Boundedly Rational Information Demand

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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.

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1 Introduction

In economics, information is valuable primarily because it guides future decisions. For example, investors read analyst reports so that they know which stocks to buy. Recruiters conduct interviews in order to select the best job candidates. Despite the fact that information value should crucially depend on the decision problem it is supposed to inform, we know surprisingly little about their empirical relationship.

In this paper, I study the demand for information about choice options in an experiment. In particular, I focus on how demand responds as the priors about the options change. This is an important question for several reasons. First, it is a near-universal assumption in information economics that information acquisition correctly responds to incentives. A test of this assumption can inform the realism of theoretical results. Second, information acquisition directly affects decision quality and overall payoffs. Hence, studying information demand across different decision problems helps us identify decisions that are most likely to be suboptimal. Third, in market settings, 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. Finally, in settings such as recruitment, admission and lending, information acquisition based on the priors about applicants has implications on diversity, equity and inclusion.

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 payoff u depends on the unobserved state of the world ω. The value of an information structure I, which is a distribution over a set of signals S_I that is correlated with the states, is given 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 which would be chosen without the information, $a(s)$ is the alternative which would be 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 higher the information value. Second, the higher the probability of such a signal, the higher the information value.

In this paper, I test these two comparative statics in a simple experiment. 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. Before the lottery choice, participants in the main treatment, *D-Info*, may receive information that fully reveals D's outcome. 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 with different values of d and a. This allows me to study how information valuations vary with the future decision problem in a within-subject design.

The information valuation question in this experiment has a simple rational answer that does not depend on risk preferences or belief-updating rules. If the information says that D will win, then participants should choose D which guarantees \$3. If, instead, the information says 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 which has 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 simple to interpret: the additional information affects the payoff only when D loses and A wins.

In the experiment, participants' information valuations differ markedly from the rational answers. Consistent with the rational benchmark, information valuations decrease as D becomes more likely to win. However, contrary to rationality, the average information valuation does not vary with A's winning chance. In addition to the average pattern, there is also sizable heterogeneity in how information demand responds to A. More participants decrease than increase information valuations as A becomes more likely to win.

The differential response of information demand to D and A could be driven by the fact that the information evaluated in the D-Info treatment is about D's outcome, not A's. This could make D's winning chance more salient than A's. To test this hypothesis, I ask participants in another treatment to 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 could come in two stages. First, people may not perfectly foresee their own choices with and without information. Second, given their choice forecasts, it may be difficult to integrate the choice payoffs to arrive at the correct information value.

To test whether difficulty in the first stage plays a role in the 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 become 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, which could be a reason why it is difficult. In the main treatments, computational complexity mainly lies in the reduction of 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, which is equal to a, does not require any computation. In spite of this, information valuation is still mostly insensitive to a, implying 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 implies 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 actually reflects the use of heuristics.

Besides computational complexity, the difficulty of payoff integration could also stem from the fact that these payoffs come 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. With the insurance, if participants choose D, they can win \$3 even if D fails, so long as A wins. Having the insurance induces the same compound lottery as receiving information about D's outcome, so their values should be the same. But unlike the information, having the insurance does not change the optimal decision—participants should choose D whether it is insured or not. Therefore, evaluating the insurance does not require integrating payoffs of multiple choices. In this treatment, participants' insurance valuations increase significantly as A becomes more likely to win. This is in stark contrast with the insensitivity of information valuation when A's winning chance changes. In another treatment, I rule out framing as an explanation for the difference between information valuation and insurance valuation. Therefore, this result confirms the hypothesis that having to integrate payoffs from multiple choices contribute to the difficulty of information valuation.

This paper contributes to the literature on demand for information with instrumental value. Several papers study 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 are rational inattention experiments such as Dewan and Neligh (2020) that study perceptual tasks with varying stakes. Their main goal is to measure attention costs under the assumption 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 result 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 find that people sometimes have preference over the amount and timing of information even when they do not affect decisions. My study controls for the 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, which has been shown to be difficult for many people (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's results contribute a new perspective to this literature: it is more difficult to integrate payoffs of multiple choices than multiple payoffs of one choice.

2 Evidence on information demand

2.1 Experimental design

In this section, I describe the design of the main experimental treatment. Designs of additional treatments are described in later sections together with their results.

Participants are presented with six scenarios in random orders. 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 pays out \$3 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 summarized 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 increasing both lotteries' winning chances by $(x-1)\%$, but I would choose increasing both lotteries' winning chances by $(x+1)\%$ over the information.[1]

[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.

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 has several advantages. First, because final payoffs are always binary, risk preference is irrelevant. Second, because participants essentially compare two increases in probability from the same status quo (d), reference dependence and probability weighting play no role. Moreover, there are additional benefits of increasing both d and a as opposed to increasing only d. First, it does not change the relative salience of the two lotteries. Second, increasing d and a by the same amount increases participants' subjective chance of winning by this amount even if they are uncertain which lottery they will choose.

After a participant answers this question for all six scenarios, one 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 that truthfully reporting information valuations is incentive compatible.[3] After that, participants choose between the two lotteries.

After the lottery choice but before the outcomes are revealed, participants are asked to provide advice to future participants on how to answer the information valuation questions. The advice is incentivized: participants are told that their advice may be shown to a future participant, and if the advisee wins a \$3 bonus, the advisor will receive an additional \$2 bonus. In an endline questionnaire, I collect sociodemographic information and ask unincentivized questions about tendencies to acquire information, make plans, and take risks in 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

[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.

answer several comprehension questions in order to proceed in the experiment. Across all treatments, 1050 participants were recruited. The median duration of the experiment is 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, but choose A if it doesn't. This strategy induces a compound lottery as depicted in Figure 1, and its total winning chance is $d + (1 - d)a$. Therefore, learning D's outcome should increase the winning chance by $(1 - d)a$. This expression does not depend on risk preferences and is not affected by deviations from Bayes' rule. It also has a straightforward interpretation: information about D's outcome steers the choice away from the default with $1 - d$ 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 variations in these two parameters across the six scenarios allow me to test these two comparative statics.

The expression $(1 - d)a$ only takes the instrumental value of information into account, but prior research has shown that people sometimes have preferences over the amount and timing of uncertainty resolution for non-instrumental reasons. In my experiment, however, the amount and timing of uncertainty resolution are carefully controlled, so the non-instrumental factors should not affect information valuations by much. First, the outcomes of the two lotteries will eventually be revealed regardless of participants' information valuations, so these valuations should not be affected 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, there isn't any long time lapse between the two revelations. In situations like this, intrinsic preferences for information timing are often weak (Nielsen, 2020). To further address this issue, I will discuss a treatment where information valuations do not affect information timing in Section 3.1.

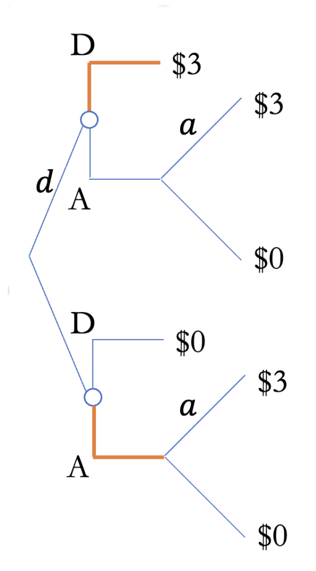

Figure 1: Payoff structure induced by the information in the D-Info treatment

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 orange branches are the optimal choices, which induce a compound lottery.

2.3 Results

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

The patterns are also confirmed in a regression analysis (see Table A2). In Regression (1), 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%. The coefficient is significantly negative ($p < 0.001$), although the magnitude is smaller ($p < 0.001$) than the rational benchmark $1 - 60\% = 0.4$. In Regression (2), 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 small and negative, contrary to rationality. The patterns remain 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

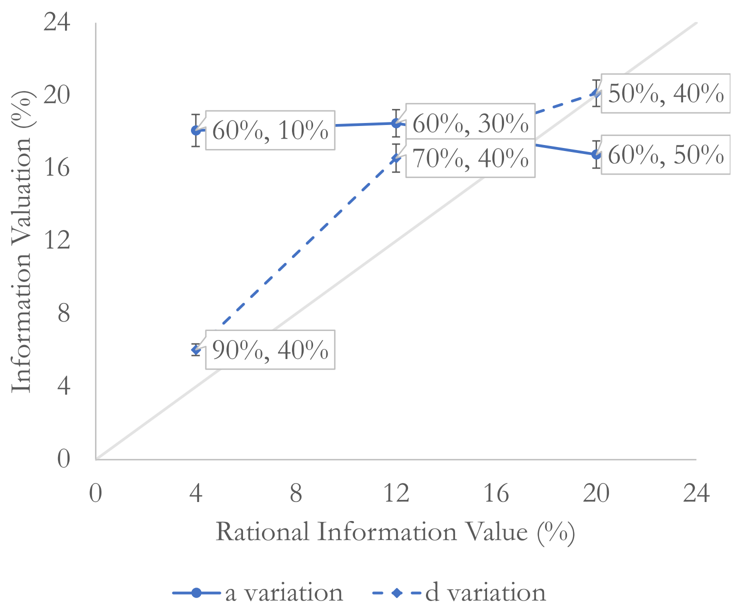

Figure 2: Information valuations in the D-Info treatment

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.

qualitative results also persist when I control for 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 (see Regression (5) and (6)).[4]

Aggregate results mask interesting patterns on the individual level. Table A3 classifies participants by the monotonicity of their information valuations with respect to changes in d and a. As d increases from 50% to 70% to 90%, 66% of participants report monotonically decreasing information valuations while almost none are monotonically increasing or constant.[5] In contrast, as a increases from 10% to 30% to 50%, 27.9% of participants report monotonically decreasing information valuations, but the other two categories are also quite substantial, each covering around

[4]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 in 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 on d 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 in a.

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

20% of participants. These patterns suggest 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.

The advice participants write for future participants on how to answer the information valuation questions can shed light on their thought processes. For each piece of advice, a research assistant marks whether it mentions d or a as a consideration for information valuations and, if it does, how. As is summarized in Table A4, 21.8% of participants mention the correct comparative statics of information valuations on d whereas 9.5% mention a comparative statics in the wrong direction. The comparative statics on a is mentioned by fewer participants—6.1% mention the correct direction and 9.5% are wrong. These results are in line with the individual-level pattern of information valuations.

2.4 A-Info treatment

In the D-Info treatment, Lottery D is the subject matter of the information. This could increase the salience of D relative to A, which could explain why information valuations are more sensitive to d. To test this potential explanation, I run another treatment called A-Info ($N = 152$) where participants evaluate the information that reveals A's outcome before the lottery choice. If participants receive this information about A, they should choose A if it wins but choose D otherwise. This strategy induces the compound lottery depicted in Figure 3 and gives participants a $a + (1 - a)d$ chance to win. 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 steers decision away from the default option with probability a, and when it happens, the winning chance increases from d to 1.

The information valuations in the A-Info treatment are strikingly similar to the D-Info treatment, both on average (Figure 4) and on the individual level (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

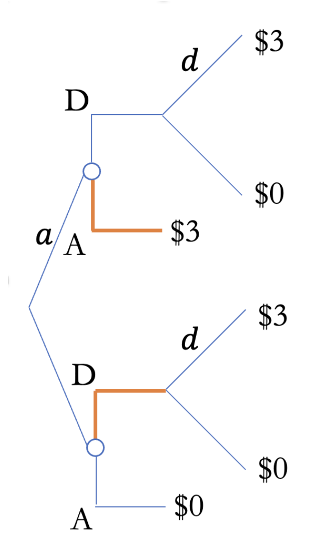

Figure 3: Payoff structure induced by the information in the A-Info treatment

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 orange branches are the optimal choices, which induce a compound lottery.

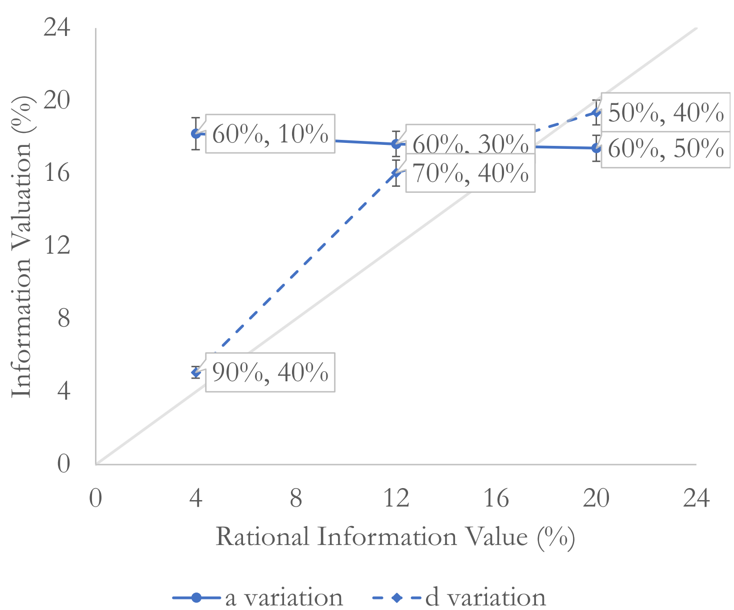

Figure 4: Information valuations in the A-Info treatment

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.

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 than those in the D-Info treatment, which suggests that Lottery A is indeed more salient when it is the subject matter of information. However, participants who mention comparative statics with respect to a are still more likely to be wrong (15.8%) than right (13.2%).

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.

One potential confound of the results is that the highest possible answer for information valuation when $d = 90\%$ and $a = 50\%$ is 10%, 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% where the range is held fixed. To further address this potential confound, I run a variation of the D-Info treatment where information valuations are elicited as willingness-to-pay, and the range of answers 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 future decision problem when evaluating information. Conceptually, the difficulty of evaluating information could come in two stages. First, people may not perfectly foresee their own choices with and without information. Second, given their choice forecasts, it may be difficult to integrate the choice payoffs to arrive at the correct information value.

3.1 Imperfect foresight

To test whether imperfect foresight of one's own choice plays a role in the deviation from rationality, I run a strategy-method version of the D-Info treatment ($N = 73$). Specifically, participants in this treatment first report their contingent lottery choices for each information realization as well as without information. 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. The fact that participants make their contingent lottery choices first ensures that they know their choices perfectly 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 shows the comparative statics of information valuations. The average information valuation increases, but only slightly and insignificantly ($p = 0.136$), 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 improvement in the sensitivity to a is also manifested on the individual level as more participants (30.1%) have information valuations increasing in a than decreasing (20.2%).[6] These results indicate that the biases in information valuations can be partly 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.[7]

[6] However, there are fewer pieces of advice mentioning that information valuations should increase in a.

[7] It is worth noting that existing models of imperfect foresight cannot generate the patterns in the experiment. For example, the noisy foresight model of Chakraborty and Kendall (2022b) can generate insensitivity to d and a, but not asymmetry between them.

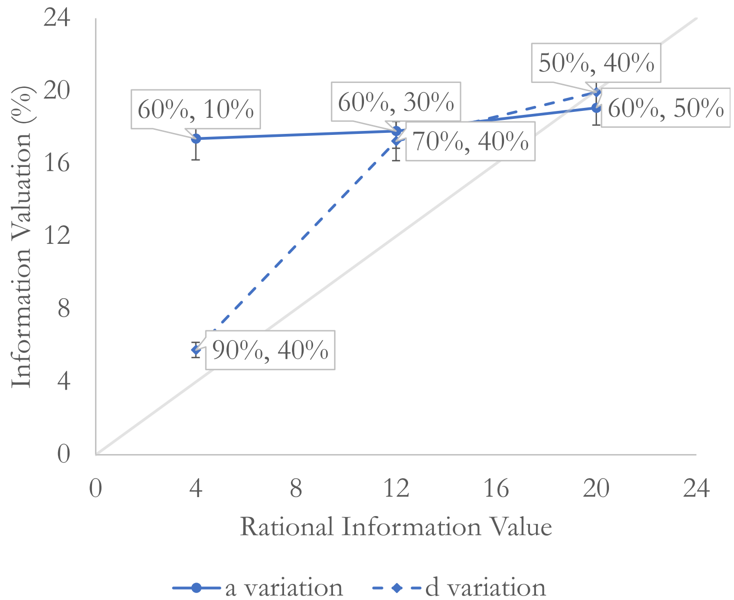

Figure 5: Information valuations in the Strategy-method treatment

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 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 integrated come from multiple choices, which could lead to additional complexity.

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 does not require 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

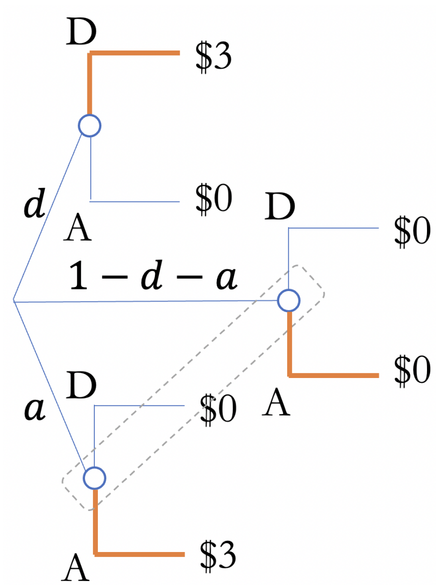

Figure 6: Payoff structure induced by the information in the Mutually Exclusive treatment

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 orange branches are the optimal choices, which induce a lottery.

depicted in Figure 6. The total winning chance of 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, hence eliminating all 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 where I vary d and a: the values of (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 in a, but the slope if very flat and indistinguishable from zero ($p = 0.478$). On 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, $p = 0.505$). This result demonstrates that information valuations do not correctly respond to the alternative option even when no computation is required.

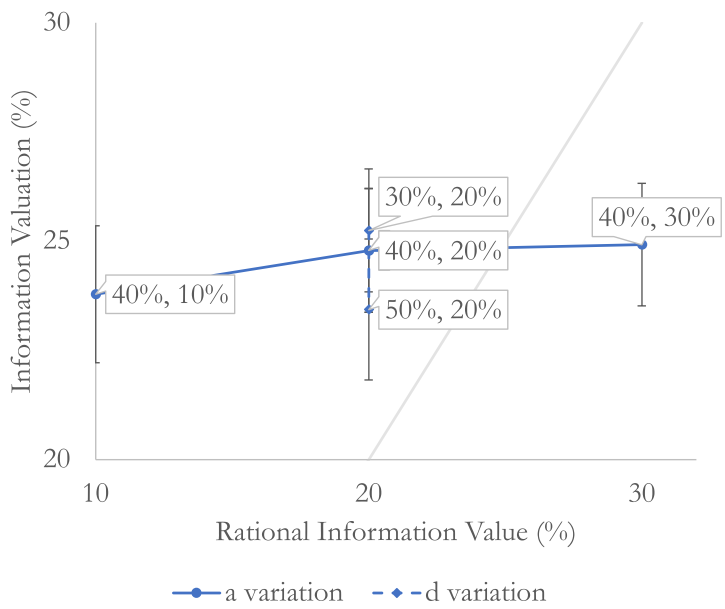

Figure 7: Information valuations in the Mutually Exclusive treatment

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.

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, $p = 0.039$) and 13.5% that (correctly) remain constant. The average information valuation is also more sensitive to d than to a, although the difference is insignificant ($p = 0.764$). This result implies that many 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 is largely due to the use of heuristics.

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. We know from prior research on contingent reasoning (Esponda and Vespa, 2014, 2021; Martínez-Marquina, Niederle, and Vespa, 2019) that people have difficulty integrating multiple potential payoffs. In this section, I ask whether payoff integration is more difficult when the payoffs come 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 by 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 when they learn about D's outcome in the D-Info treatment. Therefore, the value of insurance is $(1 - d)a$, same as the information. 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 of this one choice. In this sense, comparing information valuation in the D-Info treatment to insurance valuation in the D-Insured treatment helps us test whether integrating payoffs from multiple choices is more difficult than integrating multiple payoffs from one 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 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 the individual level. 40.9% of participants have insurance valuations that are monotonically increasing in a compared to 19% that are decreasing and 9.2% constant. Moreover, 66.2% of participants mention Lottery A in their incentivized advice,

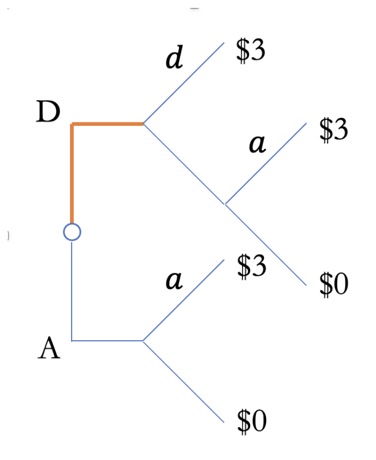

Figure 8: Payoff structure induced by the insurance in the D-Insured treatment

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.

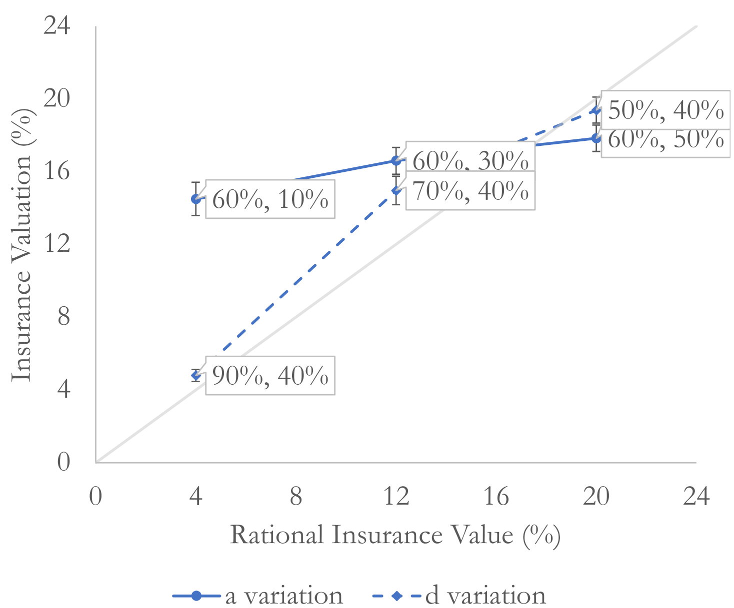

Figure 9: Insurance valuations in the D-Insured treatment

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.

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 difficult than integrating multiple payoffs from one choice. However, the difference could also result from other framing effects. For example, perhaps people are simply better at evaluating insurance than information. To rule out framing as the explanation, I conduct a treatment called A-Insured ($N = 156$) which is the analog of D-Insured 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 compound lottery as the information in the A-Info treatment (see Figure 10), so their values are the same. However, the insurance changes the optimal choice: participants should choose A if it is insured and D if it is not. As a result, they still need to integrate payoffs from more than one choice in order to evaluate the insurance, which is different from the D-Insured treatment. If integrating payoffs from multiple choices is what makes information valuation hard, then we should not expect participants to do 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 are monotonic 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 from 75.7% to 58.3% ($p < 0.001$). Among participants who mention comparative statics on d or a in their incentivized advice, far more get the directions wrong than right. Taken together, participants are worse at evaluating the 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 evalua-

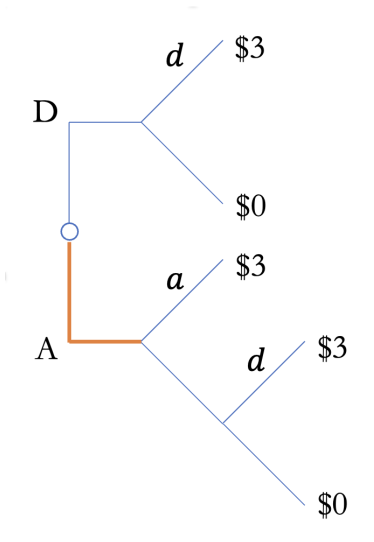

Figure 10: Payoff structure induced by the insurance in the A-Insured treatment

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.

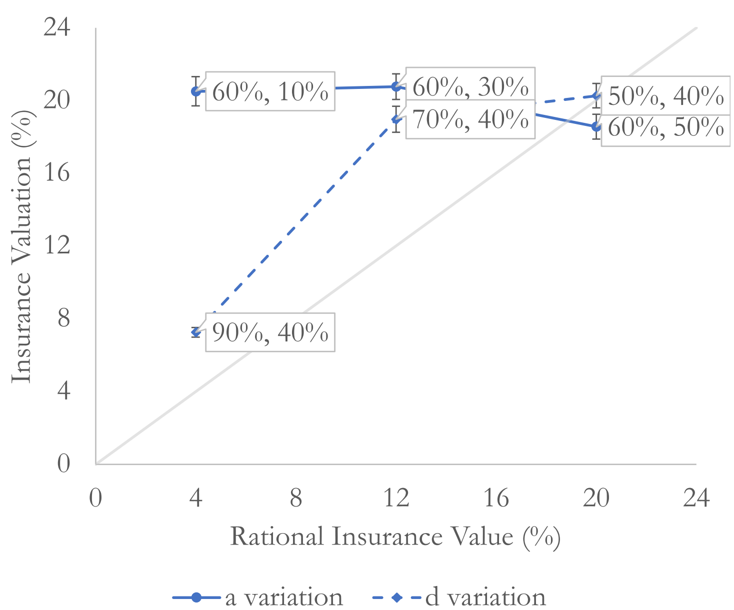

Figure 11: Insurance valuations in the A-Insured treatment

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.

tion easier, ruling out a potential confound when comparing the D-Insured and D-Info treatments. It also corroborates the preferred hypothesis: having to integrate payoffs from multiple choices makes information valuation difficult.

Another implication of this hypothesis is that information that does not change the optimal choice should be easier to evaluate. So long as people recognize that their choice won't be affected by the information realization, they should realize that this information adds no value. Arriving at this conclusion does not require any payoff integration or computation. In two additional treatments named D-Info ($a = 0$ first) and A-Info ($a = 0$ first), I add a scenario where Lottery A has no chance of winning to the beginning of the original D-Info and A-Info treatments. The information in this additional scenario has no value, allowing me to test the aforementioned implication. 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

Using an experiment, this paper studies how information demand responds to the future decision problem it is supposed to inform. On the one hand, information demand decreases as the default option of the decision problem presents higher downside risk. On the other hand, there is much heterogeneity in how information demand responds to changes in the alternative option, and on average the response is insensitive. Both patterns manifest bounded rationality.

Bounded rationality in information demand obviously affects the decision quality and overall welfare of individuals. In addition, it may also have important implications in market settings. For example, consider a simple setting where Lottery D and Lottery A in the experiment are two competing products in the market. Then, the market share of A is increasing in the proportion of consumers who acquire information about the products before buying.[8] If information acquisition

[8]To see why this is true, 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

is insensitive to A's prior a, then the marginal benefit of investing in a will be dampened. Alternatively, consider a college admission setting where D and A are two applicants. The admission officer's prior beliefs about the applicants' college-preparedness are formed by the frontpage information such as their demographics and standard test scores. By a similar logic as the consumer example, if the amount of attention the admission officer pays to the applicants' detailed profiles is insensitive to A's prior a, then A's marginal incentive to obtain a higher test score will be dampened. Of course, in order to verify these implications, further research on specific field settings is needed.

In this paper, I show 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 membership and commitment contracts are valuable because they change behaviors. Therefore, to evaluate these devices, people have to integrate payoffs of multiple behaviors. The difficulty of foreseeing future choices and integrating their payoffs could lead to biases in these valuations too.

While this paper explores why information valuation is difficult, it does not explain the specific heuristics people use to evaluate information. In particular, why do some people keep their information demand constant, or even increase it, as the alternative option worsens? Here I provide some conjectures for future research. On the one hand, insensitivity to the alternative option could be explained by the satisficing heuristic (Simon, 1955). This theory posits that people tend to settle on the default option so long as it is good enough, and they do so without considering the exact benefit of acquiring more information. On the other hand, people who demand more information as the alternative option worsens could be (mis)applying the heuristic of "look before you leap" in precarious situations. A worsening alternative option, just like a worsening default option, makes the whole situation look more dangerous. As a result, acquiring information seems more warranted.

$Pr(\text{Acquire information}) \cdot a$.

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Appendix

A Additional treatments

A.1 WTP treatment

In the D-Info treatment, the highest possible answer for information valuation when $d = 90\%$ and $a = 50\%$ is 10%, which is different from the other scenarios where the answer is allowed to be as high as 30%. To address this potential confound, I run the WTP treatment where the range of answers for the information valuation question is held fixed 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 just like in 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 has. 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 as 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 is the information valuation.

The WTP treatment has the advantage of keeping the range of answers constant across scenarios, but it has two potential shortcomings. First, the treatment may become more complex by introducing a third lottery X. Second, because information valuations are elicited through WTP, they could be affected by loss attitudes.

Figure A1 show the results of the WTP treatment. Consistent with loss aversion, WTP for information is lower than the valuations elicited in the D-Info treatment. This compression toward zero inevitably limits the variability of information valuations. In spite of this, 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 held fixed in the D-Info treatment. This

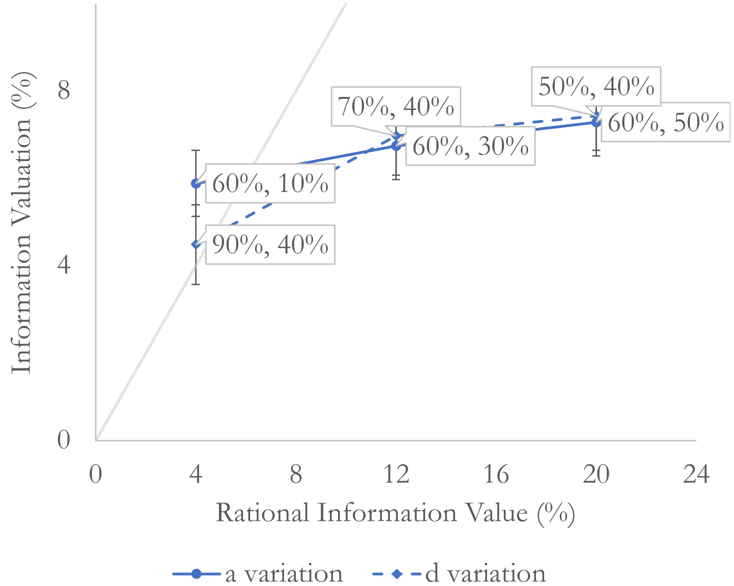

Figure A1: Information valuations in the WTP treatment

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.

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 though 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 simplifies the setting by making D and A perfect comple-

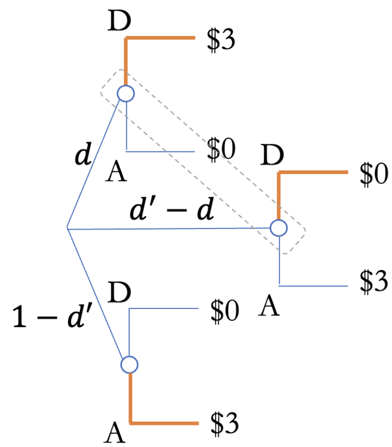

Figure A2: Payoff structure induced by the information in the Inconclusive Info treatment

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 A2. 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 values of (d, d') are (60%, 70%), (60%, 80%), (60%, 90%), (50%, 80%) and (70%, 80%).

Figure A3 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

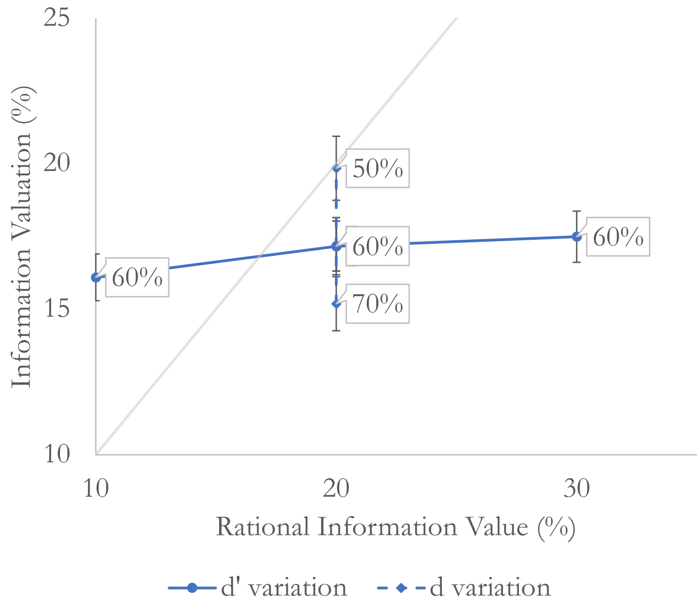

Figure A3: Information valuations in the Inconclusive Info treatment

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.

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

A.3 Evaluating information with zero value

In Section 3.2, I show that information is difficult to evaluate partly because doing so requires people to integrate multiple payoffs. An implication of this finding is that information that does not alter the choice should be easier to evaluate because no payoff integration is necessary for people to realize that such information adds 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 easier to evaluate.

Figures A4 and A5 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: $p = 0.030$;

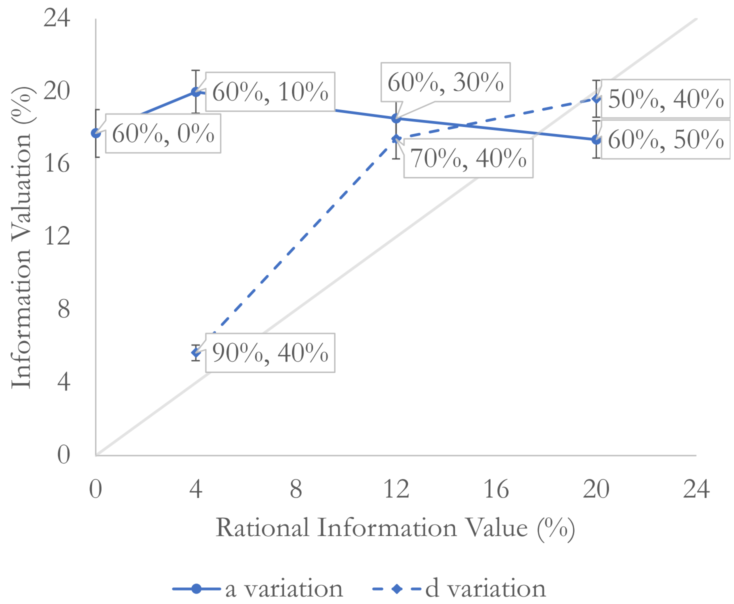

Figure A4: Information valuations in the D-Info ($a = 0$ first) treatment

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.

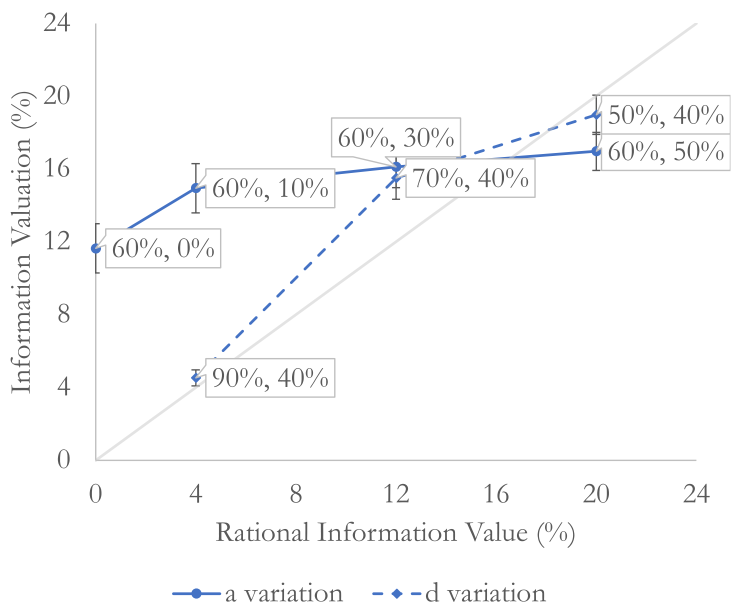

Figure A5: Information valuations in the A-Info ($a = 0$ first) treatment

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.

A-Info: $p = 0.017$), which is different from 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 on 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.

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

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 ...	D-Info	A-Info	WTP	Strategy	D-Insured	A-Insured	D-Info ($a=0$ first)	A-Info ($a=0$ first)
	Treatment							
decrease in d (correct)	21.8	22.4	38.6	21.9	28.2	6.4	25.6	12.5
respond to d (no direction)	25.2	23.7	12.9	28.8	27.5	40.4	24.4	27.8
increase in d	9.5	5.3	7.1	1.4	6.3	21.2	11.5	2.8
increase in a (correct)	6.1	13.2	2.9	1.4	28.2	4.5	5.1	20.8
respond to a (no direction)	20.4	22.4	11.4	21.9	38	31.4	20.5	20.8
decrease in a	9.5	15.8	14.3	11	0	16	19.2	8.3

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	-0.029	-0.143*
	(0.020)	(0.027)	(0.059)	(0.085)
A-Info $\times a$	0.013	0.034	0.008	0.025
	(0.029)	(0.038)	(0.028)	(0.037)
WTP $\times a$	0.068***	0.080**	0.074***	0.074*
	(0.026)	(0.034)	(0.027)	(0.038)
Strategy $\times a$	0.076**	0.110**	0.075**	0.114**
	(0.035)	(0.046)	(0.035)	(0.045)
D-Insured $\times a$	0.117***	0.199***	0.120***	0.208***
	(0.031)	(0.044)	(0.031)	(0.043)
A-Insured $\times a$	-0.015	0.044	-0.011	0.042
	(0.029)	(0.047)	(0.029)	(0.047)
D-Info ($a = 0$ first) $\times a$	-0.032	-0.036	-0.034	-0.041
	(0.034)	(0.045)	(0.035)	(0.047)
A-Info ($a = 0$ first) $\times a$	0.084**	0.128**	0.079**	0.123*
	(0.039)	(0.064)	(0.039)	(0.065)
Participant FE	Yes	Yes	Yes	Yes
Control	No	No	Yes	Yes
Selected sample	No	Yes	No	Yes
Observations	2670	1263	2670	1263
R^2	0.708	0.717	0.714	0.725

Notes: This table compares the sensitivity of information valuations to Lottery A's winning chance a across across eight treatments: D-Info, A-Info, WTP, Strategy-method, D-Insured, A-Insured, D-Info ($a = 0$ first) and A-Info ($a = 0$ first). 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***	-0.313***	-0.244***
	(0.018)	(0.024)	(0.048)	(0.064)
A-Info × d	-0.005	0.003	-0.007	0.003
	(0.024)	(0.032)	(0.024)	(0.031)
WTP × d	0.278***	0.266***	0.277***	0.271***
	(0.029)	(0.039)	(0.029)	(0.040)
Strategy × d	-0.002	0.025	-0.002	0.025
	(0.026)	(0.034)	(0.026)	(0.035)
D-Insured × d	-0.013	0.012	-0.016	0.009
	(0.025)	(0.035)	(0.025)	(0.035)
A-Insured × d	0.027	0.007	0.024	0.009
	(0.024)	(0.035)	(0.025)	(0.036)
D-Info ($a = 0$ first) × d	0.003	-0.015	0.009	-0.012
	(0.032)	(0.041)	(0.032)	(0.040)
A-Info ($a = 0$ first) × d	-0.009	0.009	-0.004	0.020
	(0.031)	(0.046)	(0.032)	(0.046)
Participant FE	Yes	Yes	Yes	Yes
Control	No	No	Yes	Yes
Selected sample	No	Yes	No	Yes
Observations	2670	1263	2670	1263
R^2	0.719	0.750	0.720	0.754

Notes: This table compares the sensitivity of information valuation to Lottery D's winning chance d across eight treatments: D-Info, A-Info, WTP, Strategy-method, D-Insured, A-Insured, D-Info ($a = 0$ first) and A-Info ($a = 0$ first). 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.