Caution in the Face of Complexity*

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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 people dislike the cognitive uncertainty they experience in the face of complexity in a way reminiscent of ambiguity aversion. The data supports this explanation: our effects increase when both cognitive uncertainty and ambiguity aversion increase. At a broad level, our results suggest that individual preferences toward complexity matter in cognitive models. At a narrower level, our paper informs the literature on non-Bayesian updating, which overlooks 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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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 risk compounding. The behavior we document is incompatible with Expected Utility, even when accounting for risk aversion, incorrect beliefs, or inattention. Instead, it suggests that individuals dislike the cognitive uncertainty they experience with complexity in a way reminiscent of ambiguity aversion and caution. In line with this interpretation, we show that aversion to complexity increases when Cognitive Uncertainty and Ambiguity Aversion are both higher.

At a broad level, our results demonstrate how most individuals react with *caution in the face of complexity*. Because our effects are substantial in magnitude, they suggest this is an important aspect of individual preferences. More narrowly, our results inform the literature on non-Bayesian updating, which in most cases overlooks complexity aversion, and the connection between compound and ambiguity aversion.

Complexity has long been recognized as an important factor in decision-making by several literatures. Our results relate to and, in some ways, connect many of these strands. A large literature studies information acquisition and (in)attention, while other papers in cognitive sciences focus on how complexity, as measured by cognitive uncertainty and confidence, may generate attenuation towards the prior. Yet, virtually all these approaches take individuals to be Expected Utility (or expected value) maximizers and not averse to complexity *per se*. Instead, we show that individual attitudes toward complexity play an important role and substantially affect values in ways incompatible with Expected Utility. Other papers study exactly this aversion to complexity for preferences under risk. We demonstrate complexity aversion in novel environments, namely 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 in the presence of difficult decisions. We demonstrate 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 cognitive uncertainty and confidence. We will discuss the vast literature in the next section.

Understanding attitudes towards complexity is central to modeling decision-making and designing policy in complex environments. If, as we demonstrate, individuals are averse to complexity, this may explain how their preference for simpler options, even when more complex alternatives appear superior to the analyst. It can also clarify why people might avoid making choices altogether, despite those choices seeming profitable. In turn, this aversion helps 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: fewer, simpler options can be more effective than an overwhelming array of 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. Rather than calculating the probabilities of each state, as in typical experiments, they asked to provide the value of bets that pay $30 under each state using a Multiple Price List (MPL). Separately, participants report their beliefs, 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 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 ambiguity.

The three experiments differ in how the state is determined. In Experiment A (updating task), 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 task), participants are shown two circles with dots, and the state is determined by identifying the circle with more dots. In Experiment C, the state results from a compound lottery. Despite these variations, the experiments follow a similar structure, including measures of cognitive 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. In Experiment A, a "mirror" treatment involved a task that was computationally identical to the updating task but conceptually simpler. In Experiment B, some tasks were significantly easier. In Experiment C, we included a mirror treatment that was computationally identical but eliminated the compounding aspect.

Main Results. 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 task), participants with lower confidence (below the median in self-reported confidence) valued their preferred bet about $1 less than a 50/50 lottery. In Experiment C (compound risk task), participants valued a non-trivial compound lottery with a 50% chance of payout $2.6 less than a 50/50 lottery (The latter is not surprising: it's the standard aversion to compound lotteries.) These effects are not only statistically significant and robust but also economically meaningful. Since the findings are already expressed in dollar values, these results have direct implications for economic choices.

Relation with Cognitive Uncertainty and Ambiguity Aversion. We next explore the mechanism. We propose that participants assign lower values when they perceive the tasks as complex *and* are caution in case of exposure to complexity. To test it, our experiments provide a direct measure of perceived complexity—cognitive uncertainty—and an indirect measure of aversion to tasks participants do not fully understand—ambiguity aversion, as reflected in Ellsberg bets. Consistent with our proposed mechanism, we find that undervaluation is strongly linked to the *interaction* between cognitive uncertainty and ambiguity. Specifically, participants who both perceive the task as complex and are ambiguity averse exhibit significantly greater undervaluation. This effect holds across all experiments and in various regression models, including both continuous interaction terms and separate regressions for high and low cognitive uncertainty.

To further validate this mechanism, we demonstrate that undervaluation nearly disappears when participants do not perceive the tasks as complex. This holds both within and between subjects: for a given question, the effect is stronger among those who find the task more complex, while across questions, the effect vanishes for tasks perceived as easier. Additionally, our effects completely disappear in the mirror treatments, where the computational demands are identical, but conceptual complexity is removed. This confirms that the results are not artifacts of the design but reflect complexity aversion.

The relationship with ambiguity has a more nuanced interpretation. One possibility is that ambiguity aversion is the root cause of the observed undervaluation: participants may perceive complex bets as inherently ambiguous. Alternatively, it may be the other way around, and what we interpret as ambiguity aversion could reflect participants' dislike of the Ellsberg task itself, which they may perceive as complex. More generally, both phenomena may represent instances of a broader tendency toward *caution* when faced with options that are not fully understood. While we tend to favor the latter interpretation, our data does not allow us to disentangle these possibilities.

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, we find that participants assign significantly lower values to bets that require updating, and their behavior after updating deviates from 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. Furthermore, the fact that these effects vanish in the mirror treatment, where updating is conceptually simplified, indicates that aversion is driven by the conceptual complexity of updating than by computational difficulty.

Similarly, many papers a correlation between ambiguity aversion and aversion to compound lotteries, interpreted as either ambiguous bets being perceived as compound or compound bets perceived as ambiguous. Our findings point towards the latter interpretation, as we find that the relationship is modulated by cognitive uncertainty and diminishes when participants do not perceive compound lotteries as complex. We elaborate on this point in the next section, where we connect our results to the relevant literature.

In the Data of Enke and Graeber (2023). To further test our mechanism, we reanalyze the data from 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. We discuss these findings in detail in Section 6.

2 Related Literature

There is an immense literature on complexity and its implications in economics, computer science, and cognitive sciences. As this is too large to discuss here, we focus on recent contributions, particularly in economics, and refer the reader to several extensive surveys.[1]

Implications of Complexity: Rational Attention and Cognitive Models. Many papers study theoretically and empirically the implications of complexity, showing how it can lead to mistakes, stochasticity, direct attention, increase the use of heuristics or salience, avoid choosing, and prefer simpler options. Empirical research spans from lab experiments on basic tasks to real-world data, such as the effects of tax code changes. Among recent contributions are Iyengar and Kamenica (2010); Agranov and Ortoleva (2015); Halevy and Mayraz (2022); Lacetera et al. (2012); Bordalo

[1]Studying the complexity requires defining it, a point tangential to our goals. Oprea (2024) reviews how complexity has been defined, measured, and modeled; see also Bossaerts and Murawski (2017) for computer science approaches applied to behavior and Van Rooij (2008); Van Rooij et al. (2019) for implications on cognitive sciences. The literature has yet to converge on a single definition; recent economic proposals include using the support size of a lottery (Puri, forthcoming), the inverse of the total factor productivity in cognitive processing (Gabaix and Graeber, 2023), or empirical regularities (Enke and Shubatt, 2023). Our work makes a limited contribution to this debate, but we do find that confidence significantly increases (and perceived complexity decreases) in our mirror treatments for updating tasks. This suggests that the complexity of updating stems more from the conceptual challenge of applying Bayes' rule than from algebraic difficulty.

et al. (2023); Molavi et al. (2023); Kendall and Oprea (2024); Arrieta and Nielsen (2024); see also the survey in Oprea (2024) and the literature review in Gabaix and Graeber (2023). Lipman (1995) and de Clippel and Rozen (2024) provide overviews of the literature on bounded rationality, while Campbell (1988) reviews relevant literature in psychology.

Two approaches to complexity have gained particular prominence in behavioral economics in recent years. First, models of *inattention*, especially rational inattention. In these models, when faced with a complex environment, individuals endogenously decide how much and what information to acquire to maximize Expected Utility. These models have been widely applied to essentially all economic settings, from IO to macro to finance; see the surveys in Gabaix (2019) and Woodford (2020). Related models on optimal stopping are common in cognitive sciences; see Fudenberg et al. (2018) for economic analysis.

Second, an expanding literature in behavioral economics shows how Bayesian models of limited cognition can generate many patterns traditionally ascribed to preferences; Woodford (2020) and Enke (2024) provide extensive reviews. In these models, 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.

A common feature of these two very 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.[2] 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 strand of the literature focuses instead precisely 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

[2]One exception is Fabbri (2024), which studies rational inattention with ambiguity aversion.

the role of such complexity as a significant driver of behavior in lottery choices. Jabarian and Lazarus (2022) documents subjects choosing dominated options to avoid ambiguous bets and interpret this behavior as complexity aversion. 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 more complex alternatives.

On the theoretical front, Puri (forthcoming) characterizes a model in which lotteries are evaluated by subtracting to the Expected Utility a cost of complexity that depends on the support size of a lottery. 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. Extending beyond lotteries, 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, and introducing new methods to elicit it. 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. This intuition is also compatible with the results of Iyengar and Kamenica (2010), which shows that individuals opt for simpler options as the complexity increases.

Ambiguity Aversion and Caution. A separate strand of the literature studies ambiguity (or uncertainty) aversion—the aversion to alternatives whose value depends on states the likelihood of which is not exogenously given; 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 probability is given. Moreover, our results show how the effect of ambiguity aversion is, in fact, modulated by cognitive uncertainty. As discussed above, 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 of complex alternatives also relate to the broader notion of *caution* introduced in 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. Exactly in line with this broad perspective, our results show experimentally that individuals generically adopt a cautious approach when faced with difficult decisions.

Additionally, our results on how complexity lowers values relate to the recent literature 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 them 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); 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 (forthcoming). In virtually all of these models, individuals may deviate from Bayes' rule but nonetheless form a well-defined posterior—a probability distribution over the states of the world—and use it following Expected Utility. Several papers suggest how 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 probabilistic inferences are complex tasks. We show how this may lead individuals to evaluate such prospects in a way that is incompatible with having a well-formed posterior and following Expected Utility, contrary to all typical models of non-Bayesian behavior. Moreover, our results also suggest that individuals are not averse to the computations involved with updating but to the conceptual complexity of updating—recall how complexity aversion disappears in our mirror treatment. 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 natural 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 in support of the latter hypothesis by showing that teaching individuals how to reduce compound lotteries eliminates compound aversion but not ambiguity aversion.

Our results provide further evidence in this direction by showing that the correlation between the two attitudes is stronger for subjects with high cognitive uncertainty about the compound lottery's payment probabilities; and by showing that aversion is not present for "trival" compound lotteries, while some aversion remains also when lotteries are transformed into one-stage maintaining some complexity. This is compatible with the view that compound lotteries' complexity generates an aversion related to ambiguity aversion.[3]

[3]Naturally, this is only partial evidence. We cannot exclude the possibility that it is, instead, only this specific subgroup that sees ambiguous bets as compound.

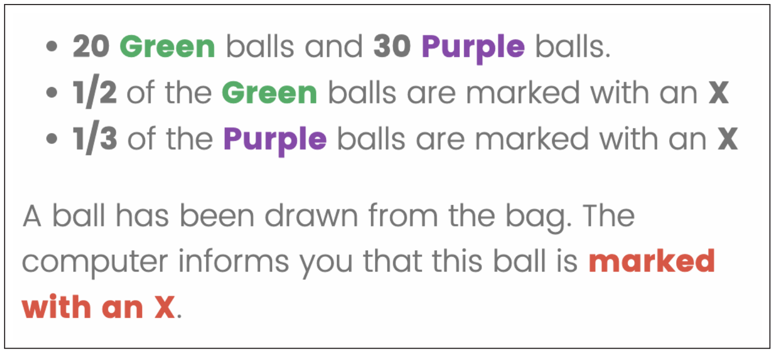


Figure 1: One of the two belief-updating scenarios.

3 Experiment A: Updating

3.1 Design

Our first experiment investigates how subjects value complex bets in a relatively high-level problem: belief updating. Subjects face some different "scenarios," in which the computer simulates the draw of a ball from a bag with green or purple balls. The first is a simple valuation task: subjects report the dollar value of a bet that pays $30 if the drawn ball is purple ($0 otherwise) when the probability of winning is 50% (the bag contains 50 purple balls and 50 green balls). This is elicited through a multiple-price list (MPL).[4,5] We refer to this bet (and a similar one later) as the "50/50 lottery."

The core of our experiment is the next two scenarios, in which the winning probability can be computed *using Bayes' rule*: Figure 1 shows one of them. All information is available, and subjects who know Bayes' rule can easily derive that the probability of purple is 50%. The other updating scenario asks the complementary question, inverting Purple and Green—as if asking the value of a bet on Green in Figure 1. (The order of the scenarios is randomized.)

For each of these updating scenarios, we first measure 1) the *dollar value* of bets that pay $30 if the drawn ball is purple, using MPLs; and then, on a separate screen, both 2) the belief of the "exact" chance that the drawn ball is purple (incentivized with binarized-scoring, $5 prize) and 3) their cognitive uncertainty (CU) about this. Specifically, following Enke and Graeber (2023), subjects indicate how confident they are about their answer about the exact chance, from 0% ("*very*

[4] 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; 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.

[5] Because subjects may or may not be indifferent at the point where they first take the sure amount, throughout this paper we follow the standard practice of taking their certainty equivalent as the average of their switching point with the preceding grid point. For instance, a subject who selects the lottery for all values $15 and above is coded as having a certainty equivalent of $14.50. At the extreme, a subject who never selects the lottery is coded as having a certainty equivalent of $30.

uncertain") to 100% ("*completely certain*") in steps of 10%; their cognitive uncertainty is then 100% minus their confidence.[6]

A vast literature used similar scenarios to test Bayes' rule, measuring beliefs after information.[7] 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. This allows us to estimate if the complexity of updating induces subjects to lower the value of bets. If subjects follow Expected Utility, thereby holding a belief about the chances of Purple vs. Green—*any* belief, Bayesian or not—they should assign to *at least one of the two bets a probability of winning of at least 50%*. But then, they cannot assign to both bets a value below that of the lottery. Our first analysis will therefore compare the value of the two updating bets with that of 50/50 lotteries; we measure *Complexity Aversion* as the difference.

Finally, subjects face two additional valuation tasks: another 50/50 lottery, similar to the first one, and a bet on a standard Ellsberg bag: subjects are only told that the bag contains 100 purple or green balls in any combination. As typical, we measure *Ambiguity Aversion* (AA) as the value difference between 50/50 lotteries and the Ellsberg bet.[8]

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.[9] The experiment was pre-registered on AsPredicted.org.[10] As required by our pre-registration, the main body of the paper

[6]That is, leading to a number from 0 to 1, with higher numbers corresponding to more CU.

[7]We deviated from the classic design of "bookbag-and-poker-chip" experiment (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, as 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).

[8]The experiment ends with an unincentivized survey questions to measure overconfidence (overprecision): subjects are asked when the telephone was invented and their (subjective) confidence. Following Ortoleva and Snowberg (2015), overconfidence is defined as the residual of a regression of confidence on a fourth-degree polynomial of accuracy.

[9] 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 paid was $11.90, with a maximal potential bonus of $30. We note that one subject somehow completed both treatments; we dropped this subject from our data.

[10]The protocol can be found at https://aspredicted.org/fzds-2r8d.pdf.

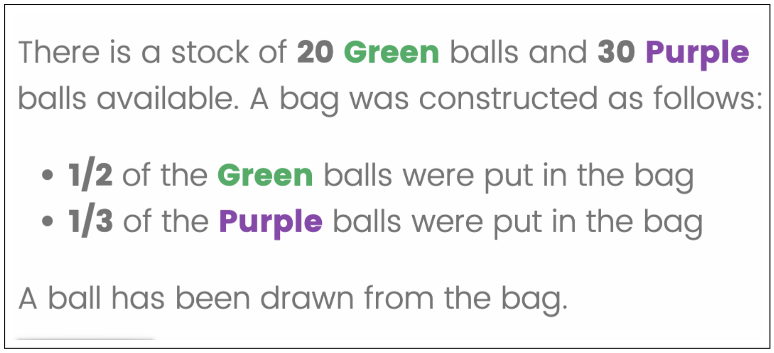


Figure 2: The Mirror counterpart of the scenario from Figure 1.

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 B replicates our analysis 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 if there is measurement noise. The typical way to circumvent this issue is to define complexity aversion and ambiguity aversion using the answers to different lottery questions. However, this increases noise as we rely on fewer measurements. Instead, we adopt an alternative approach that uses all measures but avoids spurious correlation via constrained regression—a simple method that, to the best of our knowledge, is novel in this literature.

To illustrate, denote by C, A and L the value of complex (updating) bets, of ambiguous ones, and of 50/50 lotteries, respectively; and CA and AA complexity and ambiguity aversion, where CA = L − C and AA = L − A. Imagine we want to regress CA on AA, possibly with controls, that is

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

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

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

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 including interaction terms.[11]

In the remainder of the paper, we use this constrained regression approach to estimate the impact of ambiguity aversion (and its interactions) on complexity aversion. That is, we report the imputed coefficients $\alpha, \beta, \vec{\gamma}$, etc. from the original model, not $\alpha', \beta', \vec{\gamma}'$ from the auxiliary, constrained regression. For completeness, Appendix D replicates our analysis with the traditional approach of constructing variables using different measures, using adjacent measures when possible; results are similar. We use the latter approach to generate figures when needed (e.g., as in Figure 4 below).

3.2 Results

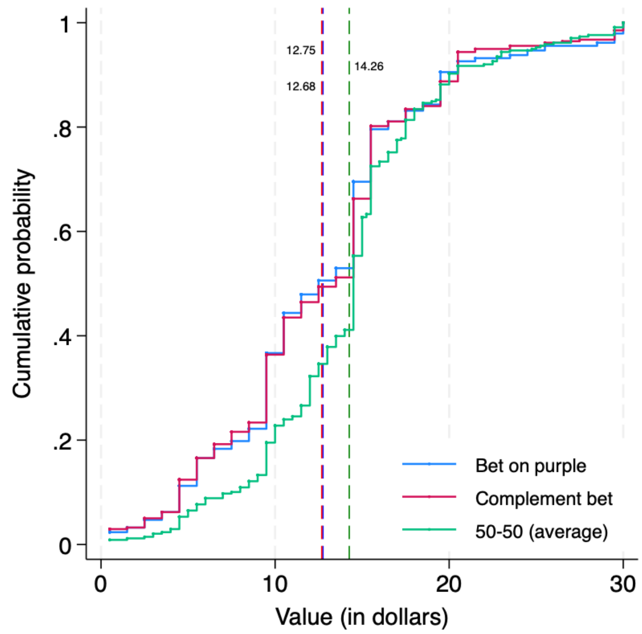
Main Results. We begin by analyzing the Main treatment. Our core question is assessing the presence of complexity aversion and the interactive role of cognitive uncertainty and ambiguity aversion in mediating this. We approach the data from two angles. We first provide summary statistics, comparing the 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) represent the CDF for the updating bet and its complement. We find that the two distributions are *nearly identical*, and *both* inferior to 50/50 lottery values[12] in terms of first-order stochastic dominance ($p < 0.01$, sign-rank test for both). 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). Define then *complexity aversion* subject by subject, as their 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: complexity aversion is \$3 or more for subjects in the top quartile. Among complexity-averse subjects, the mean is \$3.8. Complexity aversion can thus be high—at least 10%, but easily 20%, of the expected value of the lottery (\$15).

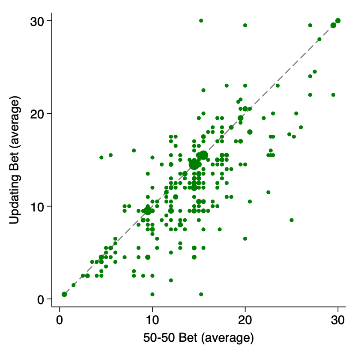
Robustness. In Figure 3(a), we compared the value of the two updating bets with 50/50 lotteries at the population level, which is close to comparing the average value of the two bets with that of 50/50 lotteries. Is comparing averages the right test? What if subjects hold incorrect, and thus asymmetric beliefs, and the values of the two bets are very different? First, note that under Expected

[11]For instance, let 1_ℓ (1_h) be a dummy variable indicating an observation where a subject expresses low (respectively, high) cognitive uncertainty. To test whether the relationship between complexity aversion and ambiguity aversion is diminished for low-CU subjects, we would ideally estimate $CA = \alpha + \beta_\ell\,(1_\ell AA) + \beta_h\,(1_h AA) + \vec{\gamma} \cdot \mathit{controls}$ (with 1_h among the controls) and check whether β_ℓ is smaller than β_h. Following similar steps as above, we can do this via the constrained regression $\mathrm{C} = \alpha' + \beta'_{1\ell}\,(1_\ell \mathrm{L}) + \beta'_{2\ell}\,(1_\ell \mathrm{A}) + \beta'_{1h}\,(1_h \mathrm{L}) + \beta'_{2h}\,(1_h \mathrm{A}) + \vec{\gamma}' \cdot \mathit{controls}$, with the constraints $\beta'_{1\ell} + \beta'_{2\ell} = 1$ and $\beta'_{1h} + \beta'_{2h} = 1$.

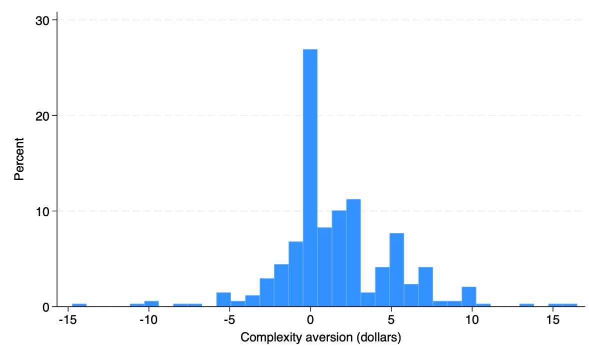
[12]For increased accuracy, we use for each subject the average of their MPL choices in the two 50/50 lottery questions.



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

Utility, as long as the utility over money is not strictly convex, then the average value of the two bets must be above that of the 50/50 lottery: comparing averages is, under Expected Utility with typical assumptions, a conservative test.[13]

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.[14] While 40% of them exhibit no complexity aversion, another 40% continue to do so: the total average is \$.79, significantly different from zero (t-test p-value $< .01$). 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.[15]

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.[16] 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.[17] But we continue to see complexity aversion: the average difference is very similar, at \$1.59 (significantly different from zero, t-test $p < .01$). As can be seen from Figure 11 in Appendix A, the CDF of maximum values for the 50/50 lotteries first-order dominates that of the bets (and these are significantly different; sign-rank $p < .01$).

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. Next, we turn to study the mechanism.

Relation with Cognitive Uncertainty and Ambiguity. If complexity aversion is a reaction to cognitive uncertainty akin to ambiguity, it should increase with cognitive uncertainty, ambiguity aversion, and, 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

[13]To see why, suppose π is the belief on purple and $(1-\pi)$ on green after updating, with u the Bernoulli utility (let $u(0) = 0$). The values of \$30 bets on each color are $u^{-1}(\pi u(30))$ and $u^{-1}((1-\pi)u(30))$, while the value of a 50/50 bet is $u^{-1}\left(\frac{1}{2}u(30)\right)$. By Jensens' inequality, the average of the first two is above the third if u is not strictly convex.

[14]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.

[15]Only 40% of subjects with the correct posterior report no cognitive uncertainty; the average confidence is 83%. This is, however, much higher than the average confidence of everyone else, which is 55%.

[16]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.

[17]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.

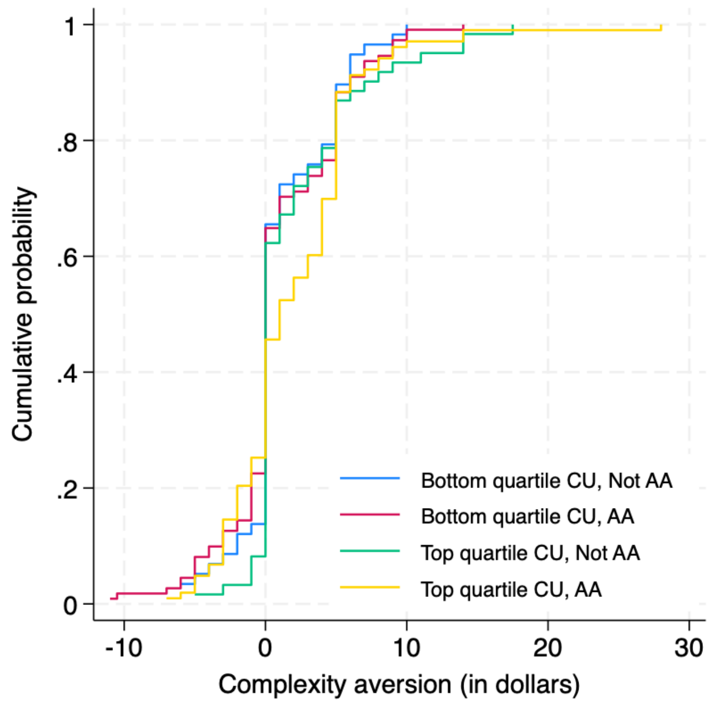


Figure 4: Complexity aversion in 4 subgroups: top and bottom quartiles of Cognitive Uncertainty, divided based on (strict) Ambiguity Aversion vs. Ambiguity Neutrality/Seeking

in the top and bottom quartiles of cognitive uncertainty, sub-divided by whether or not they are ambiguity averse.[18] It is evident that one group has higher complexity aversion than the others: 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 (p-value .02, Wilcoxon rank-sum test).

Table 1 corroborates this result in regressions. Column (1) shows the role of ambiguity aversion when subjects express CU above the median cognitive uncertainty, versus when they do not. Column (2) models a continuous interaction instead. Once again, the results are clear. In the first regression, we have a strong and highly significant effect of ambiguity aversion, but only for subjects with high cognitive uncertainty; otherwise, the effect of ambiguity aversion is not significant. (The two coefficients are statistically different, $p < .01$). With continuous interactions, once again we have a strong and significant effect of ambiguity aversion interacted with cognitive uncertainty; neither is impactful on its own.

[18]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 below that of the 50/50 lottery.

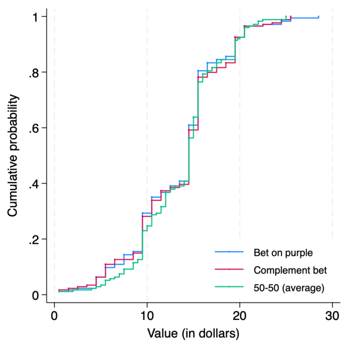
Table 1: Experiment A: The Role of Ambiguity and Cognitive Uncertainty

	Complexity Aversion	
	(1)	(2)
High Cognitive Uncertainty:		
Ambiguity Aversion	.38***	
	(.06)	
Low Cognitive Uncertainty:		
Ambiguity Aversion	.11*	
	(.06)	
Ambiguity Aversion		.09
		(.06)
CU		-.75
		(.60)
Ambiguity Aversion * CU		.43***
		(.11)
Constant	2.64***	2.65***
	(.61)	(.63)
Observations	676	676
Controls	Y	Y

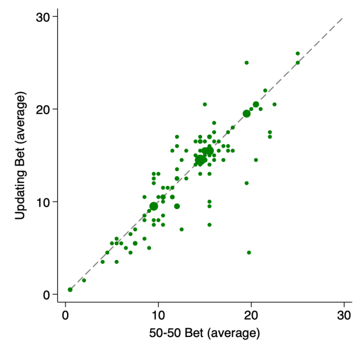
Notes: Each updating bet is an observation, with errors clustered by subject in parentheses. * $p < .1$, *** $p < .01$. Both (1) and (2) are obtained from constrained regressions following the method explained above. Controls include beliefs about probabilities and a dummy for each updating task and,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

Mirror. If complexity aversion is the reason that updating bets are undervalued, these effects should disappear 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. If our hypothesis is correct, complexity aversion should disappear. Figure 5 shows that it does: Panel (a) shows the the CDFs of values for the updating bets are the same as 50/50 lotteries, while Panel (b) shows that most people indeed report nearly identical values. That is, our Mirror treatment was effective in sharply reducing complexity, and complexity aversion disappeared.

Aside from further supporting our hypothesis, 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



(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.

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 factors 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. Additionally, 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. These observations hold across all experiments, so we will not repeat them in later sections.

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 Expected Utility that suggests 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 cognitive uncertainty and ambiguity aversion; 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

4.1 Design

While Experiment A studies complexity aversion in high-level tasks, we now consider the opposite end, a very low-level task: an experiment based on visual perception.

The main task builds on a standard design in cognitive science. 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.[19] In typical experiments, subjects are asked (1) which circle has more dots? and, sometimes, (2) their confidence. By contrast, in the valuation phase of our experiment, we ask (1) which circle has more dots?, and (2') we elicit the value, using a MPL, of the bet that pays $30 if the answer is correct. If subjects follow Expected Utility, bet values cannot be below that of 50/50 lotteries—subjects must assign to the circle they believe has more dots *at least* probability 50%. When it is fairly clear which circle has more dots, the value of the bet should well exceed that benchmark, reaching close to $30.

The experiment is similar to Experiment A, with 4 main parts. Subjects are trained in the use of MPLs and answer a comprehension quiz. In Part 1, they 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 tasks are identical to Experiment A and, like before, bets are based on the color of the ball drawn. Part 2 introduces the perceptual task described above. After a practice question, subjects face 4 such tasks with varying difficulty: one easy, one intermediate, and two hard (the easy one is always first, and one of the hard ones always last). Part 3 repeats the perceptual tasks but asks for confidence instead of the value of the bet, using a slider to report the percent chance subjects think their answer is correct (unincentivized). Finally, Part 4 has subjects again value a 50/50 lottery and an ambiguous bet. [20]

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 confidence is not the same as cognitive uncertainty in Experiment A: the latter captured the subject's understanding of the problem but did not translate directly into winning probabilities; instead, confidence is a direct measure of the expected winning probability.

[19] Our task is directly derived from neuroscience: we use figures and design principles from Kaanders et al. (2022).

[20] Like Experiment A, the experiment concludes with a survey question to assess overconfidence.

Implementation. 498 subjects participated through Prolific in April 2024;[21] the experiment was pre-registered.[22] 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 B replicates our analysis for the entire sample; once again, results are very similar.

4.2 Results

Preliminaries. We begin with two sanity checks: that the values of bets on the perceptual task vary with difficulty and confidence. Average values for easy, intermediate, and hard bets were \$28, \$18, and \$15, and these values vary substantially with confidence on the related question (all p-values $< .01$). As we are interested in studying complexity, we focus on the two hard questions.

Caution. Like in Experiment A, we are interested in comparing the value of bets with the average value of 50/50 lotteries, particularly for subjects who are unsure. Figure 6.(a) shows the CDFs of the values of the two hard questions and average values of the 50/50 lotteries for observations where confidence is below the median. Once again, we find that complex options have a lower value (sign-rank p value $< .01$ for both). Defining, like before, complexity aversion as the value difference between 50/50 lotteries and the perceptual bet, Figure 6.(c) depicts the histogram for the same group, showing that that is negative for 33%, zero for 13%, and strictly positive for 53%. Average complexity aversion is \$1, with high variance: subjects in the bottom quartile of confidence exhibit complexity aversion of at least \$5. Conditioning on complexity-averse subjects, the mean is \$5.4, the bottom quartile of confidence corresponds to complexity aversion of at least \$7. Once again, complexity aversion can be very high.

Relation with Ambiguity. We can test the relationship with ambiguity as mediated by confidence—noting, however, how confidence here has a different interpretation, as it directly captures winning probabilities. Table 2 shows the same regressions we computed for Experiment A for hard perceptual tasks for all subjects (who pass our comprehension tests). Regression (1) shows how ambiguity aversion is positively and very strongly related to complexity aversion, but *only* for subjects with low confidence (the coefficients on ambiguity aversion for high/low confidence are different, $p = .01$). Regression (2) shows that while ambiguity aversion alone does not affect complexity aversion, the interaction term with confidence is instead significant. Confidence alone is also significant, as expected, since it indicates the expected winning probability. Overall, our results mirror those of

[21]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.

[22]The protocol can be found at https://aspredicted.org/9vrx-6mm7.pdf.

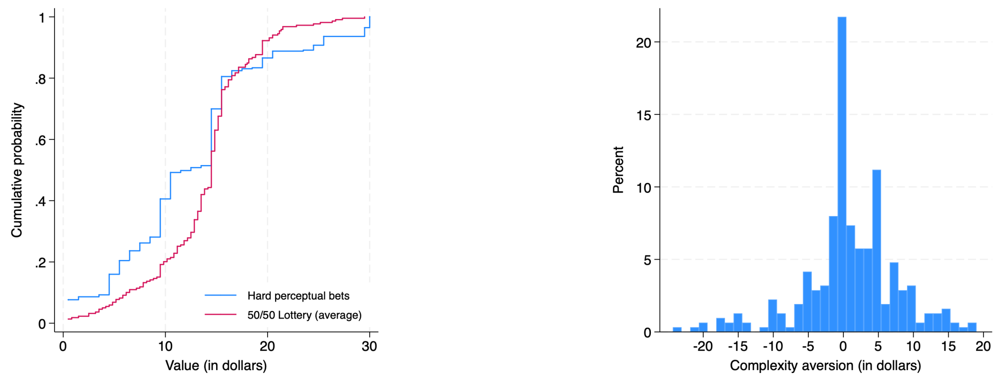


Figure 6: Two graphs on the value of hard perceptual bets and 50/50 lotteries for observations with confidence below the median. Left panel: CDFs of dollar value of hard perception bets and average value of 50/50 lottery. Right panel: histogram of complexity aversion (difference between value of hard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

Experiment A despite the substantial differences in the tasks.

Overall, Experiment B corroborates our main takeaways from Experiment A: that complex options are undervalued in a way incompatible with Expected Utility and that this phenomenon is related to ambiguity aversion but mediated by confidence. 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 on 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 cognitive uncertainty? What is the role 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 complete valuation tasks on compound bets in random order. The main ones appear in Figure 7.

Table 2: Experiment B: The Role of Ambiguity

	Complexity Aversion (1)	(2)
Low Confidence:		
Ambiguity Aversion	.60***	
	(.10)	
High Confidence:		
Ambiguity Aversion	.20	
	(.12)	
Ambiguity Aversion		.09
		(.20)
Confidence		-6.7***
		(2.26)
Ambiguity Aversion * Confidence		.76**
		(.38)
Constant	9.27***	-4.79***
	(2.42)	(1.06)
Observations	684	684
Controls	Y	Y

Notes: Each perceptual bet is an observation, with errors clustered by subject in parentheses. *** $p < .01$. 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 low confidence (i.e., in the bottom half of the confidence distribution).

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*.[23] Following these valuations, for each compound scenario (in random order), we elicit the subject's belief of the "exact" chance that the drawn card is purple (incentivized with binarized scoring, $5 prize) and the cognitive uncertainty about this belief. Subjects then complete two final valuation tasks—for another 50/50 lottery and another ambiguous bet—and the experiment concludes with an assessment of overconfidence.

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

[23]The experiment also included a third compound risk, which also reduces to a 50/50 lottery but differs from classical compound risk in that the presence of a second stage is contingent on the initial draw; we call it the *draw-again* compound lottery.

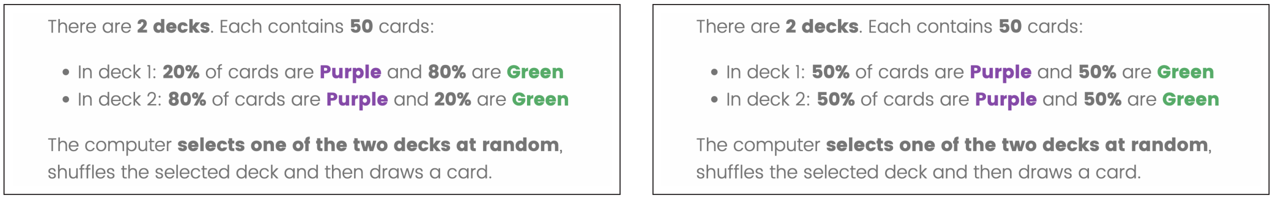


Figure 7: Compound risks, as phrased in the Main (percents) treatment. Both scenarios yield a 50/50 distribution over the card color, though this is less obvious in the left panel than the right.

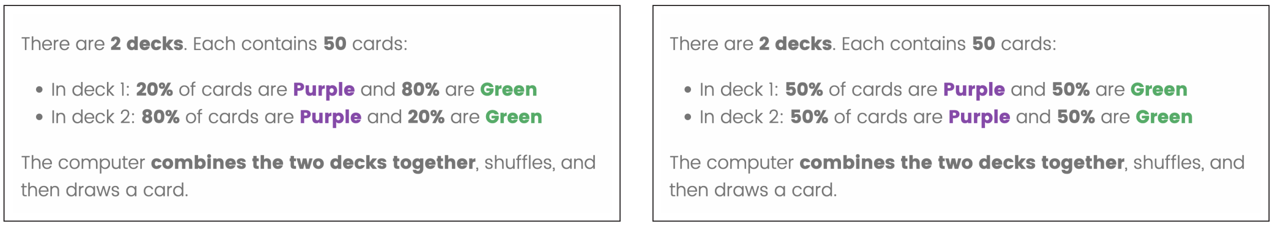


Figure 8: The One-Stage Mirror treatment counterparts of the compound risks in Figure 7.

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 treatment. Is the source of complexity in compound lotteries the computation needed to reduce the lottery or the presence of multiple stages? To test it, 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.[24] The experiment was pre-registered.[25] 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 (approximately 70% of subjects across treatments), while Appendix B replicates our analysis for the entire sample; like before, results are very similar.

[24]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.

[25]The protocol can be found at https://aspredicted.org/n7p4-6m3y.pdf.

5.2 Results

Behavior in the Percent and Graphical framing of the Main treatment was very similar.[26] In what follows, we analyze them jointly. We focus on the two traditional compound lotteries and discuss the behavior with the third one (draw-again) in Appendix C; 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, non-trivial compound lotteries are significantly undervalued; on average, by \$2.6 (16% <0, 21% =0, 63%>0). However, the trivial compound lottery shows no sign of aversion (average compound aversion is \$.19; 31%<0, 33%=0, 36%>0). This runs contrary to most theories of compound risk because, despite its simplicity, the trivial compound lottery remains a non-degenerate compound risk. While contrary to most theories, this difference is very intuitive—for it is immediate to see that the trivial compound lottery gives a 50% chance of winning. Indeed, the two compound lotteries are also very different in cognitive uncertainty, which is much higher for the non-trivial one (averages are 42% vs. 26%).

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, 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 of the non-trivial version, holding constant the number of stages. Unsurprisingly, given Figure 9, relative complexity aversion is very similar to complexity aversion, with an average of \$2.37. The right panel Figure 9 gives the histogram of complexity aversion for the non-trivial compound lottery and relative complexity aversion.

Like in 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

[26]For each of the trivial and non-trivial compound bets, neither a Kolmogorov-Smirnov test of distributions nor a Wilcoxon ranksum test can reject the null hypothesis of equality across the framings, with p-values > 0.54 in all cases. Similarly, Chow tests support pooling these two framings in all the regressions of Table 3, with p-values > 0.21 in all columns but (3), where it is a more marginal 0.067.

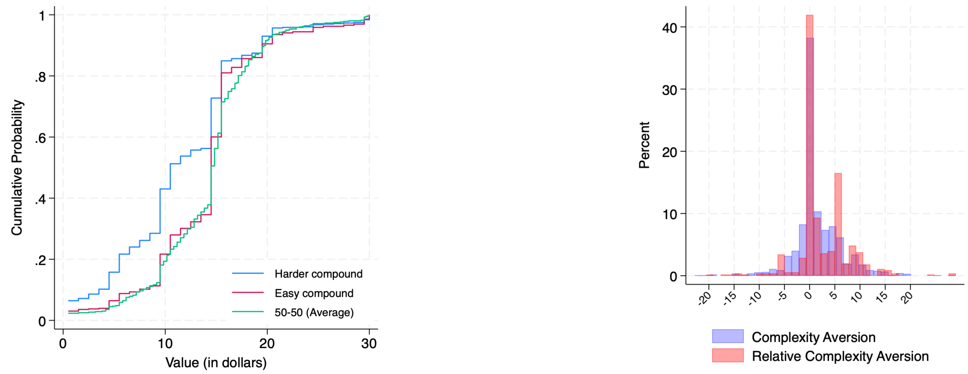


Figure 9: Left panel: CDFs of dollar value of the non-trivial and trivial compound lotteries and average value of 50/50 lottery. Right panel: histogram of complexity aversion (difference between the value of 50/50 lotteries and non-trivial compound lottery) and relative complexity aversion (difference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

complexity aversion of the non-trivial compound lottery, using *relative* cognitive uncertainty (the increase in cognitive uncertainty from the trivial to the non-trivial compound lottery; these are regular regressions, as the issue of spurious correlation does not apply).

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, possibly suggesting this may be a more appropriate measure, maybe because relative cognitive uncertainty provides a "normalization" of an otherwise subjective measure. Again, the correlation with ambiguity aversion is significantly higher when cognitive uncertainty is high rather than low (p-values .01, $<$ .01, and .02 for regressions (1), (3), (5), respectively). The same conclusion applies to continuous interaction. While these results confirm the ones of previous experiments, here ambiguity aversion maintains an effect even for subjects with low cognitive uncertainty—the coefficient is about *half* but remains significant. It is also significant by itself in continuous interactions.

These 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 (.06 standard deviation).[27] Our results suggest that it is subjects with high cogni-

[27] If we construct measures in a way to avoid spurious correlation (using different questions for ambiguity and complexity aversions), we obtain a raw correlation of .37 between compound and ambiguity aversion, not dissimilar from results in the literature (e.g., Chapman et al. 2023).

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

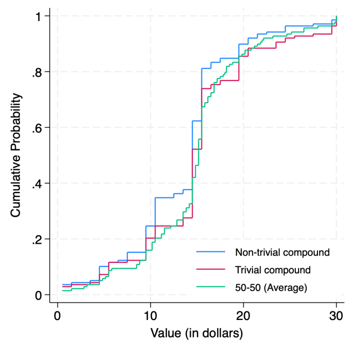
	Complexity Aversion (Trivial and non-Trivial)		Complexity Aversion (non-Trivial only)		Relative Complexity Aversion (non-Trivial only)	
	(1)	(2)	(3)	(4)	(5)	(6)
High Cognitive Uncertainty:						
Ambiguity Aversion	.38***		.60***		.53***	
	(.05)		(.04)		(.05)	
Low Cognitive Uncertainty:						
Ambiguity Aversion	.22***		.35***		.26***	
	(.05)		(.05)		(.06)	
Ambiguity Aversion		.20***		.40***		.31***
		(.05)		(.06)		(.05)
CU		-.89		-.37		-1.12
		(.61)		(.71)		(1.05)
Ambiguity Aversion * CU		.32***		.26**		.60***
		(.12)		(.11)		(.17)
Constant	2.38***	2.91***	2.19***	2.60***	3.04***	3.08***
	(.56)	(.62)	(.65)	(.82)	(1.07)	(1.05)
Observations	1116	1116	558	558	558	558
Controls	Y	Y	Y	Y	Y	Y

Notes: Standard errors in parentheses, clustered by subject in models (1) and (2), where each compound lottery (trivial and non-trivial) is an observation.** $p < .05$, *** $p < .01$. (1)-(4) are obtained from constrained regressions following the method explained above. 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 Cognitive Uncertainty (being in the top half of the CU distribution).

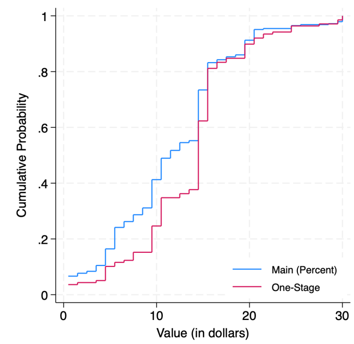
tive uncertainty that primarily drive this interaction, even though some effect does exist even for subjects with low cognitive uncertainty.

One-Stage Treatment. Recall that in our one-stage treatment, subjects faced questions that were computationally identical but involved only one stage of randomization. Does this eliminate aversion? On the one hand, the lottery remains similar in computation. On the other hand, conceptual complexity may be inherent in the randomization.

In the one-stage treatment, aversion is sharply reduced but does not disappear. The left panel of Figure 10 shows the equivalent of the left panel of 9 for this treatment: the CDF of dollar values of 50/50 lotteries, and the two "compound" lotteries (which, in this case, are not longer compound; for simplicity, we refer to them as "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-



(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 updating bets and 50/50 lotteries in the Mirror treatment.

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 \$1.3 (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 very presence of two stages adds to the complexity of compound lotteries. Once we eliminate them, the aversion is reduced sharply (by approximately half) 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: once again, we find that subjects undervalue complex options and that this effect is related to the interaction of subjective perception of complexity as measured by cognitive uncertainty with ambiguity aversion.

At the same time, our results are informative on compound lotteries *per se*. They show that the well-known correlation with ambiguity aversion appears primarily driven by subjects with high cognitive uncertainty. A possible explanation is that, like in our other experiments, this is strongly related to the inherent complexity of compound lotteries; indeed, the presence of multiple stages appears to be a source of complexity. Our one-stage treatment seems to confirm this. On the one hand, it shows that once we eliminate the multiple stages, cognitive uncertainty diminishes, and so does aversion. At the same time, aversion is not fully eliminated, even though our "pseudo-compound" lottery is no longer a compound lottery.

6 Our Mechanism in the data of Enke and Graeber (2023)[28]

If our mechanism is as prevalent as indicated by our experiments, it should also manifest in pre-existing data. We test for it in the datasets of Enke and Graeber (2023), which includes two experiments that elicit the dollar value of several risky lotteries as well as 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 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. In both experiments, lotteries paid a prize with a given probability and zero otherwise; both were chosen randomly from a set of prizes and a set of probabilities symmetric around 0.5 (probability p was equally likely as $(1-p)$).[29] However, the two experiments differ in many implementation details, elicitation methods, and pools;[30] documenting our results in both datasets would point to their robustness. 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 (randomly interspersed with other lotteries).

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

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

[29]Specifically, in Risk A prizes are chosen from $\{15, 16, \ldots, 25\}$ 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; moreover, in Risk B, half of the questions involved losses, chosen from $\{-15, -20, -25\}$.

[30]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 a probability estimate of the true value being within a given range; Risk B involved 700 on Amazon Mechanical Turk, used MPLs, studied lotteries with gain but also losses, and asked subjects to indicate the range within which they were certain the true value lies. We refer to Enke and Graeber (2023) for more details.

Table 4: Effect of cognitive uncertainty (CU) on 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***	6.13***	6.09***	-34.14***
	(.96)	(.74)	(.50)	(.46)	(.84)
N	4,524	6000	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: Standard errors in parenthesis clustered at the individual level, *** $p < 0.01$. Regressions include problem and individual fixed effects.

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 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—in line with our mechanism. Columns (2) and (4) also include the data from the complex variations of both experiments and show how effects are remarkably similar in magnitude per unit of cognitive uncertainty—even though, as already shown by Enke and Graeber (2023), cognitive uncertainty is much higher in complex variations.

One possible concern, however, 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 shows that the effect remains robustly negative and of similar magnitude even in this case.

Overall, this analysis shows how our mechanism appears to be at play in two different pre-existing experiments, emerging robustly despite the differences in many experimental 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 cognitive uncertainty induced by complexity. Supporting this, we find that aversion to complexity increases with the interaction of cognitive uncertainty and ambiguity aversion. We also validate this mechanism using the data from Enke and Graeber (2023), showing that higher cognitive uncertainty corresponds 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 also shed light on why companies often emphasize the simplicity of their offerings in marketing (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 cognitive uncertainty in available choices. Likewise, in political reforms, a complex tax policy may receive a low valuation from the public, implying the need to simplify presentation and reduce perceived complexity to enhance acceptance.

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 and cognitive uncertainty 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 ambiguity, meaning that 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 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? Developing a full model of caution in the face of complexity is beyond the scope of this paper. Several approaches are possible. One could define a measure of complexity and construct a model of complexity aversion by subtracting a complexity cost from Expected Utility—a structure similar to existing models discussed above. Alternatively, one may view complexity as generating hard-to-interpret messages and develop a model in which individuals face no ambiguity ex-ante but receive information with ambiguous interpretation, leading to uncertainty aversion. This 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 as seen in Epstein and Halevy (2024).

Preferences Matter After All? We conclude with a conceptual point. Recent research has suggested that many behavioral phenomena typically attributed to preferences may stem from cognitive factors. For instance, Enke and Graeber (2023) shows that cognitive uncertainty and attenuation can produce several well-known biases in behavioral economics. Our results complement this perspective by adding that, in addition to cognitive effects, a specific aspect of *preferences* significantly affects their valuations: How individuals cope with this cognitive uncertainty.

Appendix

A Additional analysis

We include additional analysis referenced in the text. Figure 11 displays the CDFs of maximum values for the 50/50 lotteries and updating bets in Experiment A.

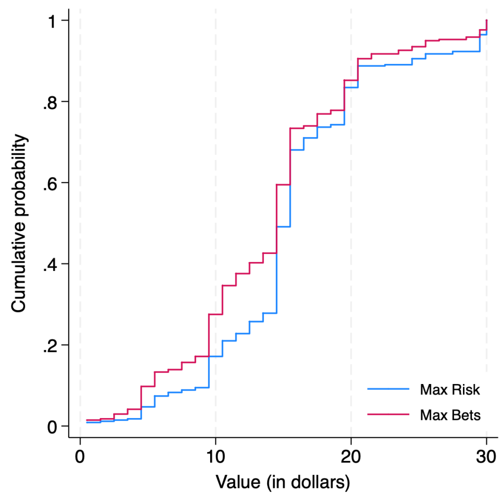
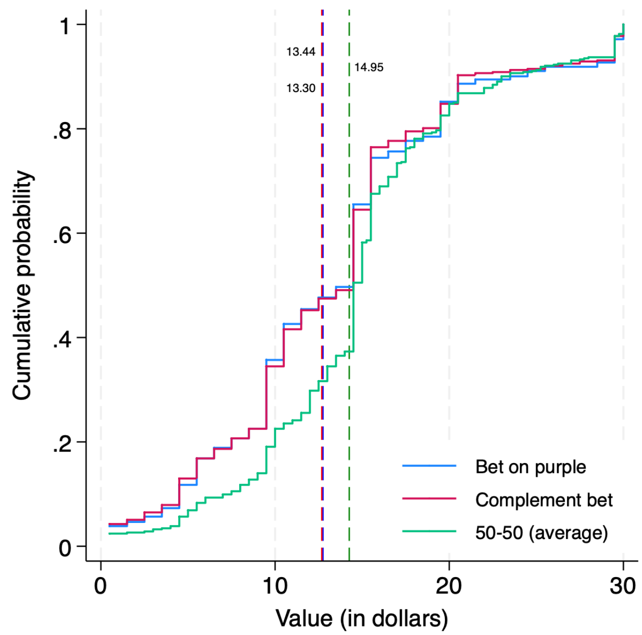


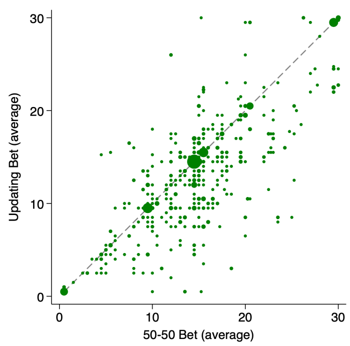
Figure 11: CDFs of maximum values for the 50/50 lotteries and updating bets.

B Including all subjects

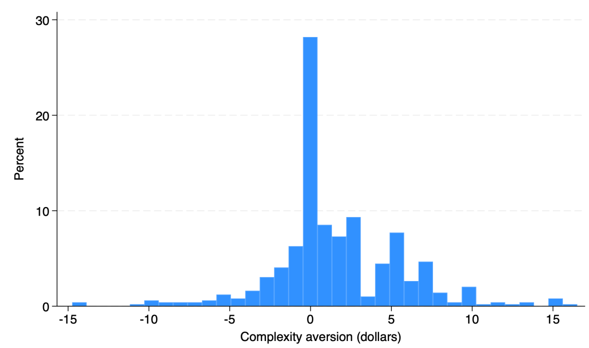
As required by our pre-registration, our analysis includes only subjects who respond correctly to our comprehension quiz on the first try. In what follows, we replicate our core results with the entire subject pool. Figures 12-14, and Table 5 replicates the corresponding ones in Experiment A; Figure 15 and Table 6 those in Experiment B; and Figure 16-17 and Table 7 those in Experiment C.



(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 12: 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.

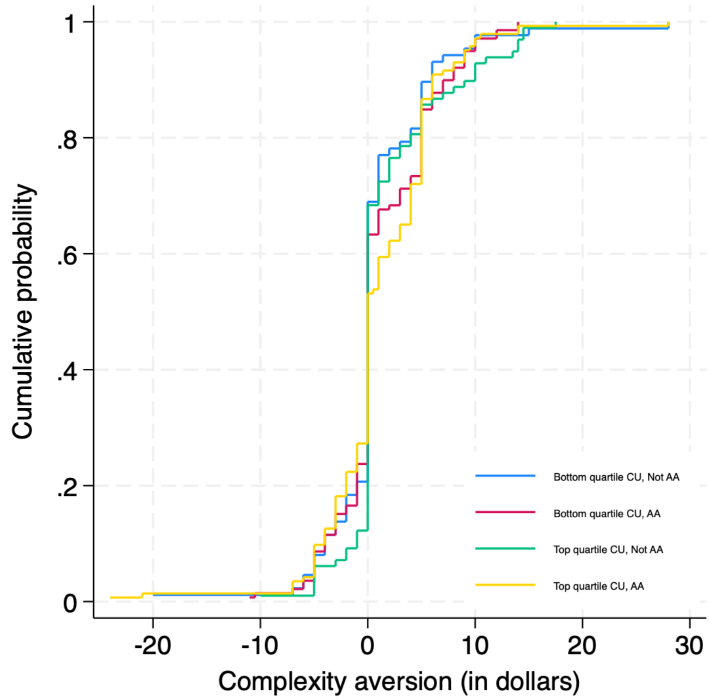
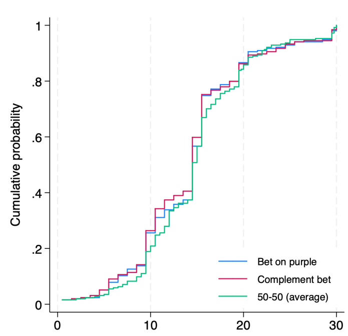
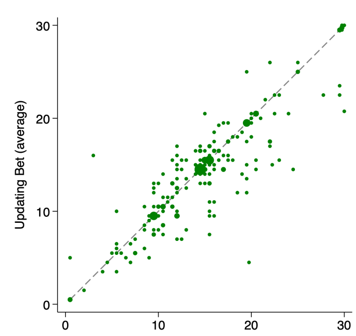


Figure 13: Counterpart of Figure 4 with all subjects. Complexity aversion in 4 subgroups: top and bottom quartiles of Cognitive Uncertainty, divided based on (strict) Ambiguity Aversion vs. Ambiguity Neutrality/Seeking.



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

Table 5: 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		.17***
		(.05)
CU		.15
		(.57)
Ambiguity Aversion * CU		.18*
		(.11)
Constant	2.09***	2.03***
	(.55)	(.63)
Observations	986	986
Controls	Y	Y

Notes: Each updating bet is an observation, with 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 Cognitive Uncertainty (being in the top half of the CU distribution). Each updating bet is an observation.

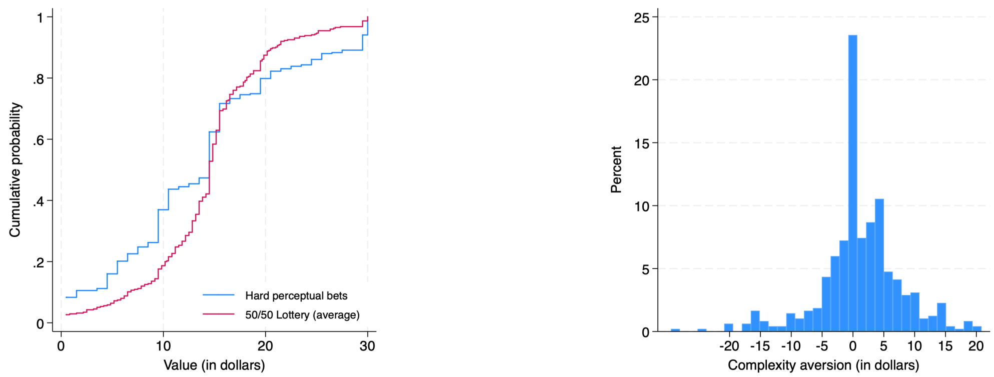


Figure 15: Counterpart of Figure 6 with all subjects. Two graphs on the value of hard perceptual bets and 50/50 lotteries for observations with confidence below the median. Left panel: CDFs of dollar value of hard perception bets and average value of 50/50 lottery. Right panel: histogram of complexity aversion (difference between value of hard perceptual bets and average value of 50/50 lotteries).

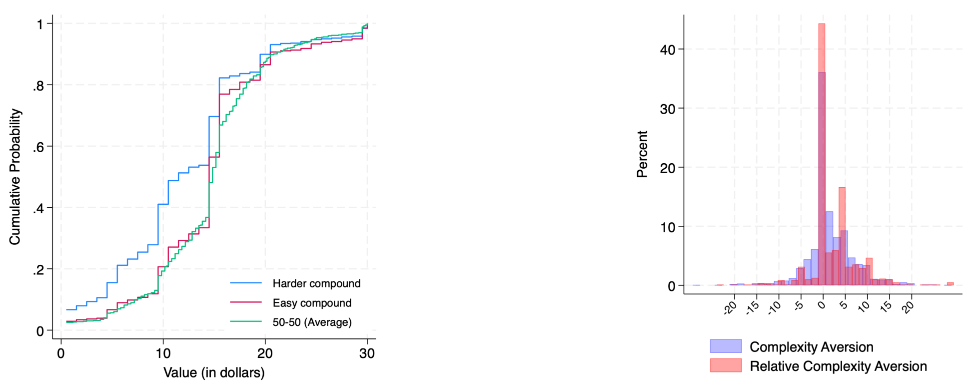
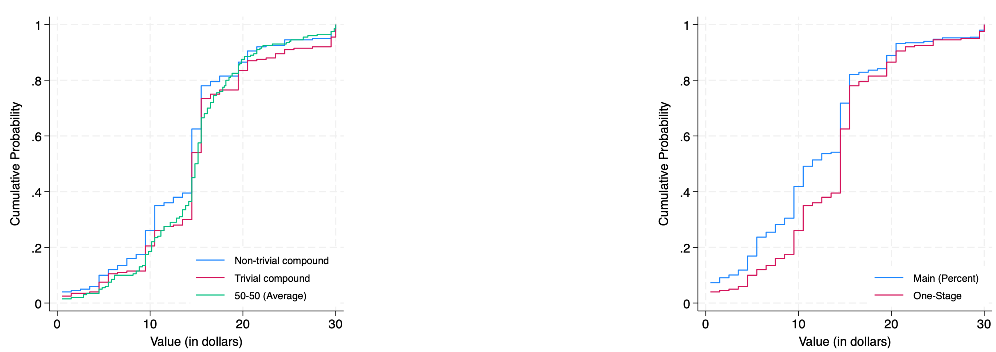


Figure 16: Counterpart of Figure 9 with all subjects. Left panel: CDFs of dollar value of the non-trivial and trivial compound lotteries and average value of 50/50 lottery. Right panel: histogram of complexity aversion (difference between the value of 50/50 lotteries and non-trivial compound lottery) and relative complexity aversion (difference between the value of the trivial and non-trivial compound lottery).

Table 6: Counterpart to Table 2 with all sample, Experiment B: The Role of Ambiguity

	Complexity Aversion	
	(1)	(2)
Low Confidence:		
Ambiguity Aversion	.53***	
	(.08)	
High Confidence:		
Ambiguity Aversion	.23**	
	(.10)	
Ambiguity Aversion		.12
		(.16)
Confidence		4.87***
		(1.69)
Ambiguity Aversion * Confidence		.65**
		(.31)
Constant	4.02*	-3.47***
	(2.31)	(0.81)
Observations	996	996
Controls	Y	Y

Notes: Each perceptual bet is an observation, with errors clustered by subject in parentheses. *** $p < .01$. 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 low confidence (i.e., in the bottom half of the confidence distribution).



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

Table 7: 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	.43***		.59***		.45***	
	(.05)		(.06)		(.05)	
Low Cognitive Uncertainty:						
Ambiguity Aversion	.22***		.31***		.18***	
	(.04)		(.05)		(.05)	
Ambiguity Aversion		.17***		.28***		.24***
		(.04)		(.05)		(.05)
CU		-.89*		-.72		-0.53
		(.52)		(.61)		(1.22)
Ambiguity Aversion * CU		.40***		.44***		.50***
		(.10)		(.09)		(.14)
Constant	2.12***	4.93***	1.86***	2.38***	1.96**	1.91**
	(.50)	(.65)	(.55)	(.71)	(0.91)	(0.89)
Observations	1558	1558	794	794	794	794
Controls	Y	Y	Y	Y	Y	Y

Notes: Standard errors in parentheses, clustered by subject in models (1) and (2), where each compound lottery (trivial and non-trivial) is an observation.** $p < .05$, *** $p < .01$. (1)-(4) are obtained from constrained regressions following the method explained above. Controls include beliefs and a dummy for each compound lottery; in model (1), (3), (5), also a dummy for High Cognitive Uncertainty (being in the top half of the CU distribution).

C 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." They 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 chose to include it as an exploration because we thought it could be an interesting and different type of non-trivial compound lottery, even though it does not admit a clear counterpart in the mirror (though a counterpart, where subjects are told the computer removes the orange card before making a draw, was included to ensure the same number of questions in both main and mirror treatments).

Unfortunately, a large fraction of subjects seem to have misunderstood this question in a way that makes the interpretation difficult. In particular, about a third of our subjects (178/558, 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 particularly 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.

D Alternative To Constrained Regressions

In the paper's main body, we adopted constrained regressions to avoid concerns of spurious correlation when we regress complexity aversion on ambiguity aversion. As indicated, we could alternatively use different measures to construct the two variables: we use the risk measures adjacent to Ellsberg bets to construct ambiguity aversion and the other risk measure to construct complexity aversion. Tables 8-10 replicate Tables 1-3 using this alternative method.

Table 8: Counterpart to Table 1 with adjacent measures, Experiment A: The Role of Ambiguity and Cognitive Uncertainty

	Complexity Aversion	
	(1)	(2)
High Cognitive Uncertainty:		
Ambiguity Aversion	.18**	
	(.08)	
Low Cognitive Uncertainty:		
Ambiguity Aversion	-.02	
	(.06)	
Ambiguity Aversion		-.03
		(.06)
CU		-.23
		(.90)
Ambiguity Aversion * CU		.27
		(.17)
Constant	2.29***	2.10**
	(.80)	(.82)
Observations	676	676
Controls	Y	Y

Notes: Each updating bet is an observation, with errors clustered by subject in parentheses. * $p < .1$,*** $p < .01$. Controls include beliefs about probabilities and a dummy for each updating task and, in model (1), a dummy for High Cognitive Uncertainty (being in the top half of the CU distribution). Each updating bet is an observation.

Table 9: Counterpart to Table 2 with adjacent measures, Experiment B: The Role of Ambiguity

	Complexity Aversion	
	(1)	(2)
Low Confidence:		
Ambiguity Aversion	.49***	
	(.01)	
High Confidence:		
Ambiguity Aversion	.01	
	(.13)	
Ambiguity Aversion		-.04
		(.20)
Confidence		8.15***
		(2.34)
Ambiguity Aversion * Confidence		.71*
		(.38)
Constant	10.44***	-4.77***
	(2.65)	(1.08)
Observations	684	684
Controls	Y	Y

Notes: Each perceptual bet is an observation, with errors clustered by subject in parentheses. *** $p < .01$. Controls include a dummy for each updating of the hard perceptual tasks and, in model (1), a dummy for low confidence (i.e., in the bottom half of the confidence distribution).

Table 10: Counterpart to Table 3 with adjacent measures, 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	.31***		.53***		.57***	
	(.06)		(.05)		(.06)	
Low Cognitive Uncertainty:						
Ambiguity Aversion	.14**		.27***		.28***	
	(.06)		(.07)		(.07)	
Ambiguity Aversion		.14**		.34***		.35***
		(.06)		(.08)		(.05)
CU		-.09		.24		-2.05*
		(.76)		(.89)		(1.23)
Ambiguity Aversion * CU		.27**		.22		.60***
		(.13)		(.14)		(.20)
Constant	2.18***	2.17**	2.14***	2.13**	1.52	1.57
	(.79)	(.91)	(.81)	(1.03)	(1.29)	(1.26)
Observations	1116	1116	558	558	558	558
Controls	Y	Y	Y	Y	Y	Y

Notes: Standard errors in parentheses, clustered by subject in models (1) and (2), where each compound lottery (trivial and non-trivial) is an observation.** $p < .05$, *** $p < .01$. Controls include beliefs and a dummy for each compound lottery; in model (1), (3), (5), also a dummy for High Cognitive Uncertainty (being in the top half of the CU distribution).

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