Boundedly Rational Information Demand

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July 13, 2023

Abstract

Acquiring information about available options before making a decision is useful because it allows decision makers to switch to a superior alternative if the default option is deemed inferior. Therefore, information demand should depend on the distribution of the options' values. In an experiment, I show that information demand increases as the default worsens, while, on average, it remains insensitive to the prior value of the alternative. These patterns reflect bounded rationality in information valuation, which stems from the difficulty of foreseeing future choices and integrating their payoffs.

*Carnegie Mellon University. Email: ycliang@cmu.edu. This study is approved by CMU IRB in Protocol 2016_000000482. The RCT registry ID is AEARCTR-0010543. Kate Yixin Huang, Jack Tianrui Lin, Allison Tribendis and Yao Yao provided excellent research assistance. Errors are mine.

1 Introduction

In economics, information is valued primarily for its ability to guide future decisions. For example, investors read analyst reports to determine which stocks to buy, while recruiters conduct interviews to identify the best job candidates. Despite the fact that information value should heavily depend on the decision problem it informs, we know surprisingly little about their empirical relationship.

This paper studies the demand for information about choice options in an experimental setting, with particular focus on how this demand responds as the prior beliefs about these options change. This question is important for several reasons. First, it is a near-universal assumption in information economics that information acquisition correctly responds to incentives. Testing this assumption informs the realism of theoretical results. Second, information acquisition directly affects decision quality and overall payoffs. Hence, analyzing information demand across different decision problems helps us identify decisions most likely to be suboptimal. Third, in market environments, buyers' information acquisition affects the purchase probability of each product. As a result, how information demand responds to the prior beliefs of the products affects sellers' incentive to invest in them. Lastly, in settings such as recruitment, admission, and lending, information acquisition based on prior beliefs about applicants carries implications for diversity, equity, and inclusion.

Demand for information is determined by its valuation, which has a well-defined rational benchmark. According to standard information economics, information has value only if it steers choice from the default option to an alternative with some probability. Moreover, the exact value of information is determined by the probability of choosing an alternative and its value-added when chosen. Formally, consider an expected utility maximizer who needs to choose from a set of options. Each option's utility u depends on the unobserved state of the world ω. The value of an information structure I (a distribution over a set of signals S_I correlated with the states) can be calculated by:

$$V(I) = \sum_{s \in S_I} \mathbb{E}[u(a(s), \omega) - u(d, \omega)|s] \cdot p(s) \tag{1}$$

where d is the default option chosen without the information, $a(s)$ is the alternative chosen if signal s is realized, and $p(s)$ is the probability of s. This expression implies two key comparative statics. First, for each signal that induces an alternative different from the default, the higher the value-added of the induced choice, the greater the information value. Second, the higher the probability of such a signal, the greater the information value.

In this paper, I study the demand for information about choice options in a simple experiment using these two comparative statics as the rational benchmark. Participants face a choice between two independent binary lotteries, D and A. Each lottery pays out \$3 if it wins and \$0 otherwise. Their winning chances are known and denoted by d and a, respectively. Lottery D is more likely to win, so it is the default option that participants should choose without additional information. In the main treatment, *D-Info*, participants may receive information that fully reveals D's outcome before the lottery choice. Participants are incentivized to report how much they think receiving this additional information would increase their chance of receiving \$3. This question essentially elicits their information valuations. In the experiment, participants answer this question in six scenarios for different values of d and a. This allows me to study how information valuations vary with the choice options in a within-subject design.

The information valuation question in this experiment has a straightforward rational answer that does not depend on risk preferences or belief-updating rules. If the information reveals that D will win, then participants should choose D, guaranteeing a \$3 win. If, instead, the information indicates D will fail, then participants should choose A, which has an a chance of winning. Essentially, if participants react to information correctly, the information induces a compound lottery with a total $d + (1 - d)a$ chance of winning. Therefore, the information increases the chance of receiving \$3 by $(1 - d)a$. This expression is easy to interpret through the lens of equation (1): the information steers the choice away from the default with a probability of $1 - d$, and when this happens, the winning chance increases from 0 to a. It also succinctly illustrates the two rational comparative statics: information valuation should decrease in d but increase in a.

In the experiment, participants' information valuations deviate markedly from the rational answers. Consistent with the rational benchmark, information valuations decrease as D becomes more likely to win. However, contradicting rationality, the average information valuation does not vary with A's winning chance. Moreover, there is substantial heterogeneity in how information demand responds to A, with more participants decreasing rather than increasing information valuations as A's chance of winning rises.

The differential response of information demand to D and A could arise from the fact that the evaluated information in the D-Info treatment relates to D's outcome, not A's, potentially making D's winning chance more salient than A's. To test this hypothesis, I introduce another treatment where participants evaluate information that reveals A's outcome, which has the same theoretical value as the information in the D-Info treatment. Results of this treatment display the same patterns as the D-Info treatment—average information valuation decreases as D becomes more likely to win but does not increase with A's winning chance. This result implies that making A more salient does not necessarily help people respond to it correctly when evaluating information.

Having established that people do not rationally account for the distribution of the options' values when evaluating information, I design additional treatments to investigate the underlying mechanisms. Conceptually, the difficulty of information valuation may arise in two stages. First, people may imperfectly foresee their own choices with and without information. Second, given their choice forecasts, it may be difficult to integrate the choice payoffs to derive the correct information value.

To explore whether difficulty at the first stage contributes to deviation from rationality, I run a treatment where participants report their contingent lottery choices with and without information before we elicit their information valuations. In this treatment, participants never make mistakes in their contingent lottery choices, and their information valuations are only slightly more sensitive to Lottery A's winning chance. This result indicates that while it helps to have the choice implications of information on top of mind, much of the difficulty of information valuation lies in the payoff integration stage.

Payoff integration often involves complex computation, potentially contributing to its difficulty. In the main treatments, computational complexity primarily lies in reducing compound probabilities, i.e., calculating $(1 - d)a$. To test whether computational complexity is key to the biases in information valuation, I design a variant of the D-Info treatment where the two lotteries are mutually exclusive. The correct information value in this treatment, equal to a, requires minimal computation. Nevertheless, information valuation remains largely insensitive to a, suggesting that computational complexity is not necessary for the bounded rationality. Moreover, although the correct information value in this treatment does not depend on d, many participants still value information less as the default becomes more likely to win. This result indicates that although the negative relationship between information valuations and the default's winning chances is consistent with rationality in the main treatments, much of it likely reflects the use of heuristics.

Besides computational complexity, the difficulty of payoff integration may also stem from the fact that these payoffs originate from multiple choices. This is a general property of information valuation because any valuable information must affect choice with some probability. To test this hypothesis, I design another treatment where instead of receiving information on a lottery's outcome, participants may "insure" Lottery D by using Lottery A as a back-up. Under the insurance, participants choosing D can still win $3 if D fails, so long as A wins. Having the insurance induces a compound lottery identical to the one resulting from receiving information about D's outcome, thus their values should be the same. But unlike information, having the insurance does not change the optimal decision — whether insured or not, participants should choose D. Therefore, the valuation of insurance does not require integrating payoffs from multiple choices. In this treatment, participants' insurance valuations increase significantly as A becomes more likely to win. This sharply contrasts with the insensitivity of information valuation when A's winning chance changes. In a separate treatment, I rule out framing as an explanation for the difference between information and insurance valuations. Therefore, this result supports the hypothesis that integrating payoffs from multiple choices indeed contributes to the difficulty of information valuation.

This paper contributes to the literature on the demand for information with instrumental value. Several studies investigate how people choose or evaluate noisy information structures (Ambuehl and Li, 2018; Ambuehl, 2021; Charness, Oprea, and Yuksel, 2021; Guan, Oprea, and Yuksel, 2023). In contrast, this paper restricts attention to fully-revealing information which is easier to understand, and focuses on how information demand depends on the future decision problem. Also related is the sequential search literature. For instance, Caplin, Dean, and Martin (2011) find that people stop searching once the status quo is good enough, thus supporting the satisficing heuristic (Simon, 1955). While their finding is consistent with rationality, my design explicitly specifies the distribution of the options' values, allowing me to detect departures from rationality. Similarly, rational inattention experiments, like Dewan and Neligh (2020), study perceptual tasks with varying stakes, mainly to measure attention costs assuming that participants understand the value of attention. In a field experiment, Bartoš et al. (2016) studies how recruiters and landlords allocate attention across applicants of different ethnicities. My experiment operates in a more controlled and abstract environment, but the results may have implications for field settings like theirs. Moreover, a large literature studies the non-instrumental value of information (e.g., Nielsen, 2020; Masatlioglu, Orhun, and Raymond, 2021; Falk and Zimmermann, 2022; Golman, Loewenstein, Molnar, and Saccardo, 2022). These papers show that people sometimes have preferences over the quantity and timing of information, even when these factors do not affect decisions. My study controls for these non-instrumental factors so that they do not confound the interpretation of the results.

The results on mechanisms in this paper relate to three behavioral economics literatures: imperfect foresight, evaluation of compound lotteries, and contingent reasoning failures. First, information valuation requires people to foresee what they will choose after the information realizes. Consistent with evidence of imperfect foresight (Binmore et al., 2002; Johnson et al., 2002; Chakraborty and Kendall, 2022a,b), this paper shows that information valuations improve when people think through their future choices first. Second, information valuation often involves reducing compound probabilities, a task found to be challenging for many (Halevy, 2007; Chew, Miao, and Zhong, 2017). While non-reduction of compound lottery may play a role in this paper's results, I show that participants do not correctly evaluate information even when no compound probabilities are involved. Third, to evaluate information, people need to integrate payoffs from different choices. Prior research has shown that people often make mistakes in decisions that require contingent thinking (Esponda and Vespa, 2014, 2021; Martínez-Marquina, Niederle, and Vespa, 2019). This paper offers a fresh insight into this literature: integrating payoffs from multiple choices is more challenging than integrating multiple payoffs from a single choice.

2 Evidence on information demand

2.1 Experimental design

In this section, I detail the design of the main experimental treatment. The designs of additional treatments will be discussed in subsequent sections alongside their results.

Participants are presented with six scenarios in random order. In each scenario, they are asked to consider a choice between two independent binary lotteries (D and A) whose winning chances (d and a) are known. The outcomes of the lotteries will be revealed after their choice. The chosen lottery yields a \$3 prize if it wins and \$0 otherwise. Lottery D is more likely to win, so it is the default option that participants should choose without additional information. Lottery A is the alternative option that is inferior to D *ex-ante*. The six scenarios differ only in the values of d and a, which are detailed in Table 1.

Table 1: Lotteries in the six scenarios

Scenario	1	2	3	4	5	6
d	60%	60%	60%	50%	70%	90%
a	10%	30%	50%	40%	40%	40%

In each scenario, I elicit participants' subjective information valuations by asking how much they think their chances of choosing a winning lottery would increase if D's outcome is revealed before the lottery choice. The information valuation question is implemented as a multiple-choice question where participants select a statement of the following form with a specific number x that best describes their preferences:

> I would choose the information over an increase in both lotteries' winning chances by $(x-1)\%$, but I would choose an increase in both lotteries' winning chances by $(x+1)\%$ over the information.[1]

The x in the statement a participant selects is interpreted as her information valuation.[2]

Calibrating information valuation by an increase in the lotteries' winning chances offers several benefits. First, because the final payoffs are always binary, risk preference is irrelevant. Second, because participants essentially compare two increments in probability from the same status quo (d), reference dependence and probability weighting play no role. Additionally, increasing both d and a instead of only d doesn't alter the relative salience of the two lotteries, and it improves the participants' subjective chances of winning by this amount, even if they are unsure about their lottery choices.

After answering this question for all six scenarios, a random scenario is implemented for real, and a random number y is generated. If the participant's information valuation in the real scenario is greater than $y\%$, then D's outcome is revealed to her; otherwise, both lotteries' winning chances increase by $y\%$. This Becker, DeGroot, and Marschak (1964)-style incentive scheme ensures truthful reporting of information valuations.[3]

Subsequently, participants choose between the two lotteries. After the lottery choice but prior to revealing the outcomes, participants are asked to offer advice to future participants on how to answer the information valuation questions. The advice is incentivized — if an advisee wins

[1] From the top of the choice list to the bottom, the number x increases from 0 to 30 in steps of 2, except for the scenario with $d = 90\%$ where the maximal x is 10. The first (second) part of the statement at the top (bottom) is omitted. Appendix A.1 addresses the difference in range across scenarios.

[2] This elicitation format is similar to the sMPL in Andersen et al. (2006), which directly asks participants to state a switching point in a multiple price list.

[3] Following Danz, Vesterlund, and Wilson (2022), the instructions simply state that it is in the participants' best interest to answer the questions based on their true preferences. The details of the incentive scheme are described in the instructions, but participants are not required to read them.

a \$3 bonus, the advisor receives an additional \$2 bonus.[4] In an endline questionnaire, I collect sociodemographic information and ask unincentivized questions about participants' tendencies to gather information, plan, and take risks in their daily life. These variables are summarized in Table A1.

The experiment was pre-registered and conducted on Prolific with a \$2 participation fee. Participants receive extensive instructions on the details of the tasks. In addition, they need to correctly answer several comprehension questions before proceeding with the experiment. A total of 1050 participants were recruited across all treatments, with the experiment's median duration being 10 minutes.

2.2 Rational benchmark

The information valuation question in the experiment has a rational answer. Without knowing D's outcome in advance, participants should choose D, which has a winning chance of d. If D's outcome is revealed before the lottery choice, participants should choose D if it wins and A if it doesn't. This strategy induces a compound lottery as illustrated in Figure 1, resulting in a total winning chance of $d + (1 - d)a$. Therefore, learning D's outcome should increase the winning probability by $(1 - d)a$. This expression is unaffected by risk preferences and any deviations from Bayes' rule. It also has a straightforward interpretation: information about D's outcome diverts the choice from the default option with a $1 - d$ probability, and when this happens, the winning chance increases from 0 to a. The rational information value decreases with d and increases with a. The variation in these two parameters across the six scenarios allows me to test these two comparative statics.

The expression $(1 - d)a$ solely considers the instrumental value of information, but prior research has indicated that people may have preferences over the amount and timing of uncertainty resolution for non-instrumental reasons. In my experiment, though, the amount and timing of uncertainty resolution are carefully controlled, thus, non-instrumental factors should have minimal

[4] Behaviors of the advisees are analyzed in Appendix A.4.

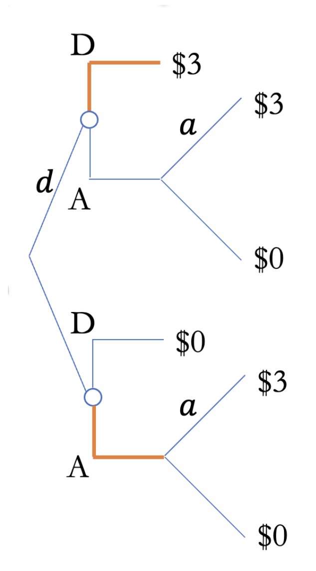

Figure 1: Payoff structure induced by the information in the D-Info treatment

Notes: This figure depicts the payoff structure induced by the information in the D-Info treatment. The straight branches represent uncertainty resolution. The letter on a straight branch represents its probability. The elbow branches are choice options. The optimal choices, shown in orange, induce a compound lottery.

impact on information valuations. First, the outcomes of both lotteries will eventually be revealed irrespective of the participants' information valuations. As a result, these valuations should not be influenced by curiosity about the lotteries' outcomes. Second, although reporting a high information valuation makes it more likely that D's outcome will be revealed before A's, the time gap between the two revelations is short. In such scenarios, intrinsic preferences for information timing are often weak (Nielsen, 2020). To address this issue further, I will discuss a treatment where information valuations do not affect information timing at all in Section 3.1.

2.3 Results

Figure 2 presents the average information valuation for each of the six scenarios in the D-Info treatment ($N = 147$). Consistent with the rational benchmark, as the winning chance of the default lottery d increases, information valuations decrease. In contrast, average information valuation stays constant and then drops as the alternative lottery A becomes more likely to win.

These patterns are further corroborated by a regression analysis (see Table A2). In Regression

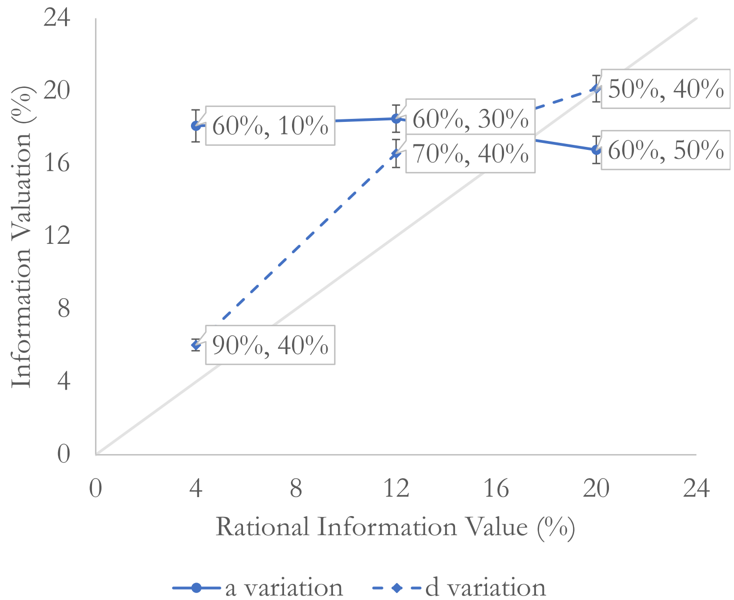

Figure 2: Information valuations in the D-Info treatment

Notes: This figure shows the average information valuations in the D-Info treatment. Each dot represents a scenario, with the tag next to it showing the d and a of that scenario. Error bars represent 95% confidence intervals.

(1), I regress information valuations on d, using observations from the three scenarios where a is fixed at 40% and d is 50%, 70%, and 90%. The coefficient is significantly negative ($p < 0.001$), albeit the magnitude is smaller ($p < 0.001$) than the rational benchmark $1 - 60\% = 0.4$. In Regression (2), I regress information valuations on a, using observations from the three scenarios where d is fixed at 60% and a is 10%, 30%, and 50%. Contradicting rationality, the coefficient is slightly negative. These patterns persist in a selected sample of participants who correctly answer all comprehension questions in one attempt, choose the optimal lottery given all available information, and spend on average 8 seconds or more on each scenario (see Regressions (3) and (4)). The qualitative results also hold when I control for the scenario order and all variables in the endline questionnaire, as well as their interactions with the main independent variable d or a (see Regression (5) and (6)).[5]

[5]Only one control variable is significantly correlated with the level of information valuations: a one-standard-deviation increase in self-reported tendency to acquire information, which is 1 on a five-point likert scale, is associated with 2.38 percentage points increase in information valuations in the three scenarios where d is 60% ($p = 0.032$). Several control variables have marginally significant associations with the sensitivity of information valuations to d

Aggregate results mask interesting patterns at the individual level. Table A3 classifies participants by the monotonicity of their information valuations in relation to changes in d and a. As d increases from 50% to 70% to 90%, 66% of participants report monotonically decreasing information valuations (which is rational), while almost none report monotonic increases or constant values.[6] In contrast, as a increases from 10% to 30% to 50%, 27.9% of participants report monotonically decreasing information valuations (which is irrational), but the other two categories are also substantial, each representing around 20% of participants. These patterns imply that while most participants respond to changes in d in the correct direction, there is substantial heterogeneity in how they respond to variations in the winning chances of the alternative lottery A.

Analyzing the advice participants provide to future participants on how to answer the information valuation questions can provide insight into their thought processes. For each advice, a research assistant notes whether it mentions d or a as a consideration for information valuations and, if so, how. As is summarized in Table A4, 25.9% of participants mention the correct comparative statics of information valuations on d, whereas 12.2% mention comparative statics in the wrong direction. Fewer participants mention comparative statics on a: 10.9% state the correct direction, and 12.9% are wrong. These results are in line with the individual-level patterns of information valuations.

Apart from comparative statics, some participants reveal the exact decision rules they try to implement in their advice. For instance, 12 participants (8.1%) state that they would choose the information unless they can increase the winning chance of D above a certain threshold. This decision rule, just like the rational rule, can generate the prevalent negative relationship between information valuations and d that we observe in the experiment. It also echoes Simon (1955)'s satisficing heuristic, which posits that decision-makers search for new options until the status quo surpasses a fixed aspiration level. Interestingly, 4 participants (2.7%) express that they prefer the information unless the winning chance of A is increased to a certain level. This incorrectly-applied

and a. Female and college-graduated participants decrease their information valuations more as d increase. Older and more risk-seeking participants have information valuations that increase more with a.

[6] Valuations are classified as decreasing (increasing) if they are weakly decreasing (increasing) but not constant everywhere.

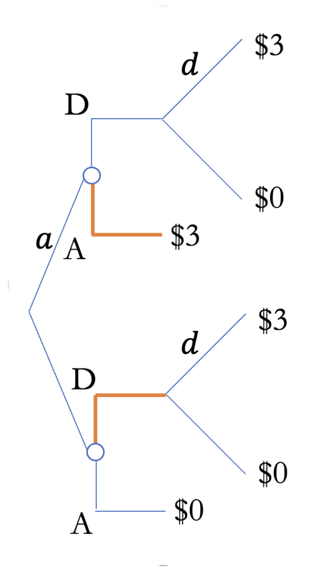

Figure 3: Payoff structure induced by the information in the A-Info treatment

Notes: This figure depicts the payoff structure induced by the information in the A-Info treatment. The straight branches represent uncertainty resolution. The letter on a straight branch represents its probability. The elbow branches are choice options. The optimal choices, shown in orange, induce a compound lottery.

satisficing heuristic could explain why information valuations sometimes respond to a in the wrong direction.

2.4 A-Info treatment

In the D-Info treatment, Lottery D is the focus of the information. This may highlight D over A, potentially explaining why information valuations are more sensitive to d. To test this potential explanation, I conduct another treatment termed A-Info ($N = 152$) where participants evaluate information that reveals A's outcome before the lottery choice. If participants receive this information about A, they should choose A if it wins and D if not. This strategy induces the compound lottery depicted in Figure 3 and gives participants a $a+(1-a)d$ probability of winning. Therefore, the value of learning A's outcome should be $a(1-d)$. Although this expression is the same as the value of learning D's outcome, the interpretations of a and $1-d$ are reversed: information about A diverts decision from the default option with a probability of a, and when it happens, the winning chance increases from d to 1.

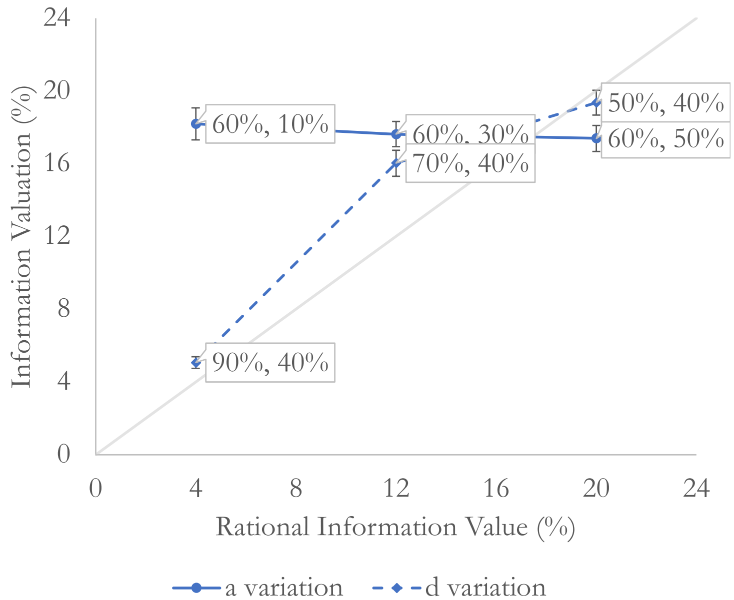

Figure 4: Information valuations in the A-Info treatment

Notes: This figure shows the average information valuations in the A-Info treatment. Each dot represents a scenario, with the tag next to it showing the d and a of that scenario. Error bars represent 95% confidence intervals.

The information valuations in the A-Info treatment are remarkably similar to the D-Info treatment, both on average (Figure 4) and in terms of the distribution of individual behaviors (Table A3). Participants respond in the correct direction to changes in d, but are mixed and on average insensitive to changes in a. (Tables A5 and A6 show in regressions that the A-Info treatment is not significantly different from the D-Info treatment with respect to the sensitivity of information valuations.) Turning to incentivized advice, more participants in the A-Info treatment mention Lottery A compared to the D-Info treatment, suggesting that Lottery A is indeed more salient when it is the subject matter of information. Nevertheless, participants who mention comparative statics with respect to a are still more likely to be wrong (19.7%) than right (18.4%).

The fact that information valuations are almost identical whichever lottery is revealed implies that merely increasing the salience of the alternative lottery does not guarantee that information valuations will respond to it correctly. Moreover, because the two kinds of information induce different choice probabilities and different winning chances conditional on each choice, variations in these features cannot explain the results.

A potential confound of these results is that the maximum permissible answer for information valuation when $d = 90\%$ and $a = 50\%$ is 10% (as information cannot increase the winning chance beyond 100%), which is different from the other scenarios where the answer is allowed to be as high as 30%. This difference in range could affect the measured sensitivity of information valuations when d increases from 70% to 90%, but it cannot explain the sensitivity as d increases from 50% to 70% as the range remains constant. To further address this potential confound, I conduct a variation of the D-Info treatment where information valuations are elicited as willingness-to-pay, and the answer range is constant across all scenarios (see Appendix A.1). In this treatment ($N = 70$), information valuations are still more sensitive to d than to a, especially as d increases from 70% to 90%. This provides assurance that the main results of the experiment are not an artifact of the elicitation mechanism.

3 What makes information valuation difficult?

The results so far have established that people do not rationally account for the choice options when evaluating information. Conceptually, the difficulty of evaluating information could come in two stages. First, people might not perfectly foresee what they will choose when the information realizes or is absent. Second, given their choice forecasts, it could be difficult to integrate the choice payoffs to derive the correct information value.

3.1 Imperfect foresight

To examine whether imperfect foresight of one's future choices plays a role in the deviations from rationality, I implement a strategy-method version of the D-Info treatment ($N = 73$). Participants in this treatment first report their contingent lottery choices for each possible realization of information and in its absence. Then, they report their information valuations. Once it is determined whether they receive information, their contingent lottery choice is implemented and the outcomes are revealed. Having participants make contingent lottery choices first ensures their knowledge of their choices when evaluating information. Moreover, because all uncertainties are resolved in one shot with or without information, preferences for the timing of uncertainty resolution are irrelevant to information valuation.

In the strategy-method treatment, all participants make optimal contingent lottery choices, suggesting that this is not a difficult task. Figure 5 presents the comparative statics of information valuations. The average information valuation shows a slight, but insignificant increase ($p = 0.136$) as Lottery A becomes more likely to win. However, this is a significant change from the D-Info treatment ($p = 0.029$) where the average information valuation decreases in a. The improved sensitivity to a is also evident at the individual level with 30.1% of participants increasing their information valuations with a, higher than the 20.4% in the D-Info treatment ($p = 0.055$).[7] These findings suggest that the biases in information valuations can partially be attributed to participants' imperfect foresight of their future choices. Moreover, the fact that participants have no trouble formulating a choice plan when prompted suggests that the imperfect foresight is not due to the inherent difficulty of choice forecasting, but rather to the failure to consider the future lottery choices when evaluating information.[8]

3.2 Payoff integration

To evaluate information, people need to integrate multiple potential payoffs, which can be difficult for at least two reasons. First, payoff integration can be computationally complex. Second, the payoffs to be integrated come from multiple choices, which could add to the complexity.

[7] However, fewer pieces of advice mention that information valuations should rise with a.

[8] It is worth noting that existing models of imperfect foresight cannot readily generate the patterns in the experiment. For example, a tremble model where the decision-maker anticipates a probability of mistakes for each information set can generate insensitivity to d and a, but not asymmetry between them.

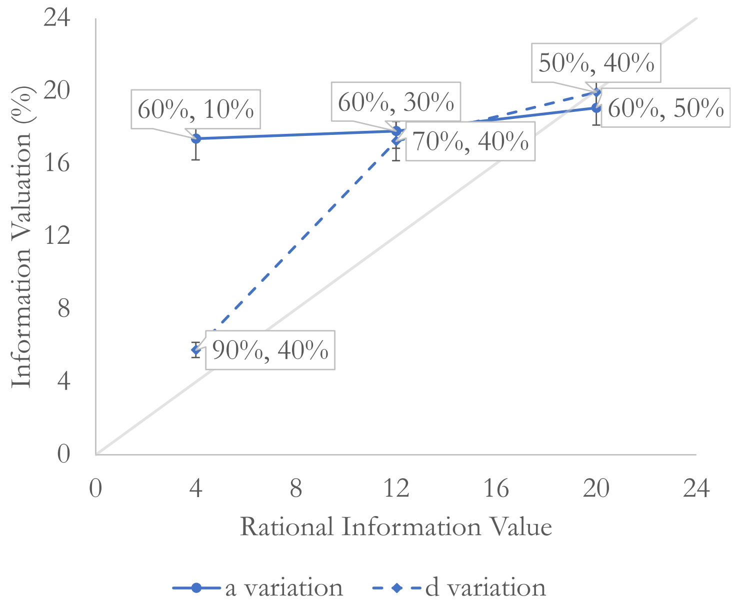

Figure 5: Information valuations in the Strategy-method treatment

Notes: This figure shows the average information valuations in the Strategy-method treatment. Each dot represents a scenario, with the tag next to it showing the d and a of that scenario. Error bars represent 95% confidence intervals.

3.2.1 Computational complexity

In the treatments discussed so far, the computational complexity of information valuation mainly comes from the reduction of compound probabilities. To investigate whether computational complexity is key to the biases in information valuation, I design a variant of the D-Info treatment, named Mutually Exclusive ($N = 74$), that eliminate the need for reducing compound probabilities. This is achieved by making D and A mutually exclusive—the two lotteries cannot both win. Same as in the D-Info treatment, participants in the Mutually Exclusive treatment should choose D if the information says it wins and choose A otherwise. This strategy leads to a lottery depicted in Figure 6. The total winning chance by following this strategy is $d + a$, which implies that the information value should be a. Note that this expression does not involve any reduction of compound probabilities, thereby significantly reducing computational complexity. It also doesn't involve d, which allows me to test whether information valuation responds to the default lottery when it shouldn't. I elicit information valuations in 5 scenarios, varying d and a: the values of

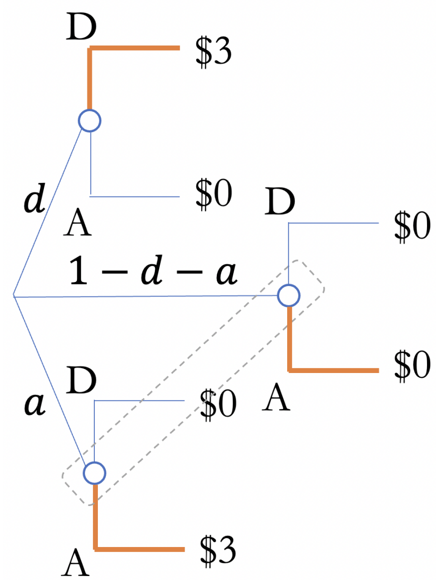

Figure 6: Payoff structure induced by the information in the Mutually Exclusive treatment

Notes: This figure depicts the payoff structure induced by the information in the Mutually Exclusive treatment. The straight branches represent uncertainty resolution, with the two nodes in the dashed rectangle being in the same information set. The letter on a straight branch represents its probability. The elbow branches are choice options. The optimal choices, shown in orange, induce a lottery.

(d, a) are (40%, 10%), (40%, 20%), (40%, 30%), (30%, 20%) and (50%, 20%). The highest allowed answer for information valuation is 40% for all 5 scenarios.

Figure 7 shows the result of the Mutually Exclusive treatment. Average information valuation increases slightly with a, but the slope is statistically indistinguishable from zero ($p = 0.478$). At the individual level, as a goes up, 27% of participants increase their information valuations, which is not significantly more than the 21.6% who decrease their valuations (Pearson's χ^2 test, $p = 0.505$). These results demonstrate that information valuations do not correctly respond to the alternative option even when the computational requirements are minimal.

Interestingly, even though the correct information value does not depend on the default lottery, many participants' information valuations do. As d increases, 40.5% of participants decrease their information valuations, which is significantly more than the 21.6% of participants who increase their valuations (Pearson's χ^2 test, $p = 0.039$) and the 13.5% who (correctly) keep theirs constant. The average information valuation is also more sensitive to d than to a, although the difference is

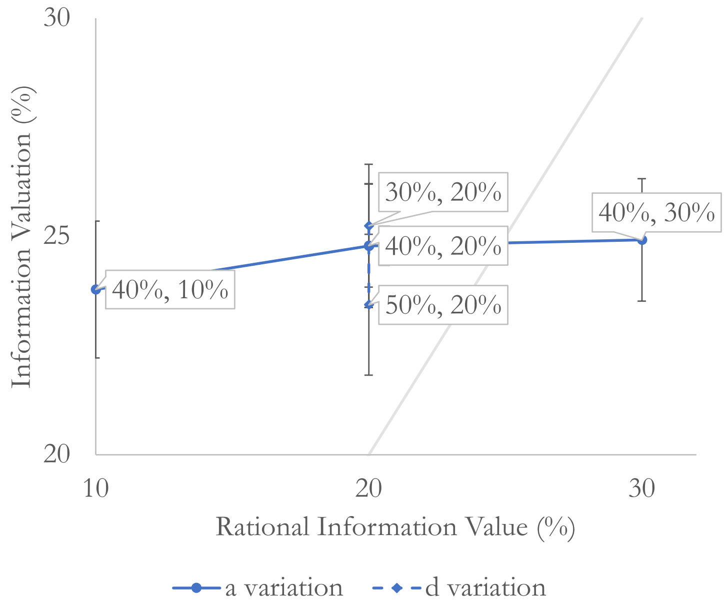

Figure 7: Information valuations in the Mutually Exclusive treatment

Notes: This figure shows the average information valuations in the Mutually Exclusive treatment. Each dot represents a scenario, with the tag next to it showing the d of that scenario. Error bars represent 95% confidence intervals.

not statistically significant ($p = 0.764$). These findings imply that many people devalue information as the default lottery becomes more likely to win, even when such a response isn't justified by the context. This context-insensitive decision-making suggests that the seemingly rational response of information valuation to the default lottery in the main treatments is likely driven by heuristic use.

3.2.2 Multiple choices

To evaluate information, people need to integrate payoffs from multiple potential choices. This is true in my experiment because participants need to integrate the payoffs of choosing D and choosing A. It is also a general feature of information valuation because information adds value only if it changes people's choice with a positive probability. Prior research on contingent reasoning (Esponda and Vespa, 2014, 2021; Martínez-Marquina, Niederle, and Vespa, 2019) suggests that integrating multiple potential payoffs can be challenging. This section examines whether this

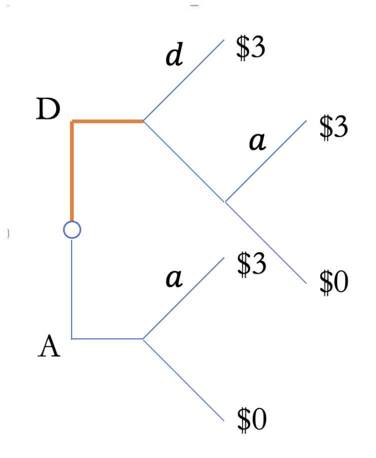

Figure 8: Payoff structure induced by the insurance in the D-Insured treatment

Notes: This figure depicts the payoff structure induced by the insurance in the D-Insured treatment. The straight branches represent uncertainty resolution. The letter on a straight branch represents its probability. The elbow branches are choice options. The orange branch is the optimal choice, which induces a compound lottery.

integration process becomes more difficult when the payoffs arise from multiple choices.

To test this hypothesis, I design a treatment where participants evaluate an object that induces the same compound lottery as information but does not involve multiple choices in its valuation. This object is an insurance. Specifically, in the D-Insured treatment ($N = 142$), participants do not learn about a lottery's outcome in advance, nor are they asked to evaluate any information. Instead, they may "insure" Lottery D using Lottery A as a back-up. With the insurance, participants can win \$3 even if they choose D and it fails, so long as A wins. This insurance leads to the compound lottery depicted in Figure 8, which is the same as learning about D's outcome in the D-Info treatment. Thus, the insurance value is the same as the information value, $(1-d)a$. Unlike the D-Info treatment, however, participants in the D-Insured treatment should always choose D whether they have the insurance or not, so insurance valuation only requires integrating different payoffs from this single choice. Thus, comparing information valuation in the D-Info treatment to insurance valuation in the D-Insured treatment allows me to test whether integrating payoffs from multiple choices is more difficult than integrating multiple payoffs from a single choice.

Figure 9 shows how average insurance valuation changes with d and a. Consistent with rationality, average insurance valuation increases with a ($p < 0.001$). This is in stark contrast with

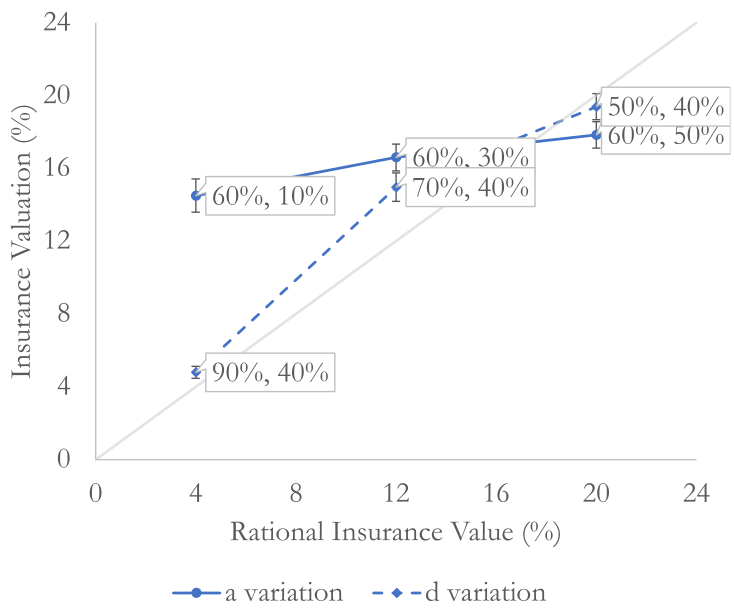

Figure 9: Insurance valuations in the D-Insured treatment

Notes: This figure shows the average insurance valuations in the D-Insured treatment. Each dot represents a scenario, with the tag next to it showing the d and a of that scenario. Error bars represent 95% confidence intervals.

the average information valuation in the D-Info treatment which is insensitive to a. The sensitivity to a in the D-Insured treatment is also reflected on an individual level: 40.9% of participants have insurance valuations that are monotonically increasing in a, compared to 19% decreasing and 9.2% remaining constant. Moreover, 67.6% of participants refer to Lottery A in their incentivized advice, none of whom mention the wrong comparative statics.

The different results from the D-Info and D-Insured treatments are consistent with the hypothesis that integrating payoffs from multiple choices is more challenging than integrating multiple payoffs from a single choice. However, the difference could also result from other framing effects. For example, people may simply be better at evaluating insurance than information. To rule out framing as the explanation, I conduct a treatment, named A-Insured ($N = 156$), which parallels the D-Insured treatment but for the A-Info treatment. Specifically, participants in the A-Insured treatment may "insure" Lottery A by using D as its back-up. With the insurance, participants can win \$3 even if they choose A and it fails, so long as D wins. This insurance induces the same

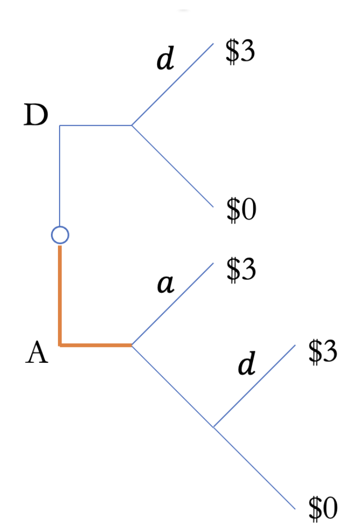

Figure 10: Payoff structure induced by the insurance in the A-Insured treatment

Notes: This figure depicts the payoff structure induced by the insurance in the A-Insured treatment. The straight branches represent uncertainty resolution. The letter on a straight branch represents its probability. The elbow branches are choice options. The orange branch is the optimal choice, which induces a compound lottery.

compound lottery as the information in the A-Info treatment (see Figure 10), so their values are identical. However, the insurance changes the optimal decision: participants should choose A if it is insured and D if it's not. As a result, they still need to integrate payoffs from more than one choice to evaluate the insurance, which distinguishes it from the D-Insured treatment. If integrating payoffs from multiple choices is what makes information valuation challenging, then we should not expect participants to perform better in the A-Insured treatment than in the A-Info treatment. If, on the other hand, the insurance framing is what helps participants in the D-Insured treatment, it should also help those in the A-Insured treatment.

Figure 11 shows the insurance valuation in the A-Insured treatment. The average valuation is decreasing in a ($p = 0.026$), showing no improvement from information valuations in the A-Info treatment. There are even signs of more deviations from rationality when we examine the individual-level results. The percentage of participants whose answers monotonically respond to a in the wrong direction increases from 27% in the A-Info treatment to 34.6% in the A-Insured treatment ($p = 0.074$). The proportion of participants with the correct monotonicity to d decreases

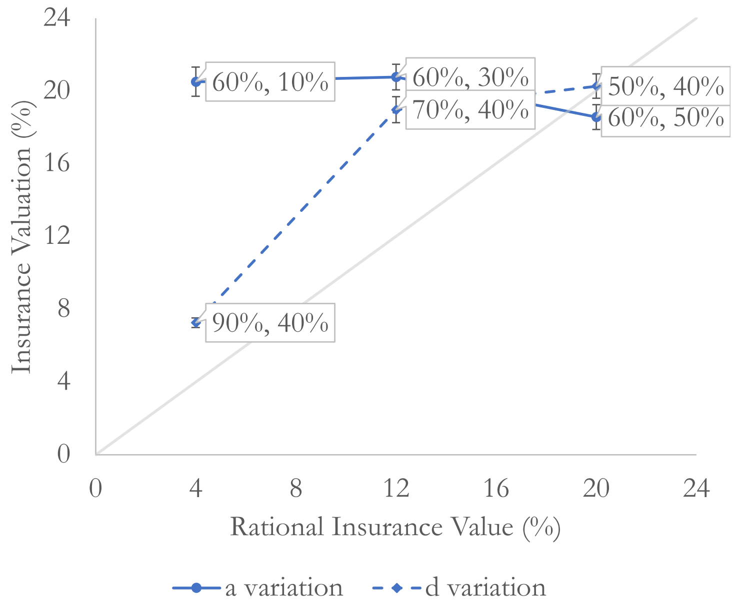

Figure 11: Insurance valuations in the A-Insured treatment

Notes: This figure shows the average insurance valuations in the A-Insured treatment. Each dot represents a scenario, with the tag next to it showing the d and a of that scenario. Error bars represent 95% confidence intervals.

from 75.7% to 58.3% ($p < 0.001$). Among participants who mention comparative statics on d or a in their incentivized advice, many more get the directions wrong than right. Taken together, participants perform worse at evaluating insurance in the A-Insured treatment than evaluating information in the A-Info treatment. This result indicates that the insurance framing *per se* does not make evaluation easier, thus ruling out a potential confound when comparing the D-Insured and D-Info treatments. It also supports our preferred hypothesis: having to integrate payoffs from multiple choices makes information valuation difficult.

Another implication of this hypothesis is that information that does not affect decisions should be easier to evaluate. So long as people recognize that the realization of information won't affect their decision, they should understand that such information holds no value. Arriving at this conclusion does not require any payoff integration or computation. To test this implication, I incorporate a scenario into the start of the original D-Info and A-Info treatments, where Lottery A has no chance of winning, hence rendering the information valueless. These adjusted treatments are termed D-Info ($a = 0$ first) and A-Info ($a = 0$ first). Consistent with the hypothesis, the average information valuation in this scenario is significantly lower than the scenario where $a = 10\%$. Details of these two treatments are relegated to Appendix A.3.

4 Discussion

This paper, through an experimental approach, explores how information demand responds to the decision problem it informs. On the one hand, information demand increases as the default option presents a higher downside risk in the decision problem. On the other hand, responses to changes in the alternative option display significant heterogeneity, and on average, are insensitive. Both patterns exhibit characteristics of bounded rationality.

Bounded rationality in information demand directly affects decision quality and overall individual welfare. Moreover, it may have important implications in market settings. Consider a simple example where Lottery D and Lottery A in the main experiment represent two competing products in the market. In this case, the market share of A increases with the proportion of consumers who acquire information about the products before purchase.[9] If information acquisition is insensitive to A's prior a, then the marginal benefit of investing in a could be diminished. Of course, to validate such implications, further research on specific field settings is required.

In this paper, I demonstrate that the complexity of information valuation is related to the difficulty of foreseeing future choices and integrating their payoffs. In additional to information valuation, these mechanisms may also affect other behaviors. For example, self-motivational devices such as gym memberships and commitment contracts derive their value from behavior change. Therefore, to evaluate these devices, people have to integrate payoffs from multiple behaviors. The difficulty of foreseeing future choices and integrating their payoffs could lead to biases in these valuations too.

[9] To understand why, suppose consumers can only acquire information about D. Then, A's market share is $Pr(\text{Acquire information}) \cdot (1 - d)$. If Consumers can only acquire information about A, then A's market share is $Pr(\text{Acquire information}) \cdot a$.

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Appendix

A Additional treatments

A.1 WTP treatment

In the D-Info treatment, the highest allowable answer for information valuation is capped at 10% when $d = 90\%$ and $a = 50\%$. This is different from the other scenarios where the answer can reach up to 30%. To address this potential confound, I run the Willingness-To-Pay (WTP) treatment where the range of answers for the information valuation question remains constant across all scenarios. In this treatment, with 50% chance, participants' final payments are determined by the outcome of their chosen lottery between D and A, mirroring the original D-Info treatment. Otherwise, their payments are determined by the outcome of a different, independent binary lottery X. The percentage winning chance of X is equal to the number of points a participant holds. In each scenario, participants start with an endowment of 60 points and answer how many points they are willing to pay to receive information about D's outcome. The question is implemented through a multiple-price list and the maximal price is 30 points across all scenarios. Because the payment is equally likely to be determined by X or the chosen lottery between D and A, the WTP in points reflects the information valuation.

The WTP treatment has the advantage of maintaining a consistent range of answers across scenarios but presents two potential drawbacks. First, the introduction of a third lottery X could increase the complexity of the treatment. Second, as information valuations are elicited through WTP, they could be affected by loss attitudes.

Figure A1 shows the results of the WTP treatment. Consistent with loss aversion, the WTP for information is significantly lower than the valuations elicited in the D-Info treatment. This compression toward zero inevitably limits the variability of information valuations. Nevertheless, WTP still exhibits significant sensitivity to d ($p = 0.001$), especially when it decreases from 90% to 70%, which is precisely the region where the range of answers is not fixed in the D-Info treatment.

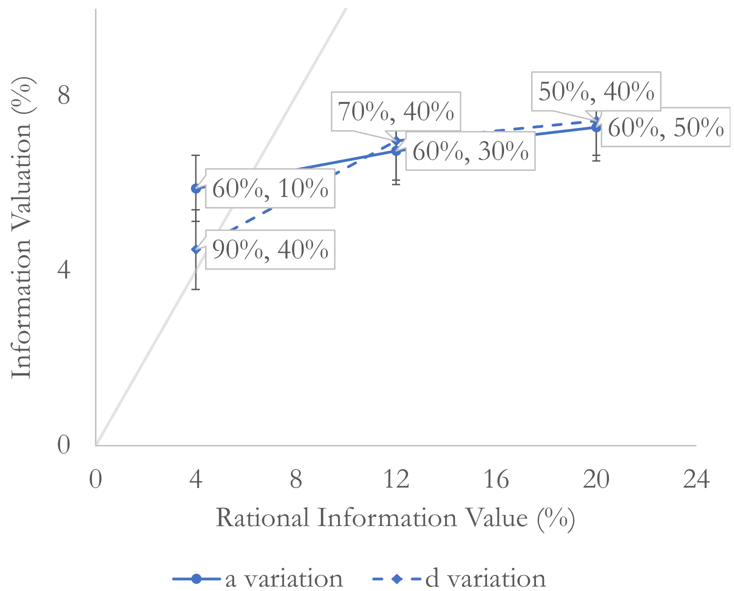

Figure A1: Information valuations in the WTP treatment

Notes: This figure shows the average information valuations in the WTP treatment. Each dot represents a scenario, with the tag next to it showing the d and a of that scenario. Error bars represent 95% confidence intervals.

This result indicates that the sensitivity of information valuations to d is not an artifact of the elicitation mechanism. Interestingly, average information valuation in the WTP treatment is also sensitive to a in the correct direction, though still less so than to d.

A.2 Inconclusive Info treatment

In this section, I report on the Inconclusive Info treatment ($N = 86$). Similar to the Mutually Exclusive treatment, results of this treatment show that information valuations respond to the default lottery even when they shouldn't. This treatment also demonstrates that the bounded rationality in information valuation persists even when the calculation doesn't involve reducing compound probabilities.

In the Inconclusive Info treatment ($N = 86$), bad news about Lottery D's outcome is conclusive but good news is not—the information reports "Lottery D wins" with probability $d' > d$. To keep the number of parameters constant, I simplify the setting by making D and A perfect comple-

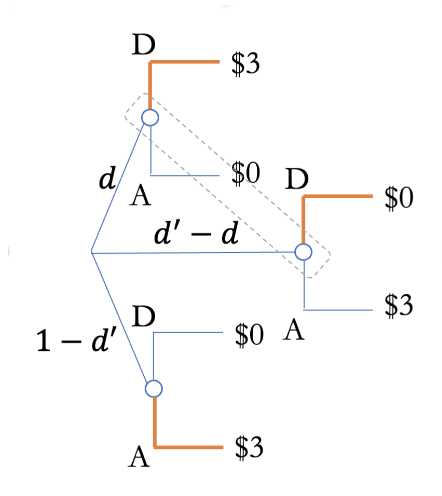

Figure A2: Payoff structure induced by the information in the Inconclusive Info treatment

Notes: This figure depicts the payoff structure induced by the information in the Inconclusive Info treatment. The straight branches represent uncertainty resolution, with the two nodes in the dashed rectangle being in the same information set. The letter on a straight branch represents its probability. The elbow branches are choice options. The orange branches are the optimal choices, which induce a lottery.

ments—A wins if and only if D loses. Same as in the D-Info treatment, participants should choose D if the information says it wins and choose A otherwise. This strategy leads to a lottery depicted in Figure A3. The total winning chance of following this strategy is $d + 1 - d'$, which implies that the information value should be $1 - d'$. Note that this expression does not involve any reduction of compound probabilities, which makes it even simpler to calculate than the information value in the main treatments. I elicit information valuations in 5 scenarios where I vary d and d': the pairs (d, d') used are (60%, 70%), (60%, 80%), (60%, 90%), (50%, 80%) and (70%, 80%).

Figure A4 shows the result of the Inconclusive Info treatment. Average information valuation is insensitive to d' ($p = 0.177$) but sensitive to d ($p < 0.001$), which is the reverse of the correct comparative statics. The participants' inability to evaluate information correctly, even when no reduction of compound probabilities is needed, suggests that computational complexity, and compound reduction specifically, are not prerequisites for the observed bias. This stark result on the comparative statics on d implies that people attach lower values to information as the default lottery becomes more likely to win, irrespective of whether it is warranted in the specific setting. This context-independent decision rule suggests that although the response of information valuations to

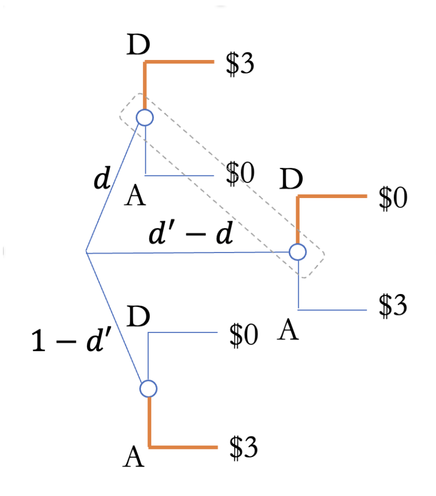

Figure A3: Payoff structure induced by the information in the Inconclusive Info treatment

Notes: This figure depicts the payoff structure induced by the information in the Inconclusive Info treatment. The straight branches represent uncertainty resolution, with the two nodes in the dashed rectangle being in the same information set. The letter on a straight branch represents its probability. The elbow branches are choice options. The orange branches are the optimal choices, which induce a lottery.

the default lottery seems rational in the main treatments, it actually reflects the use of heuristics.

Figure A4 shows the result of the Inconclusive Info treatment. Average information valuation is insensitive to d' ($p = 0.177$) but sensitive to d ($p < 0.001$), which is the reverse of the correct comparative statics. The fact that participants do not correctly evaluate information even when no reduction of compound probabilities is required indicates that compound reduction and, more generally, computational complexity are not necessary for the bias. This stark result on the comparative statics on d implies that people attach lower values to information as the default lottery becomes more likely to win, irrespective of whether it is warranted in the specific setting. This context-independent decision rule suggests that although the response of information valuations to the default lottery seems rational in the main treatments, it actually reflects the use of heuristics.

A.3 Evaluating information with zero value

Section 3.2 establishes that one of the challenges in evaluating information stems from the necessity to integrate multiple payoffs. An implication of this finding is that if the information

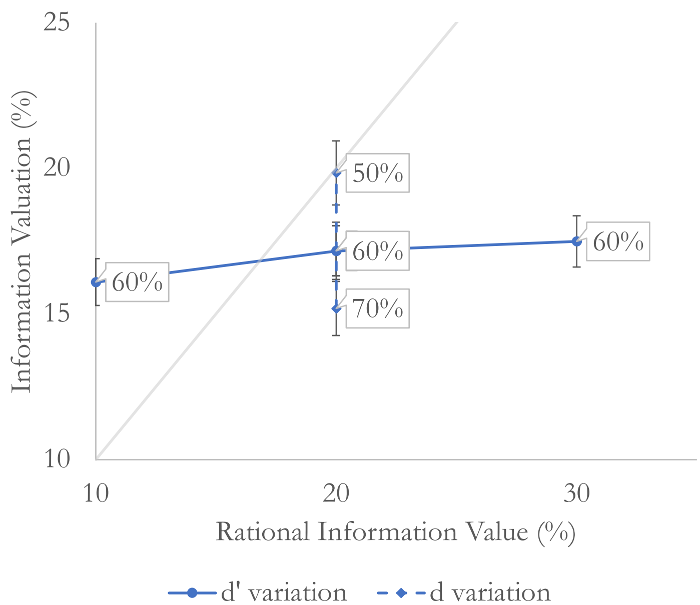

Figure A4: Information valuations in the Inconclusive Info treatment

Notes: This figure shows the average information valuations in the Inconclusive Info treatment. Each dot represents a scenario, with the tag next to it showing the d of that scenario. Error bars represent 95% confidence intervals.

does not alter the choice, its evaluation should be easier, as there's no need for payoff integration to understand that such information carries no value. In this section, I report on the D-Info ($a = 0$ first) treatment ($N = 78$) and the A-Info ($a = 0$ first) treatment ($N = 72$). These two treatments are the same as the original D-Info and A-Info treatments except that they have one additional scenario at the beginning where $d = 60\%$ and $a = 0\%$. This additional scenario allows me to investigate whether information with zero value is indeed easier to evaluate.

Figures A5 and A6 show the results of these two treatments. Consistent with the hypothesis, the average information valuation when $a = 0$ is lower than when $a = 10\%$ (D-Info: $p = 0.030$; A-Info: $p = 0.017$), contrasting with the insensitivity to a observed in the original D-Info and A-Info treatments. However, the average valuations are still far from the correct value of zero. This is also reflected at the individual level: only 19.2% of participants in the D-Info ($a = 0$ first) treatment and 37.5% in the A-Info ($a = 0$ first) treatment correctly evaluate the valueless information at zero. These findings suggest that while payoff integration is an important source of complexity for

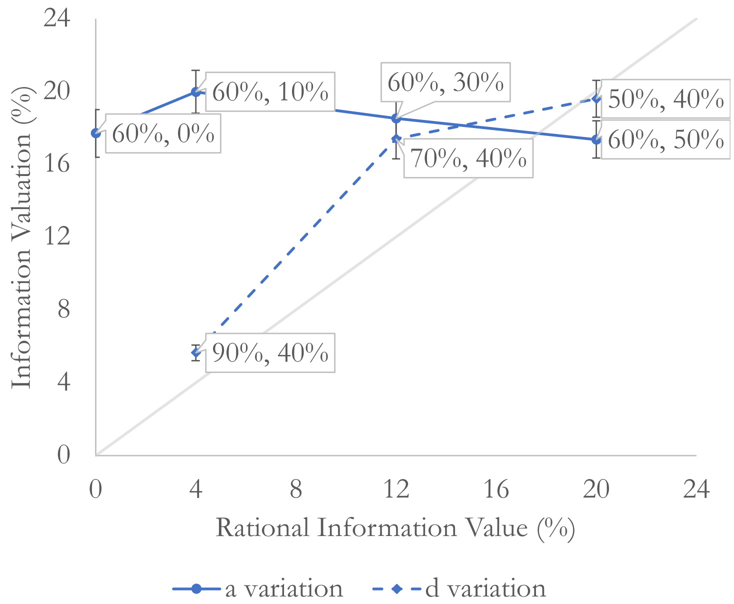

Figure A5: Information valuations in the D-Info ($a = 0$ first) treatment

Notes: This figure shows the average information valuations in the D-Info ($a = 0$ first) treatment. Each dot represents a scenario, with the tag next to it showing the d and a of that scenario. Error bars represent 95% confidence intervals.

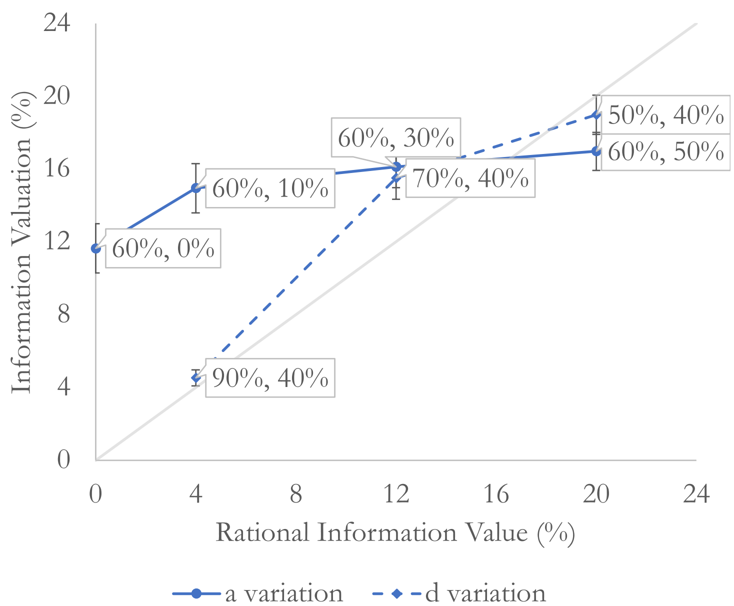

Figure A6: Information valuations in the A-Info ($a = 0$ first) treatment

Notes: This figure shows the average information valuations in the A-Info ($a = 0$ first) treatment. Each dot represents a scenario, with the tag next to it showing the d and a of that scenario. Error bars represent 95% confidence intervals.

information valuation, it is not the only one.

A.4 Advisee treatment

In this section, I report on the design and results of the Advisee treatment ($N = 51$). This treatment is identical to the D-Info treatment except that participants evaluate advice provided by previous participants after going through the instructions, but prior to encountering the scenarios. Specifically, each participant in the Advisee treatment reviews two pieces of advice written by participants from earlier treatments. One piece of advice correctly argues that information valuation should increase in a, whereas the other incorrectly asserts a reverse relationship. Before they begin to evaluate information across the six scenarios, participants indicate which piece of advice they find more persuasive or if they deem them equally convincing. The participants in the Advisee treatment are not asked to offer advice.

The number of participants identifying the correct advice as more convincing (19) is significantly larger (Pearson's χ^2, $p = 0.059$) than those misidentifying (9). This outcome implies that, on average, participants possess some capacity to discern the correct relationship between information valuation and the alternative lottery once the arguments have been laid out for them. However, this ability does not translate to any significant improvement in the sensitivity of average information valuation to a (see Figure A7 and Table A5). At the participant level, 31.4% of participants exhibit information valuations that increase monotonically with a. This percentage exceeds the 20.4% in the D-Info treatment. Nevertheless, this difference is solely driven by participants who rate the two pieces of advice as equally convincing. Among these participants, 43.5% display this correct comparative statics, whereas only 21% and 22.2% of those favoring the correct and incorrect advice, respectively, exhibit the same. Taken together, these results indicate that exposure to the advice of others has a limited effect on information valuations.

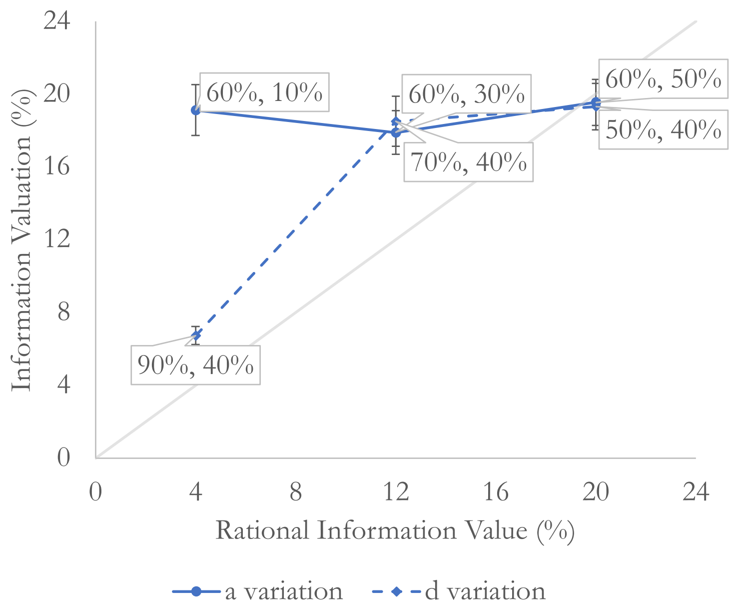

Figure A7: Information valuations in the Advisee treatment

Notes: This figure shows the average information valuations in the Advisee treatment. Each dot represents a scenario, with the tag next to it showing the d and a of that scenario. Error bars represent 95% confidence intervals.

B Additional tables

Table A1: Summary statistics of socio-demographics

	Mean	Std.	N
Age	40.19	13.66	1050
1 if female	0.49	0.50	1050
1 if employed	0.70	0.46	1050
1 if college degree	0.56	0.50	1050
1 if income > 75k	0.34	0.48	1050
1 if investing in stock	0.64	0.48	1050
Info Seeking (1-5)	3.92	0.89	980
Risk Seeking (1-5)	3.12	1.03	1050
Planning (1-5)	3.77	0.92	1050

Notes: This tables summarizes the socio-demographic questionnaire at the end of the experiment. The question on the tendency to seek information before making decision is missing from the WTP treatment.

Table A2: Sensitivity to d and a in the D-Info treatment

	Information Valuation					
	(1)	(2)	(3)	(4)	(5)	(6)
d	-0.352***		-0.378***		-0.404***	
	(0.018)		(0.024)		(0.113)	
a		-0.033*		-0.035		0.087
		(0.020)		(0.028)		(0.149)
Control	No	No	No	No	Yes	Yes
Selected sample	No	No	Yes	Yes	No	No
Observations	441	441	225	225	441	441
R^2	0.347	0.003	0.388	0.004	0.376	0.067

Notes: This table shows the sensitivity of information valuation to the two lotteries' winning chances, d and a, in the D-Info treatment. Regressions (1), (3) and (5) include observations from the three scenarios where d is 50%, 70% and 90%. Regressions (2), (4) and (6) include observations from the three scenarios where a is 10%, 30% and 50%. Control variables include the order of the scenario and all variables in the endline questionnaire, as well as their interactions with the main independent variable (d or a). The selected sample only includes participants who correctly answer all comprehension questions in one attempt, choose the optimal lottery given all available information, and spend on average 8 seconds or more on each scenario. Standard errors are clustered by participant. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table A3: Comparative statics of information valuation at the participant level

% of participants with information valuation …	Treatment D-Info	A-Info	WTP	Strategy	D-Insured	A-Insured	D-Info ($a = 0$ first)	A-Info ($a = 0$ first)	Advisee
decreasing in d (correct)	66	75.7	48.6	72.6	72.5	58.3	74.4	66.7	56.9
constant in d	4.1	1.3	18.6	1.4	2.1	1.3	2.6	5.6	0
increasing in d	0.7	0.7	11.4	0	1.4	1.3	3.9	0	0
increasing in a (correct)	20.4	20.4	31.4	30.1	40.9	19.2	21.8	34.7	31.4
constant in a	19.1	13.8	25.7	19.6	9.2	13.5	14.1	13.9	13.7
decreasing in a	27.9	27	15.7	20.2	19	34.6	33.3	22.2	23.5

Notes: This tables summarizes the responses of information demand to the default option and the alternative option at the participant level. Responses to d are classified using the three scenarios where d is 50%, 70% and 90%. Responses to a are classified using the three scenarios where a is 10%, 30% and 50%. Responses are classified as increasing (decreasing) if they are weakly increasing (decreasing) but not constant everywhere.

Table A4: Comparative statics of information valuation mentioned in advice

% of participants who write that information valuation should …	Treatment D-Info	A-Info	WTP	Strategy	D-Insured	A-Insured	D-Info ($a = 0$ first)	A-Info ($a = 0$ first)
decrease in d (correct)	25.9	27.0	47.1	24.7	29.6	9.6	29.5	19.4
respond to d (no direction)	26.5	26.3	12.9	31.5	27.5	40.4	25.6	29.2
increase in d	12.2	7.9	10.0	4.1	6.3	21.2	14.1	4.2
increase in a (correct)	10.9	19.7	12.9	6.9	29.6	7.7	11.5	26.4
respond to a (no direction)	21.8	25.0	11.4	24.7	38.0	31.4	21.8	20.8
decrease in a	12.9	18.4	17.1	13.7	0	16.0	21.8	9.7

Notes: This tables summarizes the comparative statics of information demand mentioned in the incentivized advice.

Table A5: Sensitivity to a across treatments

	Information Valuation			
	(1)	(2)	(3)	(4)
a	-0.033*	-0.035	-0.053	-0.154*
	(0.020)	(0.027)	(0.057)	(0.081)
A-Info $\times$ a	0.013	0.034	0.008	0.024
	(0.029)	(0.038)	(0.028)	(0.037)
WTP $\times$ a	0.068***	0.080**	0.072***	0.073*
	(0.026)	(0.034)	(0.027)	(0.038)
Strategy $\times$ a	0.076**	0.110**	0.073**	0.112**
	(0.035)	(0.046)	(0.035)	(0.046)
D-Insured $\times$ a	0.117***	0.199***	0.120***	0.207***
	(0.031)	(0.044)	(0.031)	(0.044)
A-Insured $\times$ a	-0.015	0.044	-0.012	0.040
	(0.029)	(0.047)	(0.029)	(0.047)
D-Info ($a = 0$ first) $\times$ a	-0.032	-0.036	-0.034	-0.040
	(0.034)	(0.045)	(0.035)	(0.046)
A-Info ($a = 0$ first) $\times$ a	0.084**	0.128**	0.079**	0.122*
	(0.039)	(0.064)	(0.039)	(0.065)
Advisee $\times$ a	0.043	0.053	0.062	0.081
	(0.042)	(0.056)	(0.042)	(0.055)
Participant FE	Yes	Yes	Yes	Yes
Control	No	No	Yes	Yes
Selected sample	No	Yes	No	Yes
Observations	2823	1332	2823	1332
R^2	0.707	0.715	0.713	0.723

Notes: This table compares the sensitivity of information valuations to Lottery A's winning chance a across nine treatments: D-Info, A-Info, WTP, Strategy-method, D-Insured, A-Insured, D-Info ($a = 0$ first), A-Info ($a = 0$ first), and Advisee. The data include observations from the three scenarios where a is 10%, 30% and 50%. Control variables include the order of the scenario and its interaction with a, as well as a's interactions with all variables in the endline questionnaire (except the question about the willingness to acquire information before making decisions, which I forgot to include in the WTP treatment). The selected sample only includes participants who correctly answer all comprehension questions in one attempt, choose the optimal lottery given all available information, and spend on average 8 seconds or more on each scenario. Standard errors are clustered by participant. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table A6: Sensitivity to d across treatments

	Information Valuation			
	(1)	(2)	(3)	(4)
d	-0.352***	-0.378***	-0.318***	-0.260***
	(0.018)	(0.024)	(0.047)	(0.063)
A-Info $\times$ d	-0.005	0.003	-0.009	0.002
	(0.024)	(0.032)	(0.024)	(0.031)
WTP $\times$ d	0.278***	0.265***	0.277***	0.271***
	(0.029)	(0.039)	(0.029)	(0.040)
Strategy $\times$ d	-0.002	0.025	-0.003	0.024
	(0.026)	(0.034)	(0.026)	(0.035)
D-Insured $\times$ d	-0.013	0.012	-0.017	0.007
	(0.025)	(0.035)	(0.025)	(0.035)
A-Insured $\times$ d	0.027	0.007	0.023	0.008
	(0.024)	(0.035)	(0.025)	(0.036)
D-Info ($a = 0$ first) $\times$ d	0.003	-0.015	0.008	-0.013
	(0.032)	(0.041)	(0.032)	(0.040)
A-Info ($a = 0$ first) $\times$ d	-0.009	0.009	-0.005	0.019
	(0.031)	(0.046)	(0.032)	(0.046)
Advisee $\times$ d	0.037	0.021	0.029	0.017
	(0.037)	(0.051)	(0.037)	(0.050)
Participant FE	Yes	Yes	Yes	Yes
Control	No	No	Yes	Yes
Selected sample	No	Yes	No	Yes
Observations	2823	1332	2823	1332
R^2	0.716	0.749	0.717	0.753

Notes: This table compares the sensitivity of information valuation to Lottery D's winning chance d across nine treatments: D-Info, A-Info, WTP, Strategy-method, D-Insured, A-Insured, D-Info ($a = 0$ first), A-Info ($a = 0$ first), and Advisee. The data include observations from the three scenarios where d is 50%, 70% and 90%. Control variables include the order of the scenario and its interaction with d, as well as d's interactions with all variables in the endline questionnaire (except the question about the willingness to acquire information before making decisions, which I forgot to include in the WTP treatment). The selected sample only includes participants who correctly answer all comprehension questions in one attempt, choose the optimal lottery given all available information, and spend on average 8 seconds or more on each scenario. Standard errors are clustered by participant. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.