Boundedly Rational Information Demand

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Abstract

The demand for information should depend on the future choice problem it informs. In an experiment, I document substantial deviations from rationality in the empirical relationship between the two. First, information demand should increase but is insensitive as the ex-ante inferior option improves. Second, people reduce their demand as the ex-ante superior option becomes better, regardless of whether it is warranted in the specific setting. These results cannot be explained by risk preferences, belief-updating biases, non-instrumental value of information, or mispredicting one's own future choice. Instead, the biases are related to the difficulty of integrating payoffs from multiple potential choices.

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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. This paper provides experimental evidence on this relationship.

According to standard information economics, the value of information depends on how it affects future choice. 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 a choice 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, denoted by d and a, are known. 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 treatments may receive information that fully reveals one lottery's outcome. In the D-Info Treatment, the revealed lottery is D, while in the A-Info Treatment, the revealed one is A. Participants are incentivized to report how much they think receiving the additional information would increase their chance of receiving \$3. This question essentially elicits their subjective value of information. In the experiment, participants answer this

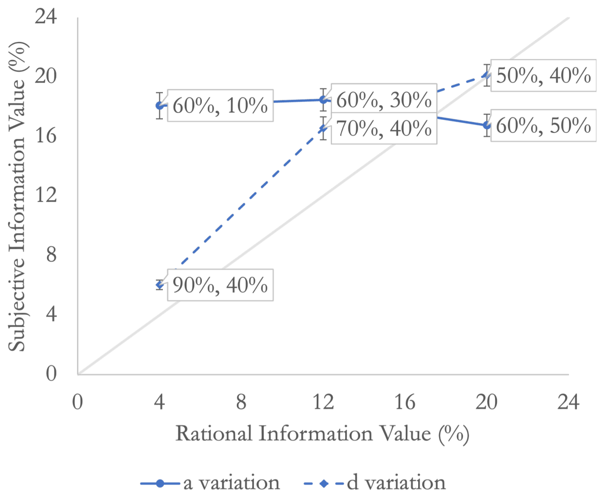

Figure 1: Subjective information values in the D-Info and A-Info treatments

Notes: The left panel shows the average subjective information values in the D-Info treatment, and the right panel the result for 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.

question in six scenarios with different values of d and a. This allows me to study how information value varies with the future decision problem in a within-subjects design.

The information value question in this experiment has a simple rational answer that does not depend on risk preferences or belief-updating rules. Applying equation (1), if participants always choose the lottery that is more likely to win, then in both D-Info and A-Info treatments, the information increases their 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.

Participants' reported values of information differ markedly from the rational answers, and the deviations in D-Info and A-Info treatments are remarkably similar (see Figure 1). Consistent with the rational answers, reported information values decrease as D becomes more likely to win. However, contrary to the rational answers, the average reported information value does not vary with A's winning chance. Due to this insensitivity, subjective information value is too high when a is low. The fact that the patterns are the same across D-Info and A-Info implies that the differential sensitivity to d and a is not driven by which lottery is mentioned in the information or which lottery's outcome is revealed first.

The experiment includes additional diagnostic treatments that further investigate the nature of the behavioral patterns in the main treatments. The sensitivity of information value to D's winning chance seems to suggest that participants rationally account for the impact of d on information values. However, the result could also be due to a boundedly-rational heuristic that happens to work in our specific experimental setting. To distinguish between the two explanations, I run a treatment where the correct information value does not depend on the default option's winning chance. Nevertheless, participants' subjective information values still decrease as the default becomes more likely to win. This result suggests that although the negative relationship between information values and the default's winning chances is consistent with rationality in the main treatments, it actually reflects the use of heuristics.

Having established that people do not rationally account for the future decision problems when evaluating information, I design additional treatments to investigate the underlying mechanisms. 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. 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 subjective information values. In this treatment, participants rarely make mistakes in their contingent lottery choices, but their information values only become slightly and insignificantly more sensitive to Lottery A's winning chance. This result indicates that understanding the choice implications of information is not sufficient for correctly evaluating the information, and it implicates payoff integration as the main challenge.

Information creates values by helping people choose better. This property of information makes it necessary to integrate the payoffs of multiple choices when calculating its value, which could be difficult for people. 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 back-up, participants can win \$3 even if they choose D and it fails, so long as A wins. Having the back-up leads to the same payoffs as receiving information about D's outcome, so their values should be the same. But unlike information about a lottery's outcome, having the back-up does not change the optimal decision. Before the lottery choice, participants report how much they think having the back-up would increase their winning chances. Their answers increase significantly as A becomes more likely to win. This is in stark contrast with the insensitivity of subjective information values when A's winning chance changes. In another treatment, I rule out framing as an explanation for the difference between information valuation and back-up valuation. Therefore, this result confirms the hypothesis that having to consider multiple choices makes it difficult to evaluate information. It also offers a new perspective to the contingent reasoning literature: it is more difficult to integrate payoffs of multiple choices than multiple payoffs of one choice.

This paper contributes to the literature on demand for information with instrumental value. Several papers compare information choices across different future decision problems. Bartoš et al. (2016) find that high-prior options receive more attention in "cherry-picking" tasks whereas low-prior options receive more attention in "lemon-dropping" tasks. Ambuehl (2021) finds that people prefer positively-biased information structures more when an option's upside is larger. These papers focus on the *type* of information people choose, and their results are consistent with rationality. In comparison, my paper focuses on demand for information and finds deviations from rationality. Also related is a set of papers that study how people choose and evaluate different information structures when the future decision problem is held fixed (Ambuehl and Li, 2018; Charness et al., 2021; Guan et al., 2023). Moreover, a large literature studies the non-instrumental value of information (e.g., Nielsen, 2020; Masatlioglu et al., 2021; Falk and Zimmermann, 2022; Golman et al., 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 carefully 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 also relate to three behavioral economics literatures: evaluation of compound lotteries, imperfect foresight, and contingent reasoning failures. First, information valuation often involves reducing compound probabilities, which has been shown to be difficult for many people (Halevy, 2007; Chew et al., 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. Second, information valuation also requires people to foresee what they will choose after the information realizes. While prior research has documented evidence of imperfect foresight (Chakraborty and Kendall, 2022a,b), it cannot explain this paper's results because even when participants have committed to their future choices, their evaluations of information still deviate from the rational benchmark. 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 et al., 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 overview the design of the main experimental treatment. Designs of additional treatments are described in later sections together with their results (See Table **??** for a summary). Screenshots of the experimental interface can be found in the Online Appendix.

Participants are presented with six scenarios in random orders, summarized in Table **??**. 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.

In each scenario, I elicit participants' subjective values of information 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.[1] 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 reported information value 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 BDM-style incentive scheme ensures that the information value elicitation is incentive compatible.[2] 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 value questions. The advice is incentivized: participants are told that their advice may be shown to a future participant, and if

[1] The information value question is implemented as a multiple-choice question where participants select a statement of the following form 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.

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. The x in the statement a participant selects is interpreted as her subjective value of information.

[2] Following Danz et al. (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.

the advisee wins a \$3 bonus, the advisor will receive an additional \$2 bonus. I also conduct a questionnaire that collects sociodemographic information and asks unincentivized questions about tendencies to acquire information, make plans, and take risks in daily life.

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 in order to proceed in the experiment.

2.2 Rational benchmark

The information value question in the experiment has a correct 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. The winning chance of this strategy 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 correct 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.

2.3 Results

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

In addition to the comparative statics, the levels of subjective information values also deviate from the rational benchmark. Participants value information too much in the four scenarios with larger gaps between d and a, especially when $d = 60\%$ and $a = 10\%$. Subjective information values are too low when $d = 50\%$ and $a = 40\%$, and are rational on average when $d = 60\%$ and $a = 50\%$.

Aggregate results mask interesting patterns at the individual level. Table **??** classifies participants by the monotonicity of their subjective information values with respect to changes in d and a. As d increases from 50% to 70% to 90%, 66% of participants report monotonically decreasing information values while almost none are monotonically increasing or constant. In contrast, as a increases from 10% to 30% to 50%, 28% of participants report monotonically decreasing information values, but the other two categories are also quite substantial, each covering around 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 value questions can shed light on their thought processes. Twenty-two percent of participants mention the correct comparative statics of information values on d whereas 10% mention a comparative statics in the wrong direction. The comparative statics on a is mentioned by fewer participants—6% mention the correct direction and 10% are wrong. These results are in line with the individual-level pattern of reported information values.

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 subjective information values 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 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 subjective information values in the A-Info treatment are strikingly similar to the D-Info treatment, both on average (Figure **??**) and at the individual level (Table **??**). Participants respond in the correct direction to changes in d, but are mixed and on average insensitive to changes in a. 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 (16%) than right (13%).

The fact that subjective information values are almost identical whichever lottery is revealed implies that the differential sensitivity to d and a cannot be attributed to the content of information. 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 value 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 values 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 values are elicited as willingness-to-pay, and the range of answers is constant across all scenarios. In this treatment ($N = 70$), subjective information values 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 Rational or boundedly rational?

The result that subjective information values respond correctly to changes in the default lottery's winning chance seems to suggest that participants rationally account for the latter's impact when evaluating information. However, the pattern could also result from a boundedly-rational heuristic that happens to work in our experimental setting.

To distinguish the two explanations, I conduct a treatment where the default lottery's winning chance should not affect information values. Specifically, 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 complements—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 winning chance of $d + 1 - d'$, implying that the information value should be $1 - d'$. Note that this expression does not involve reducing compound probabilities, which makes it even simpler than the information value in the main treatments. I elicit subjective information values in six scenarios where I vary d and d' (see parameter values in Table **??**).

Figure **??** shows the result of the Inconclusive Info treatment. Average subjective information value is insensitive to d' but sensitive to d, 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 subjective information values to the default lottery seems rational in the main treatments, it actually reflects the use of heuristics.

4 What makes evaluating information difficult?

The results so far have established that people do not rationally account for the future decision problems 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.

Imperfect foresight of one's own choices is unlikely to be the sole explanation for the observed biases since any probability assigned to suboptimal choices will only lower information values. This is inconsistent with the experimental results where subjective information values are often too high. Nevertheless, imperfect choice forecasts could still be one of several factors at play. To test whether it plays any 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 subjective information values. 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.

In the strategy-method treatment, ??% of participants make optimal contingent lottery choices. Figure **??** shows the result for the strategy-method treatment. The average subjective information value increases, but only slightly and insignificantly, as Lottery A becomes more likely to win. This result suggest that imperfect foresight of one's own future choice plays at best a minor role in the biases in subjective information values. The main challenge to correctly evaluating information must lie in the payoff-integration stage.

To evaluate information, people need to integrate payoffs of multiple choices. This is true in my experiment because participants need to integrate the payoffs when they choose D and when they choose A. It is also a general feature of information evaluation because information adds value only if it changes people's choice with a positive probability.

To investigate whether integrating payoffs from multiple choices adds to the difficulty of information evaluation, I design a treatment called D-Insured ($N = 142$) where correct evaluation only requires integrating payoffs of one choice. In this treatment, 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 back-up, participants can win \$3 even if they choose D and it fails, so long as A wins. This increases the winning chance of choosing D by $(1 - d)a$. Hence, participants should always choose D when they have the back-up, and the resulting compound lottery is the same as when they learn about D's outcome in the D-Info treatment. Because participants should choose D whether they have the back-up or not, evaluating the back-up only requires integrating different payoffs of this one choice. This is different from evaluating information in the D-Info treatment where they need to integrate payoffs of choosing D and choosing A. Therefore, by eliciting subjective values of having the back-up and comparing them to subjective values of information in the D-Info treatment, I can test whether integrating payoffs from multiple choices is more difficult than integrating multiple payoffs from one choice.

Figure **??** shows how subjective values of the back-up change with d and a. Consistent with rationality, average subjective value increases with a. This is in stark contrast with the subjective information values in the D-Info treatment which is insensitive to a. The sensitivity to a in the D-Insured treatment is also reflected at the individual level. Forty-one percent of participants have subjective back-up values that are monotonic to a in the correct direction compared to 19% that are wrong. Only 9% of them are completely insensitive, which is the lowest percentage among all treatments. Moreover, 66% of participants mention Lottery A in their incentivized advice, none of whom mention the wrong comparative statics.

The different results from the D-Info and D-Insured treatment are consistent with the hypothesis that integrating payoffs from multiple choices is more difficult than integrating multiple payoffs from one choice. However, the different results could also result from other framing differences between the two treatments. For example, perhaps people are simply better at evaluating back-ups 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 back-up, participants can win \$3 even if they choose A and it fails, so long as D wins. This increases the winning chance of choosing A to $a + (1 - a)d$, making it the optimal choice. The resulting compound lottery is also the same as when A's outcome is revealed in the A-Info treatment. However, having the back-up in the A-Insured treatment changes the optimal choice from D to A, making it necessary to integrate payoffs of both choices when calculating the value of the back-up. If integrating payoffs from multiple choices is what makes evaluating information 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 "back-up" framing is what helps participants in the D-Insured treatment, it should also help those in the A-Insured treatment.

Figure **??** shows the subjective values of back-up in the A-Insured treatment. The average subjective value is insensitive to a, showing no improvement compared to subjective information values 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 35% in the A-Insured treatment. The proportion of participants with the correct monotonicity to d decreases from 76% to 58%. 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 back-up in the A-Insured treatment than evaluating information in the A-Info treatment. This result indicates that the back-up framing does not make evaluation 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 evaluating information difficult.

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