.1. Point estimates are always in the same direction and similar magnitude; with approximately half the subjects in each regression, there is some loss of significance, but it is almost always restored if we consider the full sample (i.e., without the quiz exclusion).

[16]To be precise, we define the cutoff within each frame, although cutoffs turn out to be identical across frames for subjects who pass our comprehension checks. The same applies for high relative CU below.

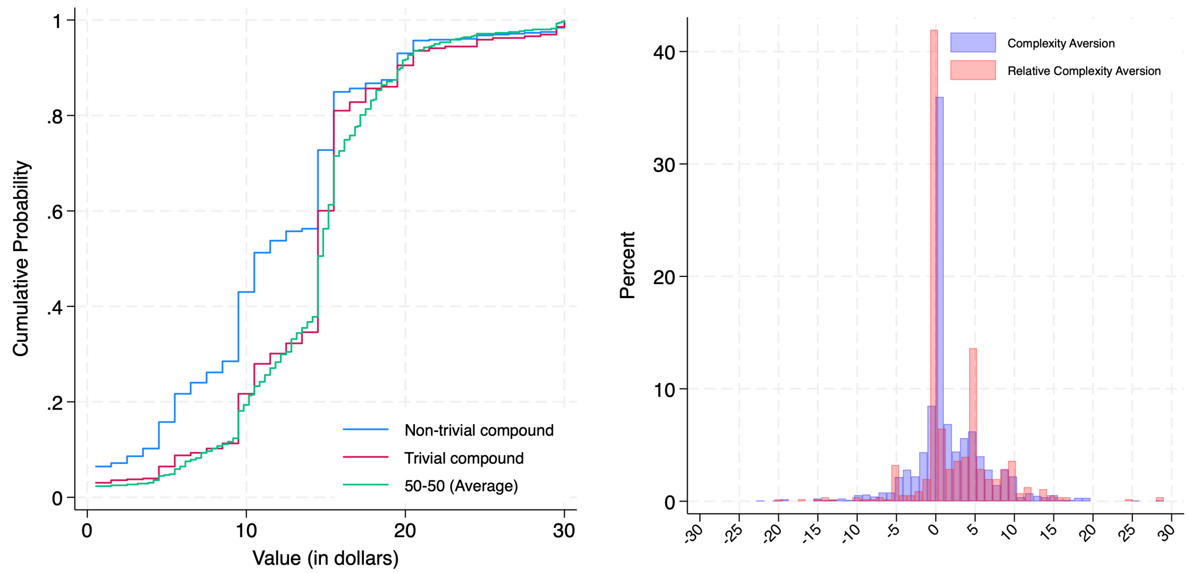


Figure 9: Left panel: CDFs of dollar value of the non-trivial and trivial compound lotteries and average value of 50/50 lottery. Right panel: histogram of complexity aversion (value difference of 50/50 lotteries and non-trivial compound lottery) and relative complexity aversion (value difference of the trivial and non-trivial compound lottery).

complexity aversion is simply compound aversion. In this experiment, we can also define *relative complexity aversion*: the value difference between the trivial compound lottery and the non-trivial one. This captures changes in value due to the added complexity holding constant the number of stages. Unsurprisingly, given the left panel of Figure 9, relative complexity aversion is similar to complexity aversion, with an average of $2.37. The right panel of Figure 9 gives the histogram of complexity aversion for the non-trivial compound lottery and relative complexity aversion. In this vein, we may also consider a notion of *relative* cognitive uncertainty: the increase, at the individual level, in cognitive uncertainty from the trivial to the non-trivial compound lottery. We say a subject has high relative CU if they are in the top half of the relative CU distribution.

Like in our previous experiments, we can test the relation of complexity aversion with both cognitive uncertainty and ambiguity aversion; we can do the same with relative complexity aversion. These appear in Table 3. Columns (1) and (2) report the same constrained regressions we run for the other experiments using complexity aversion; Columns (3) and (4) repeat this focusing only on the non-trivial compound lottery. Columns (5) and (6) run similar regressions on relative complexity aversion using relative cognitive uncertainty.

Our results confirm the findings in Experiments A and B. The interaction of compound and ambiguity aversion affects complexity aversion. Results for relative complexity aversion are similar but stronger in magnitude and significance: this may be a more appropriate measure, probably because

Table 3: Experiment C: The Role of Ambiguity and Cognitive Uncertainty

	Complexity Aversion (Trivial and non-Trivial)		Complexity Aversion (non-Trivial only)		Relative Complexity Aversion (non-Trivial only)	
	(1)	(2)	(3)	(4)	(5)	(6)
High Cognitive Uncertainty:						
Ambiguity Aversion	$.39^{***}$		$.60^{***}$		$.53^{***}$	
	(.05)		(.08)		(.09)	
Low Cognitive Uncertainty:						
Ambiguity Aversion	$.21^{***}$		$.35^{***}$		$.26^{***}$	
	(.06)		(.08)		(.07)	
Ambiguity Aversion		$.20^{***}$		$.40^{***}$		$.31^{***}$
		(.05)		(.08)		(.06)
CU		-.89		-.37		-1.12
		(.61)		(.74)		(1.05)
Ambiguity Aversion × CU		$.32^{***}$		$.26^{*}$		$.60^{***}$
		(.12)		(.15)		(.20)
Constant	2.54^{***}	2.91^{***}	2.18^{***}	2.60^{***}	3.04^{**}	3.08^{***}
	(.60)	(.62)	(.75)	(.75)	(1.26)	(1.27)
Observations	1116	1116	558	558	558	558
Controls	Y	Y	Y	Y	Y	Y

Notes: Robust standard errors in parentheses, clustered by subject in models (1) and (2), where each subject appears in two observations. * $p < .1$, ** $p < .05$, *** $p < .01$. (1)-(4) are obtained from constrained regressions. In (5)-(6), CU refers to relative cognitive uncertainty. Controls include beliefs and a dummy for each compound lottery; in model (1), (3), (5), also a dummy for high CU.

relative cognitive uncertainty provides a "normalization" of a subjective measure. Again, the correlation with ambiguity aversion is significantly higher when cognitive uncertainty is high rather than low (p-values .0407, 0.0330, and 0.0158 for regressions (1), (3), (5)). The same conclusion applies to continuous interaction. While these results confirm those of the previous experiments, here ambiguity aversion maintains an effect even for subjects with low cognitive uncertainty—the coefficient is about *half* but remains significant. Ambiguity aversion is also significant by itself in continuous interactions.

Broadly, our results have implications for interpreting the interaction between compound lotteries and ambiguity aversion. Like the previous literature, we find a strong correlation between ambiguity aversion and compound aversion; for example, if we run a constrained regression similar to model (3) on Table 3 without separating High and Low cognitive uncertainty, the coefficient on

Ambiguity aversion is .51 (std. err. .06).[17] Our results suggest that it is subjects with high cognitive uncertainty whom are primarily driving this interaction, even though some effect does exist even for subjects with low cognitive uncertainty.

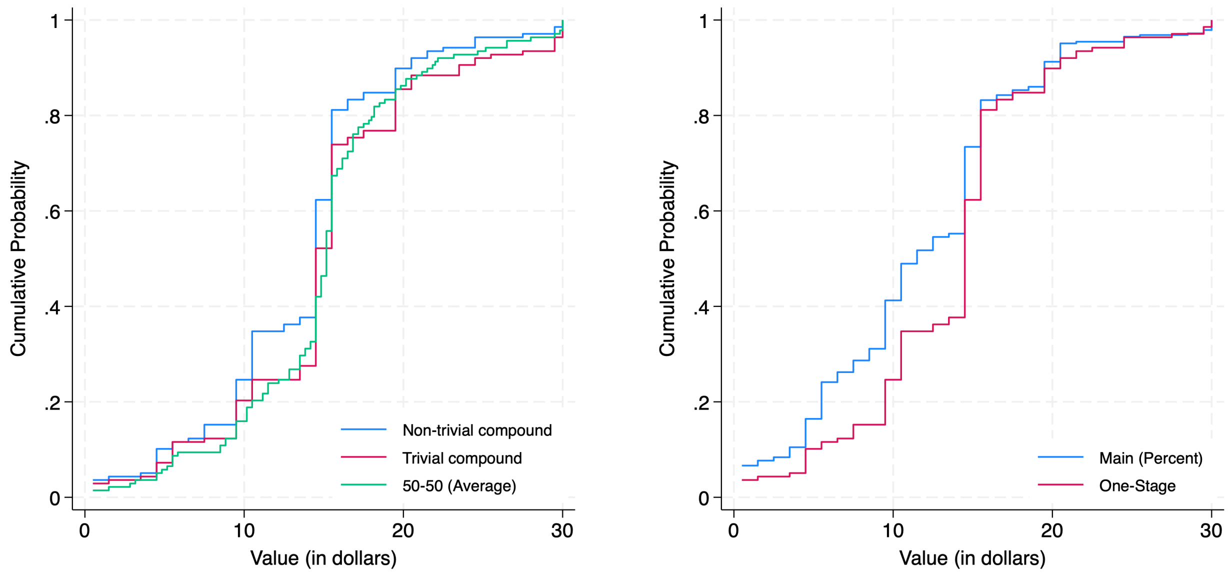
One-Stage Treatment. In our one-stage treatment, subjects faced questions that were computationally identical but involved only one stage of randomization. Does this eliminate aversion?

In the one-stage treatment, aversion is sharply reduced but does not disappear. The left panel of Figure 10 shows the analogue of the left panel of Figure 9 for this treatment: the CDF of dollar values of 50/50 lotteries and the two "compound" lotteries (which are no longer compound; we call them "pseudo-compound"). The right panel of Figure 10 compares CDFs of the dollar values of our main lottery of interest, the non-trivial compound lottery, in the One-Stage and the Main treatments (focusing on the Percent framing as it is the direct correspondent). The aversion to "pseudo-compound" is much smaller than that to compound. However, it has not disappeared: average aversion is $1.4 (vs. $2.5 before), and 47% of subjects still have a strictly positive measure. Notably, this is associated with a reduction in cognitive uncertainty: average cognitive uncertainty is 23% for the non-trivial pseudo-compound, against 42% for the equivalent in our Main treatment.

These results appear in line with the following interpretation. The presence of two stages adds to the complexity of compound lotteries. Once we eliminate them, the aversion is reduced sharply (by approximately 44%) but does not disappear—because not all complexity is eliminated.

Summary of Results. Experiment C suggests that the same key forces we documented in previous experiments may be at play in the evaluation of compound lotteries as well: subjects undervalue complex options and this effect is related to the interaction of ambiguity aversion with cognitive uncertainty. At the same time, our results are informative on compound lotteries *per se*. They show that the well-known correlation with ambiguity aversion appears to be primarily driven by subjects with high cognitive uncertainty. This also seems to be related to the inherent complexity of the multiple stages of compound lotteries. Our one-stage treatment, on the one hand, shows that once we eliminate the multiple stages, cognitive uncertainty diminishes, and so does aversion. On the other hand, aversion is not fully eliminated, even though our "pseudo-compound" lottery is no longer a compound lottery.

[17] If we construct variables using different questions for ambiguity and complexity aversions (instead of using constrained regression), we obtain a raw correlation of .44 between compound and ambiguity aversion, not dissimilar from results in the literature (e.g., Chapman et al. 2023).



(a) One-Stage Treatment: CDFs of dollar values of the trivial and non-trivial compound bets, along with average value of 50/50 lotteries.

(b) CDF of dollar values of the non-trivial compound bets in the One-Stage treatment versus the Percentages version of the Main treatment.

Figure 10: The value of compound bets and 50/50 lotteries in the Mirror treatment.

6 Our Mechanism in the data of Enke and Graeber (2023)[18]

If our mechanism is as prevalent as our results suggest, it should also manifest in other datasets as well. We test for it in the data of Enke and Graeber (2023), which includes two experiments that elicit the dollar value of several risky lotteries and the cognitive uncertainty for each valuation. Enke and Graeber (2023) shows that cognitive uncertainty induces "attenuation:" when CU is high, lottery values are less responsive to parameters and are attenuated towards intermediate options. If our mechanism is also at play, high CU should also correspond to *lower* values of bets overall. This is precisely what we find.

Data. Of the many experiments and tasks reported in Enke and Graeber (2023), only two include dollar valuations and are of interest to our goals: *Risk A* and *Risk B*, both of which measured *i*) the certainty equivalents of binary lotteries and *ii*) the cognitive uncertainty about this valuation—how confident participants are that the actual value is within a range of their choice. Lotteries paid a prize with a given probability and zero otherwise; both prizes and probabilities were chosen randomly from a set of prizes and a set of probabilities, where possible probabilities were symmetric

[18]We thank Ben Enke for his valuable help analyzing the data discussed in this section and for suggesting the exact regressions to run.

around 0.5 (drawing probability p was equally likely as $(1-p)$).[19] However, the two experiments differ in many implementation details, elicitation methods, and pools;[20] documenting our results in both datasets would point to their robustness. In the original datasets, CU is normalized to be from 0 to 1, while certainty equivalents are normalized as a percentage of the winning prize. In addition, both experiments include a *Complex* manipulation: in Risk A, this involved presenting win probabilities as an algebraic expression and was conducted between subjects; in Risk B, this involved presenting lotteries as compound lotteries and was run within-subjects; our analysis below is run both excluding and including complex manipulations. We refer to Enke and Graeber (2023) for additional details.

Tests. The main finding of Enke and Graeber (2023) is that when cognitive uncertainty is high, decisions are heavily attenuated functions of objective probabilities, and values are attenuated towards those of an intermediate option, the 50/50 lottery. To test our mechanism, we can evaluate whether cognitive uncertainty further *lowers* the values in addition to attenuation. In principle, this analysis may be complicated by the interaction with attenuation: for high probabilities, attenuation already induces lower values, making it difficult to disentangle the effects of our mechanism; for low probabilities, attenuation induces higher values, countering the effect we aim to document. Luckily, this is not a concern in this data: because winning probabilities are designed to be "balanced" around the intermediate point of 0.5, for any high probability where attenuation induces a decrease in value, there is a counterpart low probability where attenuation induces an increase in value. We can then simply regress certainty equivalents on cognitive uncertainty on the whole dataset, knowing that if only attenuation were at play, we should find no effects. Additional effects must, therefore, be due to external forces.

Results. Columns (1) and (3) in Table 4 show the effect of cognitive uncertainty on normalized certainty equivalents in the standard-lottery data of Risk A and Risk B experiments. Results are clear: there is a very strong and very significant effect of cognitive uncertainty in lowering the value of lotteries—as predicted by our mechanism. Note the effect size: in Risk A, going from a CU of 0 to 1 lowers the normalized certainty equivalent of 15 percentage points of the winning prize. Since average normalized certainty equivalents in that experiment are around 55% of the winning prize, this means that certainty equivalents decrease by about 27%. The effect is not only

[19] Specifically, in Risk A prizes are chosen uniformly from $\{15, 16, \dots, 25\}$ and probabilities (percentages) from $\{1, 5, 10, 25, 35, 50, 65, 75, 90, 95, 99\}$. In Risk B, these were $y = \{15, 20, 25\}$ and $\{5, 10, 25, 50, 75, 90, 95\}$, respectively. In addition, in Risk B, half of the questions involved losses, chosen from $\{-15, -20, -25\}$.

[20] Risk A involved 500 subjects on Prolific, elicited certainty equivalents using the BDM technique of Healy (2018), used lotteries with only gains, and measured cognitive uncertainty as the probability that the true lies within a given range. Risk B involved 700 on Amazon Mechanical Turk, used MPLs, studied lotteries with gains but also losses, and measured CU by asking subjects to indicate the range within which they were certain the true value lies.

Table 4: Effect of cognitive uncertainty (CU) on normalized certainty equivalents (CE)

	Risk A		*Risk B*		
	(1) CE	(2) CE	(3) CE	(4) CE	(5) CE
CU	-15.17 ***		-11.36***		-12.21***
	(3.57)		(2.83)		(4.62)
CU × *Baseline*		-15.94***		-8.54***	
		(2.94)		(2.55)	
CU × *Complex*		-16.71***		-9.14***	
		(2.28)		(2.81)	
constant	59.73***	59.42***	6.16***	6.09***	-34.14***
	(.96)	(.74)	(.50)	(.46)	(.84)
N	4,524	6,000	2,890	4,200	1,328
Complex variation	No	Yes	No	Yes	No
Fixed Effects	Yes	Yes	Yes	Yes	Yes
Gains/Losses	Gains	Gains	Gains/Losses	Gains/Losses	Losses

Notes: CU is normalized to be from 0 to 1. Normalized certainty equivalents are computed as the certainty equivalent as a percentage of the winning prize of the lottery. Robust standard errors in parenthesis clustered at the individual level, *** $p < 0.01$. All regressions include problem and individual fixed effects.

statistically significant, it is also very large.

Columns (2) and (4) add the data from the complex variations of both experiments and find effects remarkably similar in magnitude per unit of cognitive uncertainty—even though, as shown by Enke and Graeber (2023), cognitive uncertainty is much higher in complex variations.

One possible concern with this analysis is that attenuation may still partially explain these results if some subjects attenuate towards zero instead of 50/50. Fortunately, we can test this by focusing exclusively on lotteries involving losses in Risk B: if the culprit is attenuation towards zero, cognitive uncertainty should have a positive effect here; if caution is at play, the effect should remain negative. Column (5) of Table 4 runs our regression focusing on lotteries with only losses and shows that our effects remain robustly negative and of similar magnitude even in this case.

All regressions in Table 4 contain between 6 and 12 certainty-equivalents per subject and include individual fixed effects (to capture individual variations of risk attitudes or how cognitive uncertainty is interpreted). However, this makes the tests slightly different from those of our experiments, which are typically between subjects and use one or two measures of complexity aversion (and associated CU) per subject. To get closer to our previous approach, we can replicate this analysis focusing only on the first or first two answers given by each subject (as the order is random) without individual fixed effects; Tables B.5 and B.6 show how we continue to get significant negative effects of similar magnitude in all but the last column (where the lack of significance is likely because, since we are selecting only on the few negative prizes, numbers drop considerably).

This analysis shows how our mechanism appears to be at play also in two preexisting datasets, emerging robustly despite the differences in many implementation details, pools, and approaches.

7 Discussion

This paper demonstrates that most individuals undervalue options they perceive as complex. We establish this in three large-scale, preregistered experiments examining updating, visual perception, and compound lotteries. We propose a mechanism suggesting that individuals react with caution to the "internal ambiguity" induced by complexity. Supporting this, we find that aversion to complexity increases with the interaction of ambiguity aversion with the individual subject's perception of uncertainty, cognitive uncertainty. We also validate this mechanism using the data from Enke and Graeber (2023), showing that higher cognitive uncertainty corresponds not only to attenuation but also to lower valuations.

Implications. Our findings have several implications. First, they may explain certain market behaviors, such as why individuals avoid complex options—even when they appear advantageous to analysts—or abstain from choosing altogether. They may also shed light on why marketing campaigns often emphasize the simplicity of the offerings (e.g., "a simple plan!").

Second, understanding attitudes toward complexity is crucial in policy design. When individuals are complexity-neutral, governments might present carefully tailored but intricate options to address specific needs. However, as our findings show, if individuals are complexity-averse, overly complex options may remain unused. Recognizing when and how complexity aversion applies allows for refined policy design that avoids these pitfalls. For instance, our results suggest policymakers should aim to minimize subjects' individual perceptions of uncertainty in available choices.

Third, our results indicate that popular models used to study decision-making under complexity—such as rational inattention and cognitive noise models—may overlook a critical component: the significant effect of aversion to complexity on valuation and choice.

Fourth, our findings have implications for models of updating and compound lotteries. They suggest that many models of non-Bayesian behavior may be missing an important aspect: aversion to the complexity involved in updating. Moreover, they support the view that compound lottery aversion might be rooted in an aversion to the complexity of the compounded structure itself.

Interpretation. While our mechanism suggests that caution arises in response to complexity, interpreting the relationship with ambiguity aversion is more nuanced. Complexity may generate a form of internal ambiguity, and our results may be a form of ambiguity aversion; if so, ambiguity could be more prevalent than assumed, emerging in updating and perceptual tasks alike. Alternatively, the primary driver could be an aversion to complexity itself, with ambiguous tasks like Ellsberg bets merely representing extreme cases of complexity. Or, both ambiguity and complexity aversion might reflect a broader tendency toward caution. We hope future research will clarify which of these interpretations holds.

Models? While developing a full model of caution in the face of complexity is beyond the scope of this paper, we can briefly discuss possible approaches. A natural starting point is to define a measure of the complexity of an alternative and construct a model of "first-order" complexity aversion that subtracts a complexity cost from the Expected Utility of the option—as in existing approaches in the literature such as Puri (forthcoming) and Gabaix and Graeber (2023). For example, given a set of states Ω and consequences X, for any act $f \in X^{\Omega}$, define $k : X^{\Omega} \to \mathbb{R}$ a measure its perceived complexity by the individual, captured by cognitive uncertainty. Then, for some utility $u : X \to \mathbb{R}$, prior π on Ω, and $\theta \in \mathbb{R}$, any act $f \in X^{\Omega}$ is evaluated by

$$V(f) = \mathbb{E}_{\pi}[u(f)] - \theta\, k(f).$$

In this simple functional form, the parameter θ captures the degree of aversion towards complexity. If $k(f)$ relates to subjects' complexity-induced uncertainty (cognitive uncertainty) and θ correlates with ambiguity aversion, as is natural, then a model of this kind would predict our empirical results that the undervaluation of complex options is strongly related to the *interaction* of the two. As it is well-known, however, models of this type may generate violations of first-order stochastic dominance unless properly disciplined.

Alternatively, one may view complexity as generating hard-to-interpret messages and develop a model where individuals face no ambiguity ex-ante but receive information with ambiguous interpretation, leading to uncertainty aversion. This generates a model of second-order complexity aversion that could resemble the Smooth Ambiguity model of Klibanoff et al. (2005), but with ambiguity concerning the joint probability between messages and states, reminiscent of models of ambiguous information like Epstein and Halevy (2024). A natural avenue of further research is to develop these models and study their implications.

Preferences Matter After All? We conclude with a conceptual point. A recent strand of research has argued for the importance of cognitive factors in economic decision-making, emphasizing the role of complexity over that of preferences; for example, Enke and Graeber (2023) and Enke et al. (2023) contend that cognitive uncertainty and attenuation can produce several well-known biases in behavioral economics. Our results show the importance of how individuals *cope* with this cognitive uncertainty—a specific aspect of *preferences* that interacts with, but is distinct from, purely cognitive aspects.

Appendix

A Constrained regressions

In this appendix, we elaborate further on constrained regression models described above. Consider first a discrete model like (1) from Table 1, where the coefficient on Ambiguity Aversion depends on a discrete CU category (high vs. low).[21] Let 1_ℓ (1_h) be a dummy variable indicating an observation where a subject expresses low (respectively, high) cognitive uncertainty. Suppose we aim to estimate:

$$\text{CA} = \alpha + \beta_\ell\,(1_\ell\text{AA}) + \beta_h\,(1_h\text{AA}) + \vec{\gamma}\cdot \textit{controls} + \textit{error},$$

where the controls include the dummy 1_h and possibly other variables (e.g., elicited belief about the probability of winning in that task). To test whether the relationship between complexity aversion and ambiguity aversion is diminished for low-CU subjects, we would like to check whether β_ℓ is smaller than β_h. To perform this estimation, recall that CA = L − U and AA = L − E. Making these substitutions above and solving for U, we find

$$\text{U} = -\alpha + (1-\beta_\ell)\,(1_\ell\text{L}) + \beta_\ell\,(1_\ell\text{E}) + (1-\beta_h)\,(1_h\text{L}) + \beta_h\,(1_h\text{E}) - \vec{\gamma}\cdot \textit{controls} - \textit{error}.$$

Hence, we can run the constrained regression

$$\text{U} = \alpha' + \beta'_{1\ell}\,(1_\ell\text{L}) + \beta'_{2\ell}\,(1_\ell\text{E}) + \beta'_{1h}\,(1_h\text{L}) + \beta'_{2h}\,(1_h\text{E}) + \vec{\gamma}'\cdot \textit{controls} + \textit{error}'$$

using the constraints $\beta'_{1\ell} + \beta'_{2\ell} = 1$ and $\beta'_{1h} + \beta'_{2h} = 1$. Then our main coefficients of interest are found via $\beta_\ell = \beta'_{2\ell}$ and $\beta_h = \beta'_{2h}$, while $\alpha = -\alpha'$ and $\vec{\gamma} = -\vec{\gamma}'$.

Next, consider a continuous model like (2) from Table 1.[22] Suppose we want to study if ambiguity aversion and cognitive uncertainty impact complexity aversion separately and through their interaction:

$$\text{CA} = \alpha_0 + \alpha_1\text{AA} + \alpha_2\text{CU} + \beta(\text{CU} * \text{AA}) + \vec{\gamma}\cdot \textit{controls} + \textit{error}.$$

To perform this estimation, we again make the substitutions CA = L − U and AA = L − E and solve for U to find:

$$\text{U} = -\alpha_0 + (1-\alpha_1)\text{L} + \alpha_1\text{E} - \alpha_2\text{CU} - \beta(\text{L} * \text{CU}) + \beta(\text{E} * \text{CU}) - \vec{\gamma}\cdot \textit{controls} - \textit{error}.$$

[21] Models (1) and (3) from Table 3 are similar, replacing only U with the value of the compound bets. Model (1) from Table 2 is also of this form, only replacing high/low CU with high/low uncertainty and U with the value of the perceptual bets.

[22] Again, similar analysis holds for model (2) in Table 2 and models (2) and (4) in Table 3.

Then, we can run the constrained regression

$$\text{U} = \alpha_0' + \alpha_1''\text{L} + \alpha_1'\text{E} + \alpha_2'\text{CU} + \beta''(\text{L} * \text{CU}) + \beta'(\text{E} * \text{CU}) + \vec{\gamma}' \cdot \textit{controls} + \textit{error}',$$

using the constraints $\alpha_1' + \alpha_1'' = 1$ and $\beta' = -\beta''$. The interaction term of interest is $\beta = \beta'$, while we find the other terms using $\alpha_0 = -\alpha_0'$, $\alpha_1 = \alpha_1'$, $\alpha_2 = -\alpha_2'$, and $\vec{\gamma} = -\vec{\gamma}'$.

B Additional Figures and Tables

We include here additional figures referenced in the text.

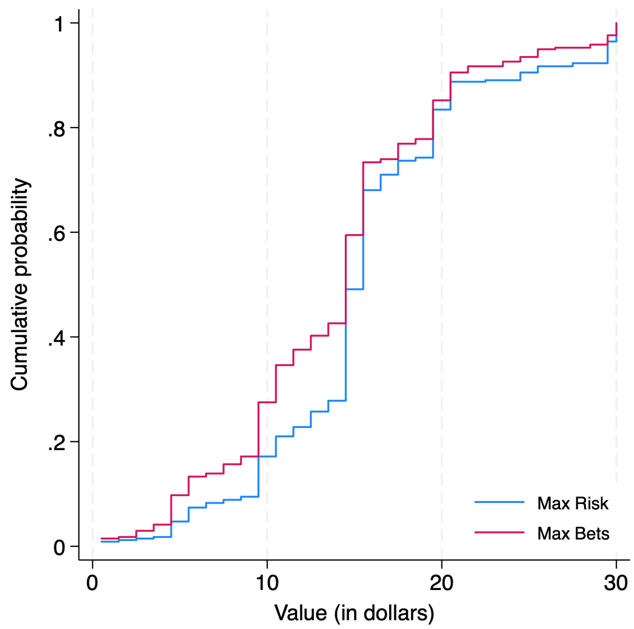
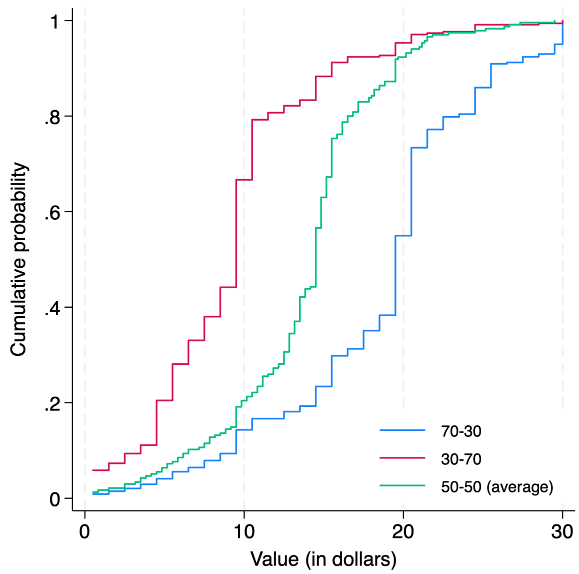
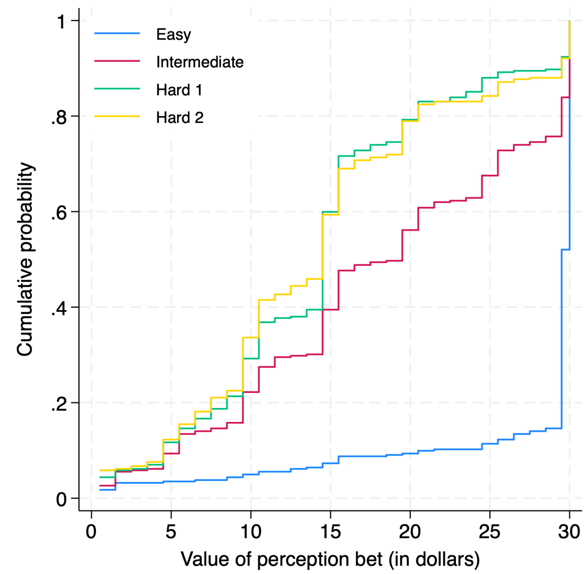


Figure B.11: CDFs of maximum values for the 50/50 lotteries and updating bets (Experiment A).

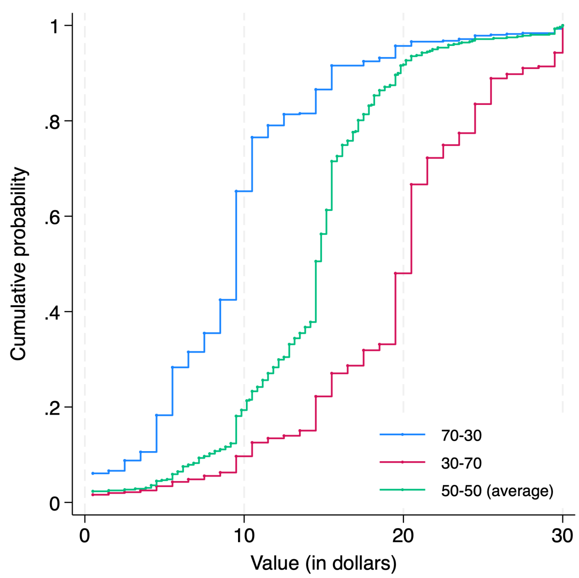


(a) CDFs of values for lotteries.

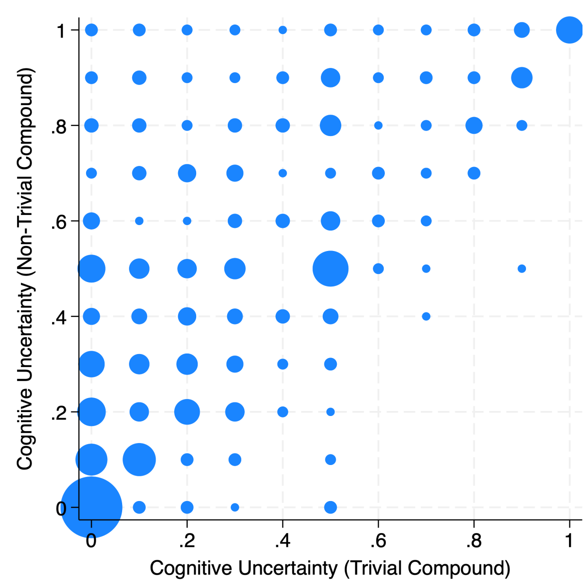


(b) CDFs of values for perceptual bets.

Figure B.12: Additional figures for Experiment B.



(a) CDFs of values for lotteries.



(b) Scatterplot of CU for Non-Trivial vs. Trivial.

Figure B.13: Additional figures for Experiment C, Main (two-stage) treatment.

Table B.5: Effect of CU on normalized certainty equivalents (CE), First Instance Only

	Risk A		*Risk B*		
	(1) CE	(2) CE	(3) CE	(4) CE	(5) CE
CU	-19.53 ***		-13.04**		-10.61
	(6.82)		(5.24)		(8.83)
CU × *Baseline*		-14.94**		-10.35**	
		(6.05)		(4.67)	
CU × *Complex*		-13.70***		-17.36***	
		(4.57)		(6.30)	
constant	61.55***	58.93***	9.15***	6.90***	-32.20***
	(1.94)	(1.73)	(1.36)	(1.22)	(2.10)
N	491	746	491	699	231
Complex variation	No	Yes	No	Yes	No
Problem Fixed Effects	Yes	Yes	Yes	Yes	Yes
Gains/Losses	Gains	Gains	Gains/Losses	Gains/Losses	Losses

Notes: All regressions include only the first lottery individuals see (round ≤ 1), except in Column 2, since Complex lottery appear only starting from round 7; in that case, we include only the first non-complex lottery seen and the first round in which complex lotteries appear (round ≤ 1 for non-complex, round ≤ 7 for Complex). CU is normalized to be from 0 to 1. Normalized certainty equivalents are computed as the certainty equivalent as a percentage of the winning prize of the lottery. Robust standard errors in parenthesis clustered at the individual level, ** $p < 0.05$, *** $p < 0.01$. All regressions include problem fixed effects.

Table B.6: Effect of CU on normalized certainty equivalents (CE), First Two Instances Only

	Risk A		*Risk B*		
	(1) CE	(2) CE	(3) CE	(4) CE	(5) CE
CU	-13.24 ***		-9.69**		-8.96
	(5.05)		(3.95)		(6.33)
CU × *Baseline*		-11.18**		-8.34**	
		(4.77)		(3.68)	
CU × *Complex*		-14.63***		-10.80**	
		(3.56)		(4.64)	
constant	58.93***	57.63***	7.84***	6.54***	-34.02***
	(1.44)	(1.38)	(1.08)	(1.01)	(1.70)
N	1,000	1,492	969	1,400	461
Complex variation	No	Yes	No	Yes	No
Problem Fixed Effects	Yes	Yes	Yes	Yes	Yes
Gains/Losses	Gains	Gains	Gains/Losses	Gains/Losses	Losses

Notes: All regressions include only the first two lotteries individuals see (round ≤ 2), except in Column 2, since Complex lottery appear only starting from round 7; in that case, we include only the first two non-complex lotteries seen and the first two rounds in which complex lotteries appear (round ≤ 2 for non-complex, round ≤ 8 for Complex). CU is normalized to be from 0 to 1. Normalized certainty equivalents are computed as the certainty equivalent as a percentage of the winning prize of the lottery. Robust standard errors in parenthesis clustered at the individual level, ** $p < 0.05$, *** $p < 0.01$. All regressions include problem fixed effects.

C Including all subjects

As required by our pre-registration, our analysis in the main body of the paper includes only subjects who respond correctly to our comprehension quiz on the first try. In what follows, we replicate our core results with the entire subject pool. The results are similar overall. Figures C.14-C.16, and Table C.7 replicates the corresponding ones in Experiment A; Figure C.17 and Table C.8 those in Experiment B; and Figure C.18-C.19 and Table C.9 those in Experiment C.

Table C.7: Counterpart to Table 1 with all sample, Experiment A: The Role of Ambiguity and Cognitive Uncertainty

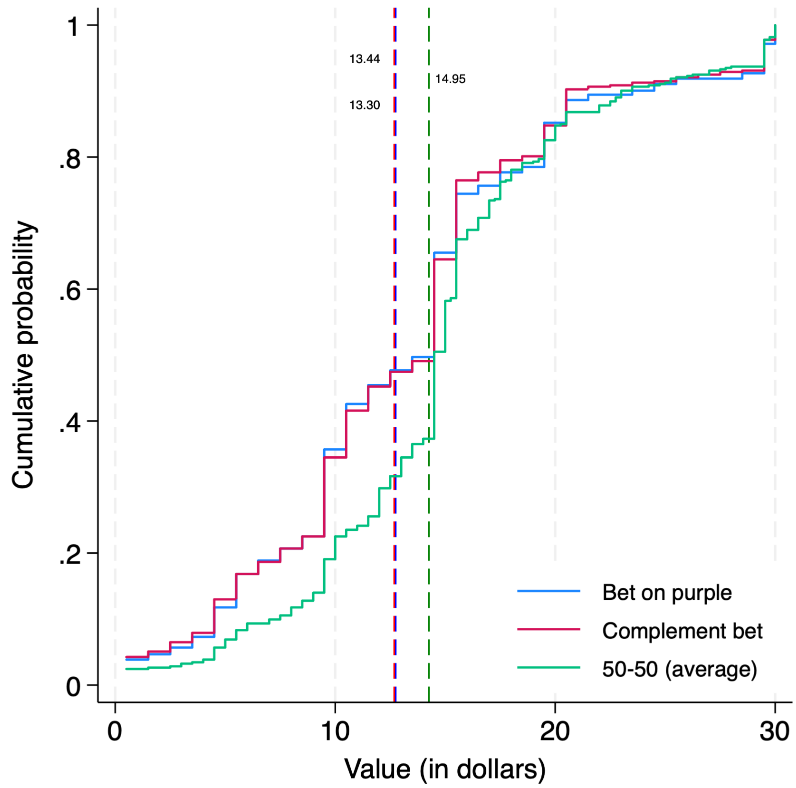
	Complexity Aversion	
	(1)	(2)
High Cognitive Uncertainty:		
Ambiguity Aversion	.31***	
	(.05)	
Low Cognitive Uncertainty:		
Ambiguity Aversion	.18***	
	(.04)	
Ambiguity Aversion		.18***
		(.05)
CU		.15
		(.57)
Ambiguity Aversion × CU		.18*
		(.10)
Constant	2.09***	2.03***
	(.55)	(.63)
Observations	986	986
Controls	Y	Y

Notes: Each updating bet is an observation, with robust standard errors clustered by subject in parentheses. * $p < .1$,*** $p < .01$. Both (1) and (2) are obtained from constrained regressions following the method previously explained. Controls include beliefs about probabilities and a dummy for each updating task and, in model (1), a dummy for high CU.

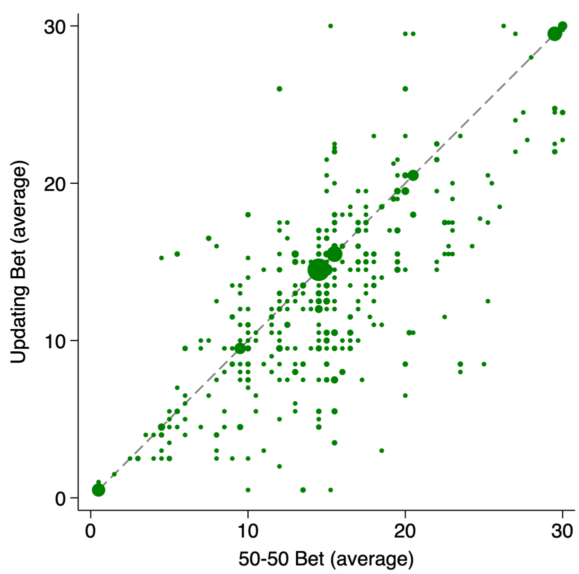
Table C.8: Counterpart to Table 2 with all sample, Experiment B: The Role of Ambiguity

	Complexity Aversion	
	(1)	(2)
High Uncertainty:		
Ambiguity Aversion	.54***	
	(.08)	
Low Uncertainty:		
Ambiguity Aversion	.23**	
	(.10)	
Ambiguity Aversion		.12
		(.16)
Uncertainty	5.75***	4.87***
	(2.10)	(1.70)
Ambiguity Aversion × Uncertainty		.65**
		(.31)
Constant	-3.65***	-3.52***
	(.81)	(0.83)
Observations	996	996
Controls	Y	Y

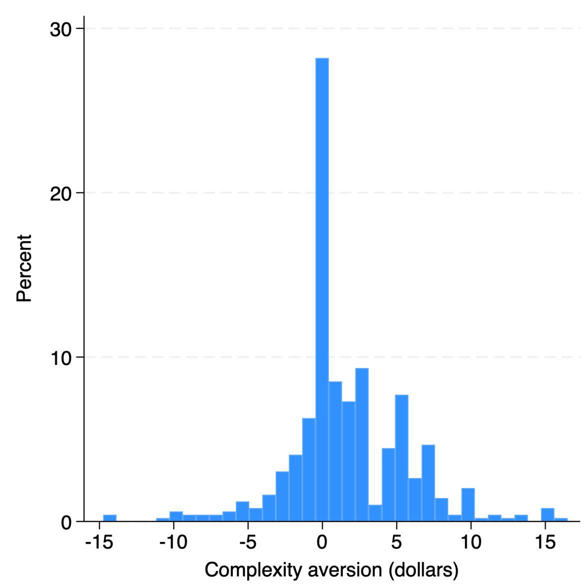
Notes: Each perceptual bet is an observation, with robust standard errors clustered by subject in parentheses. ** $p < .05$, *** $p < .01$. Both (1) and (2) are obtained from constrained regressions, following the method explained earlier. Controls include a dummy for each updating of the hard perceptual tasks and, in model (1), a dummy for high uncertainty.



(a) CDFs of the value of updating bets and the average value of 50/50 lotteries, with the sample means marked.



(b) Frequency-weighted scatter plot of the average values of updating bets and the 50/50 lotteries.



(c) Histogram of complexity aversion (the difference between the average value of updating bets and 50/50 lotteries)

Figure C.14: Three graphs on the value of updating bets and 50/50 lotteries in the Main treatment of Experiment A. Counterpart of Figure 3 with all subjects.

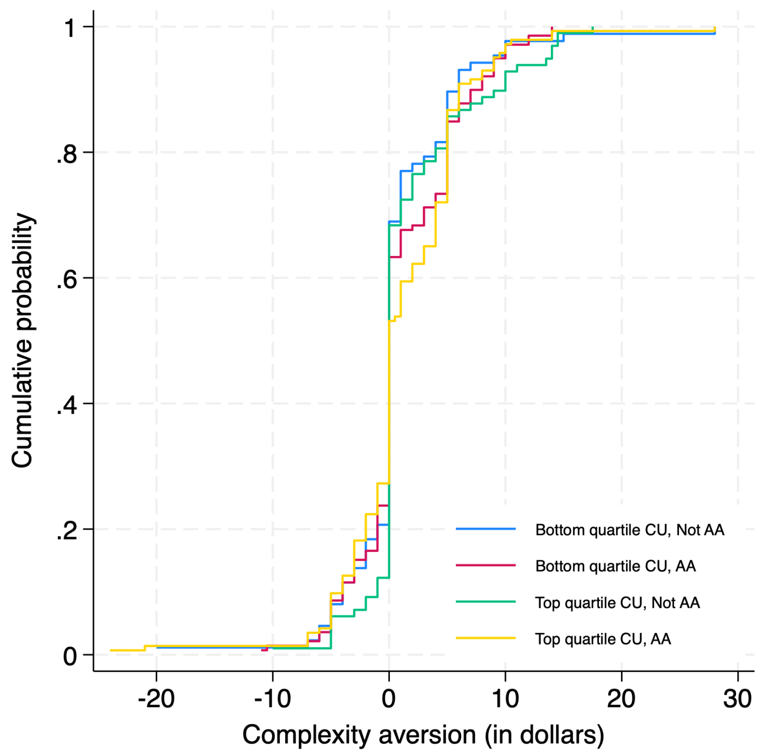
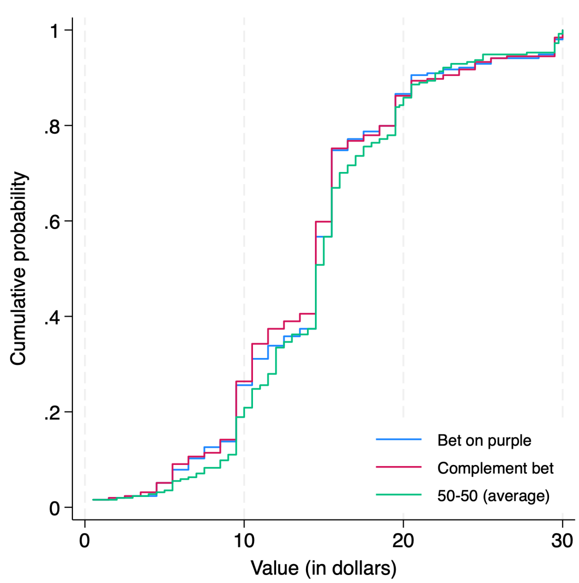
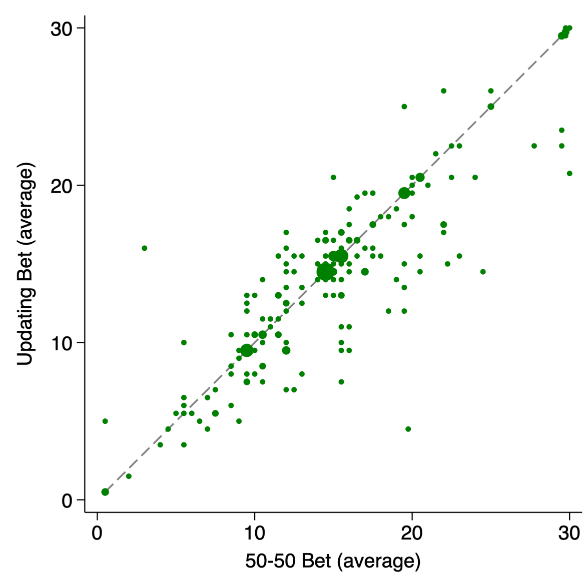


Figure C.15: Counterpart of Figure 4 with all subjects. Complexity aversion in 4 subgroups: top and bottom quartiles of Cognitive Uncertainty, divided based on (strict) Ambiguity Aversion vs. Ambiguity Neutrality/Seeking.



(a) Mirror Treatment: CDFs of dollar values of updating bets and average value of 50/50 lotteries.



(b) Mirror Treatment: Scatter Plot of average dollar value of updating bets and 50/50 lotteries.

Figure C.16: Counterpart of Figure 5 with all subjects. The value of updating bets and 50/50 lotteries in the Mirror treatment.

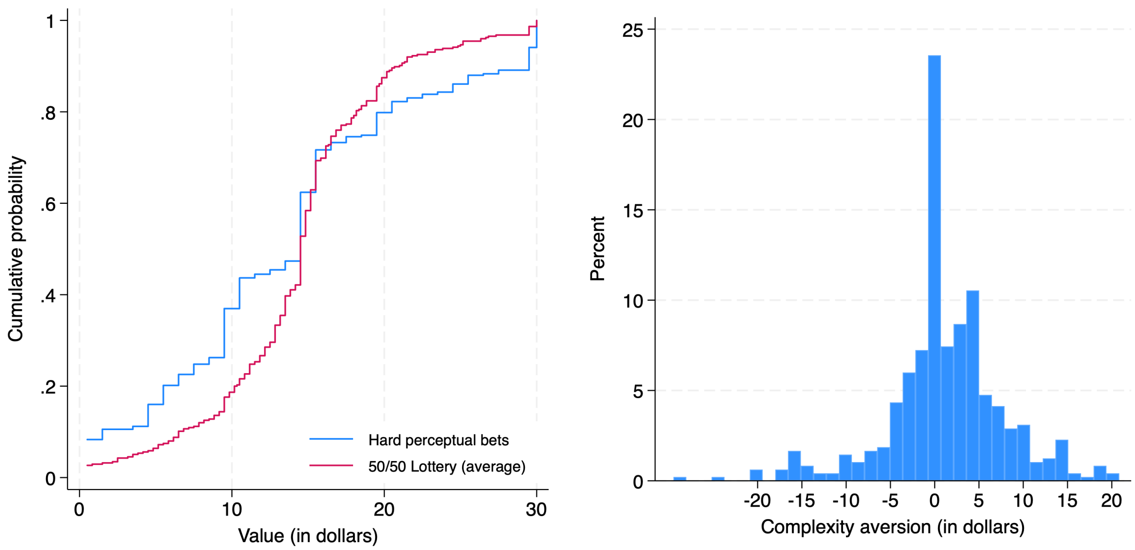


Figure C.17: Counterpart of Figure 6 with all subjects. Two graphs on the value of hard perceptual bets and 50/50 lotteries for observations with confidence below the median. Left panel: CDFs of dollar value of hard perception bets and average value of 50/50 lottery. Right panel: histogram of complexity aversion (difference between value of hard perceptual bets and average value of 50/50 lotteries).

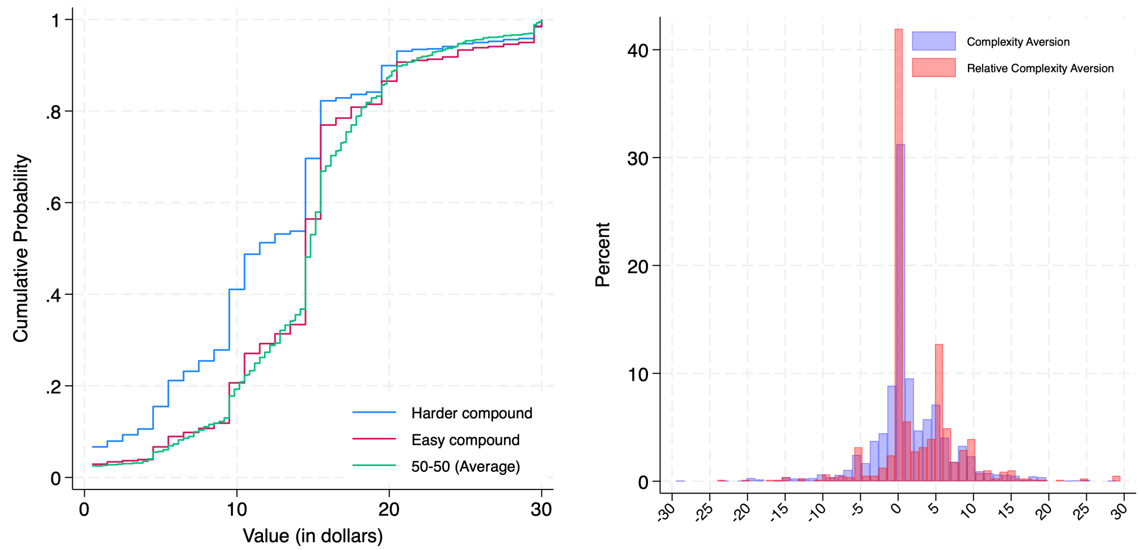
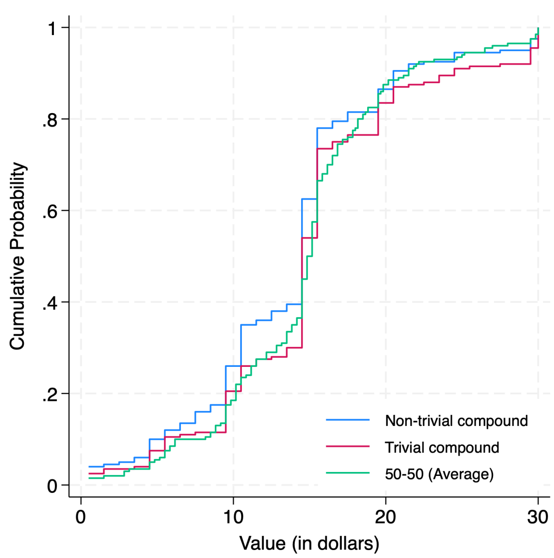
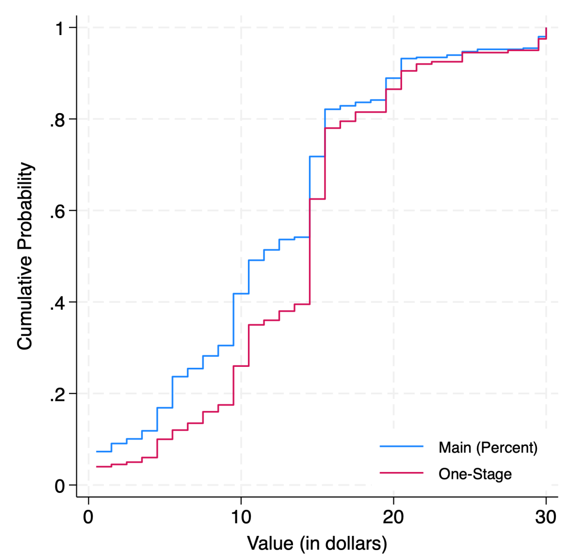


Figure C.18: Counterpart of Figure 9 with all subjects. Left panel: CDFs of dollar value of the non-trivial and trivial compound lotteries and average value of 50/50 lottery. Right panel: histogram of complexity aversion (difference between the value of 50/50 lotteries and non-trivial compound lottery) and relative complexity aversion (difference between the value of the trivial and non-trivial compound lottery).



(a) One-Stage Treatment: CDFs of dollar values of the trivial and non-trivial compound bets, along with average value of 50/50 lotteries.



(b) CDF of dollar values of the non-trivial compound bets in the One-Stage treatment versus the Percentages version of the Main treatment.

Figure C.19: Counterpart of Figure 10 with all subjects. The value of updating bets and 50/50 lotteries in the Mirror treatment.

Table C.9: Counterpart to Table 3 with all sample, Experiment C: The Role of Ambiguity and Cognitive Uncertainty

	Complexity Aversion (Trivial and non-Trivial)		Complexity Aversion (non-Trivial only)		Relative Complexity Aversion (non-Trivial only)	
	(1)	(2)	(3)	(4)	(5)	(6)
High Cognitive Uncertainty:						
Ambiguity Aversion	.44***		.59***		.45***	
	(.05)		(.06)		(.08)	
Low Cognitive Uncertainty:						
Ambiguity Aversion	.19***		.28***		.18***	
	(.04)		(.07)		(.06)	
Ambiguity Aversion		.17***		.28***		.24***
		(.04)		(.06)		(.05)
CU		-.89*		-.72		-0.53
		(.52)		(.65)		(1.22)
Ambiguity Aversion × CU		.40***		.44***		.50**
		(.10)		(.12)		(.22)
Constant	2.32***	2.68***	1.86***	2.38***	1.96*	1.91*
	(.53)	(.58)	(.65)	(.71)	(1.08)	(1.08)
Observations	1558	1558	794	794	794	794
Controls	Y	Y	Y	Y	Y	Y

Notes: Robust standard errors in parentheses, clustered by subject in models (1) and (2), where each compound lottery (trivial and non-trivial) is an observation.* $p < .1$, ** $p < .05$, *** $p < .01$. (1)-(4) are obtained from constrained regressions following the method explained earlier. In (5)-(6), CU refers to relative cognitive uncertainty. Controls include beliefs and a dummy for each compound lottery; in model (1), (3), (5), also a dummy for high CU.

D Additional details for Experiment C

D.1 Details for Percents vs. Graphical Framings

The top left (right) panel of Figure D.20 depicts the CDFs of the values of the trivial and non-trivial compound lotteries and the average value of 50/50 lotteries in the Percents (Graphical) framing. Our key findings holds in each framing, where the non-trivial compound lottery is undervalued: the average is \$2.60 in the Percents framing (< 0 for 19%, $= 0$ 18%, > 0 63%); and \$2.52 in Graphical (< 0 for 14%, $= 0$ for 24%, > 0 62%). The trivial compound lottery shows no sign of such aversion in either framing (averages are .17 and .22; in either framing, it is < 0 for 31%, $= 0$ 33%, > 0 36%). In both framings, the two compound lotteries are very different in cognitive uncertainty, which is much higher for the non-trivial one (average CU is 43% vs. 26% in the Percents framing and 40% vs. 25% in the Graphical framing). Relative complexity aversion is similar to complexity aversion, with an average of \$2.43 in the Percents framing and \$2.30 in the Graphical framing. The bottom panels of Figure D.20 show the histogram of complexity aversion for the non-trivial compound lottery and relative complexity aversion.

Table D.10 replicates our Table 3 for each frame for both our selected sample used in the main body of the paper (reporting correct answer to the quiz question on the first try) and the whole sample. The letter suffix indicates which column of Table 3 is replicated: a) Percent, selected sample; b) Graphical, selected sample; c) Percents, whole sample; d) Graphical, whole sample. As is clear from the table, point estimates are always in the same direction and similar magnitude to the original table; with approximately half the subjects in each regression, there is some loss of significance, but it is almost always restored if we consider the full sample.

D.2 The Third Compound Lottery in Experiment C

As we discussed above, Experiment C also included a third type of compound lottery, which we call "draw-again." Subjects were told: "A deck contains 3 cards: one Purple, one Green, and one Orange. The computer shuffles the deck and draws a card:

- If the drawn card is Purple or Green it stops.
- If it is Orange, it discards that card and draws again from the deck."

Subjects were then asked for their valuation of a \$30 bet if the final card was Purple. (Figures Online-A.63 and Online-A.64 in the Online Appendix show the screenshots.) This is a compound lottery, but of a form very different from typical ones because the presence of a second stage is contingent on a random event. We included it as an exploration because we thought it could be an interesting and different type of non-trivial compound lottery.

Table D.10: Experiment C: The Role of Ambiguity and Cognitive Uncertainty.

	Complexity Aversion (Trivial and non-Trivial)								Complexity Aversion (non-Trivial only)								Relative Complexity Aversion (non-Trivial only)							
	(1a)	(1b)	(1c)	(1d)	(2a)	(2b)	(2c)	(2d)	(3a)	(3b)	(3c)	(3d)	(4a)	(4b)	(4c)	(4d)	(5a)	(5b)	(5c)	(5d)	(6a)	(6b)	(6c)	(6d)
High Cognitive Uncertainty:																								
Ambiguity Aversion	.37***	.41***	.37***	.52***					.50***	.70***	.55***	.62***					.41***	.66***	.45***	.44***				
	(.08)	(.07)	(.07)	(.07)					(.11)	(.09)	(.09)	(.09)					(.09)	(.12)	(.10)	(.11)				
Low Cognitive Uncertainty:																								
Ambiguity Aversion	.24**	.19***	.22***	.17***					.37***	.33***	.28***	.29***					.18*	.37***	.16**	.19**				
	(.10)	(.07)	(.07)	(.04)					(.13)	(.10)	(.09)	(.08)					(.10)	(.09)	(.08)	(.09)				
Ambiguity Aversion					.21**	.18***	.20***	.13**					.39***	.39***	.30***	.24***					.19**	.45***	.17***	.30***
					(.09)	(.07)	(.07)	(.06)					(.12)	(.10)	(.09)	(.09)					(.08)	(.08)	(.06)	(.08)
CU					-.80	-1.09	-.48	-1.27					-.11	-1.01	-.33	-1.12					-2.53	.24	-3.50**	1.40
					(.96)	(.74)	(.82)	(.64)					(1.15)	(.81)	(.99)	(.81)					(1.59)	(1.35)	(1.69)	(1.45)
Ambiguity Aversion × CU					.27	.40**	.27*	.52***					.14	.47**	.35**	.54***					.71***	.56*	.87***	.24
					(.17)	(.19)	(.15)	(.13)					(.20)	(.22)	(.17)	(.18)					(.24)	(.29)	(.26)	(.28)
Constant	3.79***	1.68**	2.85***	2.48***	4.22***	2.06***	2.94***	2.58***	3.88***	1.20	3.08**	1.98***	4.38***	1.70**	3.20**	2.03***	4.42**	2.26	4.24**	0.59	4.69**	2.03	4.43**	0.52
	(1.01)	(.71)	(.98)	(.62)	(1.02)	(.77)	(1.08)	(.66)	(1.48)	(.73)	(1.34)	(.64)	(1.50)	(.77)	(1.48)	(.70)	(2.19)	(1.46)	(1.88)	(1.30)	(2.25)	(1.48)	(1.91)	(1.28)
Observations	572	544	794	794	572	544	794	794	286	272	397	397	286	272	397	397	286	272	397	397	286	272	397	397
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes: Robust standard errors in parentheses, clustered by subject in models (1) and (2), where each subject appears in two observations. * $p < .1$, ** $p < .05$, *** $p < .01$. (1)-(4) are obtained from constrained regressions. In (5)-(6), CU refers to relative cognitive uncertainty. Controls include beliefs and a dummy for each compound lottery; in model (1), (3), (5), also a dummy for high CU. a: Percents (correct answer to the quiz on first try); b: Graphical (correct answer to the quiz on first try); c: Percents (whole sample); d: Graphical (whole sample).

Unfortunately, a large fraction of subjects seem to have misunderstood this question in a way that makes the interpretation difficult. In particular, close to a third of our subjects in the main treatment (171/558, even focusing on those that pass the comprehension quiz) report beliefs that the probability of Purple in this question is around 1/3 (between 30 and 35). It looks like they did not understand the possibility of a second draw and only considered the chances of Purple in the first draw. Naturally, this leads them to report very low values for this bet. While this is in the direction we are trying to demonstrate (people undervalue complex options), it seems to happen for reasons unrelated to complexity aversion. For this reason, we are leaving this question aside.

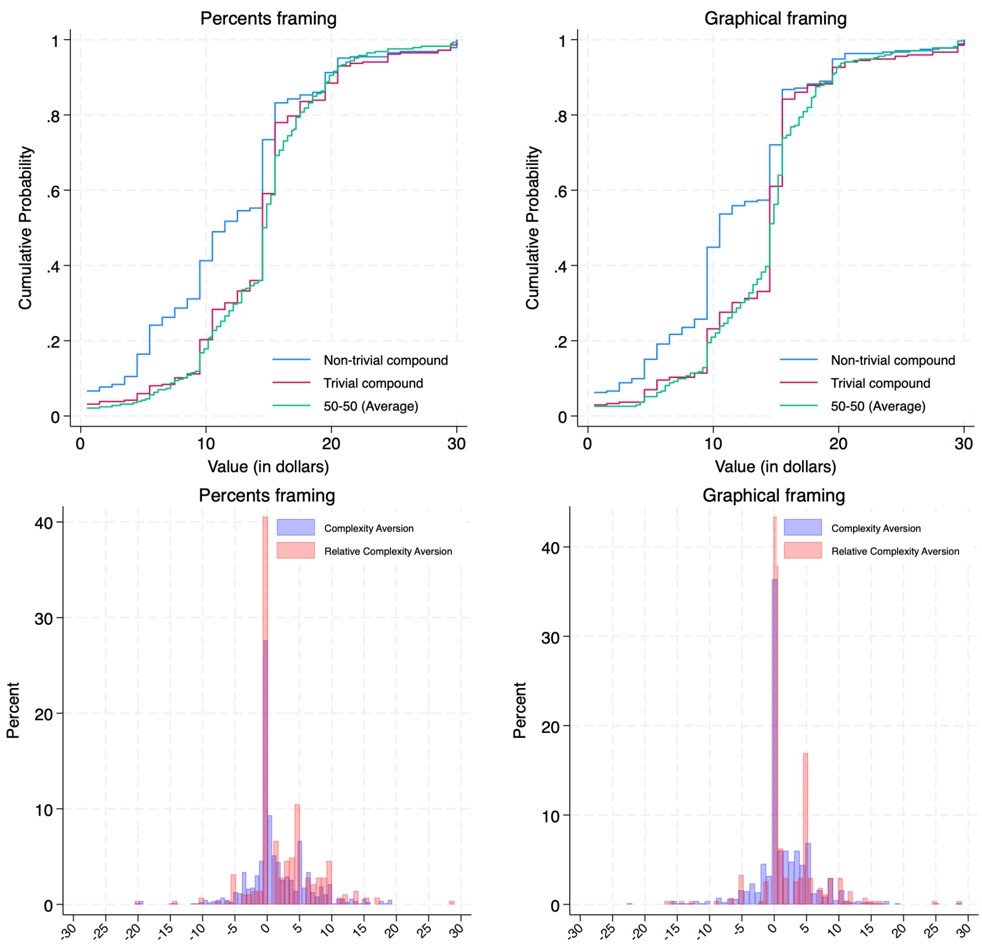


Figure D.20: Top Panels: CDFs of dollar value of the non-trivial and trivial compound lotteries and average value of 50/50 lottery. Left Percents framing. Right: Graphical framing. Bottom panels: Histogram of complexity aversion and relative complexity aversion, for each framing.

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