Does the Size of the Signal Space Matter?*

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Abstract

This paper provides the first experimental evidence that information receivers consider the size of the signal space, which represents the number of possible signals. When subjects predict the binary outcomes of compound lotteries, their values of signals for the outcome (Study 1) and values of lotteries they play (Study 2) in varying sizes of the signal space were measured. The results showed that the size of the signal space was positively correlated with the value of the signals, but not the value of the equivalent lotteries. The preference for larger signal space suggests users find a five-star rating system more attractive than a binary recommendation system. These experimental findings cannot be explained by leading theoretical frameworks.

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1 Introduction

Signal transmission is an essential part of the literature on game theory, in which a vast amount of theoretical and empirical research has been conducted. However, the desirable size of the signal space in the literature has often been overlooked. In the context of information acquisition, the size of the signal space denotes the number of possible signals. In many cases, theorists assume that the signal space equals the action space when discussing the size of the signal space. They have shown that assuming an equivalence between the signal space and the action space is sufficient to find the equilibrium, making a larger signal space unnecessary. This assumption has been taken for granted, but its validity could be limited if the receiver prefers a larger signal space. This paper investigates whether a preference exists for the size of the signal space, independent of the signal accuracy.

Consider the example of an investor contemplating whether or not to invest in a company. State $\theta \in \{G, B\}$ represents the type of the company, where G and B stand for a good company and a bad company respectively. The investor does not know whether the company is good or bad, but she thinks the probability that the company is good is 0.5. She wants to invest only if the company is good. Without loss of generality, suppose she gets utility 1 for investing in the good company or for not investing bad company, and utility 0 for investing in the bad company or for not investing in the good company.[1]

To reduce uncertainty about the investment decision, she is considering hiring a financial advisor with more knowledge of the company. There are two advisors she is considering: Advisor A and Advisor B. They both provide informative signals to the investor. Advisor A will send the investor one of thse two signals with equal probability: "invest" or "not invest." If his signal is "invest," the probability that the company is good is 70% ($Pr(G|\textit{“invest”}) = 0.7$). If his signal is "not invest," the

[1]Note that she will be as happy not to invest in a bad company as to invest in a good company, considering the opportunity cost.

probability that the company is good is 30% ($Pr(G|\text{“}\textit{not invest}\text{”}) = 0.3$). Since the number of possible signals sent from Advisor A is 2, the size of his signal space is 2. Note that Advisor A is the kind of sender commonly assumed by theorists: the action space (invest or not) is equal to the signal space.

On the other hand, Advisor B has a larger signal space. Advisor B will send the investor one of these five signals with equal probability: “must invest,” “invest,” “no opinion,” “not invest,” or “never invest.” The respective probabilities that the company is good when each signal is sent are 0.8, 0.7, 0.5, 0.3, and 0.2. The size of his signal space is 5.

The advisor's signal accuracy is defined by “winning” probability when receiving the signal from the advisor, which is consistent with the expected utility conditional on the signal. For example, if the investor receives and follows the signal from Advisor A, her winning probability is 0.7 whether she receives “invest” or “not invest.” Hence, Advisor A's signal accuracy is 0.7. In the same way, Advisor B's signal accuracy is also 0.7.[2] Therefore, if the investor is rational and maximizes expected utility, she will be indifferent between Advisors A and B. The question is, does the size of the signal space affect the preference between advisors? This paper's experimental results say yes: the investor prefers Advisor B to A because Advisor B has a larger signal space.

This paper presents the first empirical evidence that the size of the signal space matters in information acquisition. In Study 1, subjects in a lab experiment placed bets on the binary outcomes of four lotteries. Before betting, they could purchase a signal for each lottery. For each lottery, while the signal accuracy was identical, the size of the signal space varied from 2 to 5. The results revealed that subjects' willingness to pay for the signal increased as the size of the signal space increased, even with fixed signal accuracy. Despite individuals' tendency to prefer simpler situations when making decisions, the preference for a larger signal space may seem counterintuitive because a larger signal space generates a more complex environment.

[2]See Appendix A.1.1 for detailed calculations.

One possible explanation for the preference for a larger signal space could be that individuals mistakenly believe that a larger signal space indicates higher signal accuracy. However, in a second study, this explanation was falsified. In Study 2, the willingness of subjects to pay for playing each of the four lotteries from Study 1 was measured when the signal was provided for free. In other words, subjects in Study 2 always received the signal in each lottery. If decision-makers truly believed that a larger signal space implies higher signal accuracy, then subjects in Study 2 should have valued more lotteries with larger signal space. However, the results revealed that subjects no longer preferred a larger signal space; they were indifferent to the size of the signal space. This suggests that the value of signals is not necessarily the same as that of equivalent lotteries. Furthermore, the subjects showed different risk attitudes towards them, exhibiting risk-seeking behavior when valuing signals and risk-averse behavior when valuing lotteries.

Curiosity provides the most plausible interpretation of the experimental findings. Curiosity indicates an intrinsic motivation for seeking knowledge that might not have instrumental value. When subjects purchase a signal, curiosity makes their view myopic: they tend to focus on the signal itself instead of the outcome. When the size of the signal space is larger, the probability of choosing the "correct" signal becomes smaller. Hence, subjects pay more to uncover the uncertainty regarding the signal. A detailed explanation will be provided later in Section 5.

Receiving a signal and playing a simple lottery based on the signal's information can be perceived as a two-stage lottery. In this environment, the preference for a larger signal space could be interpreted as a violation of the reduction of compound lottery axiom (ROCL). When a decision-maker can reduce compound lottery, there is no reason to pay more to a signal with a larger space under the same signal accuracy. Halevy (2007) revealed that ambiguity neutrality and reduction of compound lotteries are tightly associated. If his findings can be applied to this environment, the preference for a larger signal space should be correlated with ambiguity neutrality.

However, the results of this paper did not find the correlation.

Does a smaller or larger signal space enable better decision-making? In some environments, limiting the size of the signal space might restrict the optimal outcome. For example, in most standard sender-receiver literature, a small size of signal space might lead to inefficient outcomes (Crawford and Sobel, 1982; Heumann, 2020). Hence, in these cases, a larger signal space allows better decision-making. In the experimental design of this paper, however, the size of the signal space is independent of the efficiency of the outcomes: the signal accuracy of each signal is the same. Therefore, there is no behavioral or theoretical reason to prefer a larger signal space.

On the other hand, a decision-maker might prefer a simpler environment—a smaller signal space—if the signals are too complicated to understand. For example, a worker might want to receive direct instructions on what to do rather than receive abstract signals from the boss and interpret her intent. This preference could be related to complexity aversion, which illustrates a preference for simpler lotteries over complex ones, even though the expected values are the same (Huck and Weizsäcker, 1999; Sonsino et al., 2002; Halevy, 2007; Moffatt et al., 2015). However, the experimental results of this paper did not find evidence for complexity aversion.

This paper has two main contributions. First, the empirical findings of this paper suggest how to deliver information from the view of information providers. Information providers, such as financial advisors, medical test providers, or film critics, can make their services look more attractive by simply increasing the size of the signal space. For example, the result of this paper suggests that users are more attracted to a five-star rating system than a binary suggestion, even if the two systems are equally accurate. Hence, if a service provider switches its recommendation system from a binary suggestion to a five-star rating, demand for the service will increase, even without improving the system's accuracy. This implication is aligned with the experimental findings of Jin et al. (2022), called complex disclosure, suggesting senders get more benefits from using complex reports than from using easier ones.

Another contribution involves the theoretical aspect of the context of information design (Kamenica and Gentzkow, 2011). Without loss of generality, most theoretical studies of information design have restricted the sender's signal to be "straightforward," which is a signal of recommended action such as Advisor A in the investor example. A straightforward signal, where the signal space is equal to the action space, allows for simplifying the design of the signal structure. However, the experimental findings of this paper suggest that the receiver might prefer the environment where the signal space is larger than the action space.

Section 3 provides theoretical predictions from various models, but none of them can explain the preference for larger signal space. The expected utility model predicts the same value for each signal. The recursive smooth ambiguity model of Klibanoff et al. (2005), the rank-dependent utility model (Quiggin, 1982), and prospect theory (Kahneman and Tversky, 1979, 1992) suggest different values for different signals, but they do not predict the systemic preference for the signal space size and the behavioral difference between Study 1 and Study 2.

This paper proceeds as follows. Section 2 describes the experimental design and procedure. Section 3 provides theoretical predictions of the results from various models. Section 4 reveals experimental results, and Section 5 concludes.

2 Experimental Design

Participants were assigned to one of two studies: Study 1 or Study 2. Each study consists of two parts: part 1 measured the value of signals (Study 1) or lotteries (Study 2) under isomorphic environments, and part 2 measured ambiguity attitudes by Ellsberg (1961) questions.

2.1 Part 1: The Value of Signals/Lotteries

There are four lotteries in Part 1. Each lottery contains several boxes, with each box containing ten balls, either red or blue. In each lottery, the computer draws a ball in two stages. In the first stage, the computer randomly selects one of the boxes with an equal probability. In the second stage, the computer randomly draws a ball from the selected box. Between the first and the second stages, subjects predict the color of the ball which will be drawn. If their prediction is correct, they receive 100 points, where each point is equal to 0.01 USD. Figure 1 illustrates the four lotteries.[3]

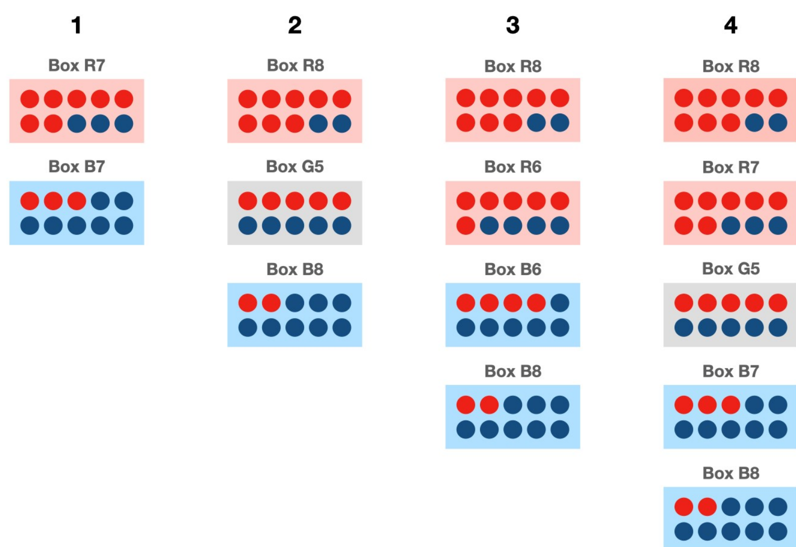

Figure 1: Four lotteries

Each box is denoted by Box Xn, where $X \in \{R, B, G\}$ and $n \in \{5, 6, 7, 8, 9\}$.[4] X and n represent the majority color of the balls in the box and the number of balls in the box, respectively. For example, Box R7 has more red balls than blue balls, and

[3]To avoid the possibility of cognitive load, the maximum size of the signal space is 5.

[4]Ambuehl and Li (2018) elicited the demand for informative signals and found that people significantly prefer information that might yield certainty. Therefore, to avoid the certainty effect, I exclude the box of $n = 10$.

the number of red balls is 7.[5]

In Study 1, subjects did not know which box was selected. However, before the prediction, they had a chance to "buy" a costly signal with their 100 endowment points. If they purchased a signal, the computer would tell them which box had been selected. This signal increased their probability of winning but required a cost, whether they won or lost.

For example, in lottery 2, there are three boxes: Box R8, Box G5, and Box B8. Suppose Box R8 is randomly selected. Without the signal, subjects do not know which box was chosen. Their winning probability is 50% whether they bet on a red or blue ball because there is a total of 15 red balls and 15 blue balls in lottery 2. If they buy the signal, they learn that Box R8 was selected and the ball will be drawn from Box R8. The signal "Box R8" increases the odds of winning to 80% because Box R8 contains 8 red and 2 blue balls.

One of the key features of this experiment is that each lottery always has 50% red balls and 50% blue balls. This implies that the prior, the winning probability without the signal, is 50% for all lotteries. Another essential feature is that the signal accuracy for each lottery is the same. If participants purchase the signal, the winning probability increases to 70% for all four lotteries. The only difference between them is the number of boxes, representing the possible number of signals.

In Study 2, the values of the four lotteries were measured when the signals were provided for free: before predicting the ball's color, subjects could observe which box was selected without purchasing signal. If subjects had a preference over the size of the signal space in Study 1, they should have had the same preference in Study 2. To quantify the values of the lotteries, the subjects' willingness to pay to play each lottery was measured. Figure 2 shows the timeline of both studies.

To measure the willingness to pay, I employed the Becker-DeGroot-Marschak

[5] In the actual experiment, boxes are represented as Box R, Box B, Box G, Box RR (if there is more than one Box R in the same lottery), and Box BB (if there is more than one Box B in the same lottery). Numerical labels are not used to provide an environment where participants rely more on intuition.

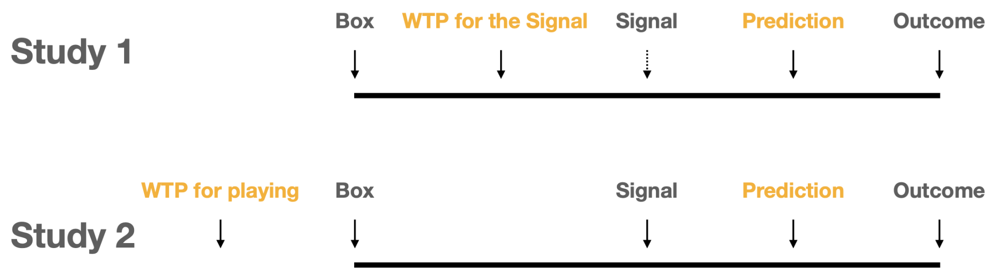

Figure 2: Timeline of both studies

(BDM) mechanism (Becker et al., 1964). In Study 1, subjects submitted the maximum points they were willing to pay for each lottery, which represented the values of the signals. After submitting values for signals for all four lotteries, one of them was randomly selected. A random number between 1 and 100 was generated, representing the price for the signal for the selected question in the chosen lottery. If a subject's submitted value in the selected lottery was greater than the price, she could see the signal and pay the price. However, if the submitted value in the selected lottery was equal to or lower than the price, she did not receive the signal and pay nothing. After the signal was revealed or not revealed, subjects predicted the color of the ball. Table 1 displays the questions in the BDM.

Q#	**Option A**	Choices	**Option B**
1	Buying a Signal for 1 point		Not Buying a Signal
2	Buying a Signal for 2 points		Not Buying a Signal
3	Buying a Signal for 3 points		Not Buying a Signal
4	Buying a Signal for 4 points		Not Buying a Signal
⋮	⋮	⋮	⋮
97	Buying a Signal for 97 points		Not Buying a Signal
98	Buying a Signal for 98 points		Not Buying a Signal
99	Buying a Signal for 99 points		Not Buying a Signal
100	Buying a Signal for 100 points		Not Buying a Signal

Table 1: The BDM mechanism in Study 1

The procedure of the BDM in Study 2 was similar to that in Study 1 (See Table 2). Prior to playing the lotteries, subjects were asked to submit the maximum number of points they were willing to pay for playing each lottery. After submitting four values for four lotteries, one of the lotteries was randomly selected. Then, a random number between 1 and 100, representing a substitute prize, was generated. If the submitted value for the selected lottery was greater than the prize, the subject played the lottery. Otherwise, she received the substitute prize without playing. If the subject played the lottery, they observe which box was selected and predict the color of the ball from that box.

Q#	**Option A**	Choices	**Option B**
1	Playing the lottery		Receiving 1 point
2	Playing the lottery		Receiving 2 points
3	Playing the lottery		Receiving 3 points
4	Playing the lottery		Receiving 4 points
⋮	⋮	⋮	⋮
97	Playing the lottery		Receiving 97 points
98	Playing the lottery		Receiving 98 points
99	Playing the lottery		Receiving 99 points
100	Playing the lottery		Receiving 100 points

Table 2: The BDM mechanism in Study 2

The major issue with the BDM mechanism is its difficulty, which can lead to biased results in some environments.[6] To minimize the confusion, subjects were asked to indicate their maximum willingness to pay for the signal, rather than making 100 choices between Option A and B. Additionally, before subjects made their actual decision, an example was provided to illustrate how the mechanism works when a specific value was submitted. Furthermore, even if the results biased, whether upward or downward, it does not undermine the primary purpose of the BDM mechanism in this paper, which is to compare preferences between signals and between lotteries,

[6] See Noussair et al. (2004) and Cason and Plott (2014) for discussions about the biased results of the BDM.

rather than to elicit their exact values.

There are two hypotheses to test. Study 1 measured subjects' willingness to pay for the signal. If signal accuracy is the only factor that determines the value of the signal, the demand for signals for all four lotteries should be the same. If c_i indicates the cost that subjects are willing to pay for the signal of lottery i,

$$c_1 = c_2 = c_3 = c_4. \tag{1}$$

Hypothesis 1. *The size of the signal space does not affect the demand for the signal.*

If L_i denotes lottery i, let $V_i^{signal}(c)$ represent a value of L_i with the signal with the cost c. Then, Study 2 measured $V_i^{signal}(0)$ for four lotteries. Suppose a subject values the signal for lottery i more than the signal for lottery j. Then, she will also value lottery i more than lottery j even when the signal is free: $c_i > c_j \implies V_i^{signal}(0) > V_j^{signal}(0)$. Then, the following hypothesis holds.

Hypothesis 2. *The rank among c_i is identical to the rank among $V_i(0)$.*

To avoid subjects focusing only on the size of the signal space, lotteries were presented in the order of $L_1 - L_3 - L_2 - L_4$ in both studies.

2.2 Part 2: Ellsberg Questions

After eliciting the value of signals, subjects' ambiguity attitudes were measured using two questions from Ellsberg (1961). Ambiguity attitude is closely related to two-stage lotteries, particularly to the ability to reduce compound lotteries (Halevy, 2007; Seo, 2009). Halevy (2007) showed a strong association between ambiguity neutrality and the reduction of compound lotteries. Since a preference for a larger/smaller signal space can be interpreted as a failure to reduce compound lotteries, this task helps to understand how ambiguity attitude relates to a preference for the size of the signal space.

The following statement describes the task.

> Consider there is a bag containing 90 ping-pong balls. 30 balls are blue, and the remaining 60 balls are either red or yellow in unknown proportions. The computer will draw a ball from the bag. The balls are well mixed so that each ball is as likely to be drawn as any other. You will bet on the color that will be drawn from the bag.

Subjects were asked to choose their preferred options between A and B and between C and D. Table 3 illustrates the four options.

Options	
Option A	receiving 100 points if a blue ball is drawn.
Option B	receiving 100 points if a red ball is drawn.
Option C	receiving 100 points if a blue or yellow ball is drawn.
Option D	receiving 100 points if a red or yellow ball is drawn.

Table 3: Ellsberg questions

If a subject prefers option A to B and option D to C, there is no subjective probability formulation that can rationalize this preference. This preference is interpreted as a consequence of ambiguity aversion.

After the rewards from parts 1 and 2 were determined, one of the parts was randomly selected, and subjects received the points in the selected part. Each point was converted to 0.01 USD.

2.3 Procedural Details

A total of 467 subjects participated in the experiments through Prolific, which is an online platform for recruiting research participants.[7] Specifically, 179 and 158 subjects participated in studies 1 and 2, respectively. Also, an additional 130 subjects

[7] Gupta et al. (2021) demonstrated that Prolific can be a reliable source of high-quality data. For details on Prolific's subject pool, see Palan and Schitter (2018). In both studies, only US subjects participated.

participated in a robustness study, which is discussed below. On average, subjects spent 10 minutes and earned \$3.32, including a \$2.20 base payment.

2.4 Robustness Study

In addition to the main studies, an additional study was implemented to investigate the robustness of the results. The robustness study provides evidence on whether subjects understood the procedure correctly.

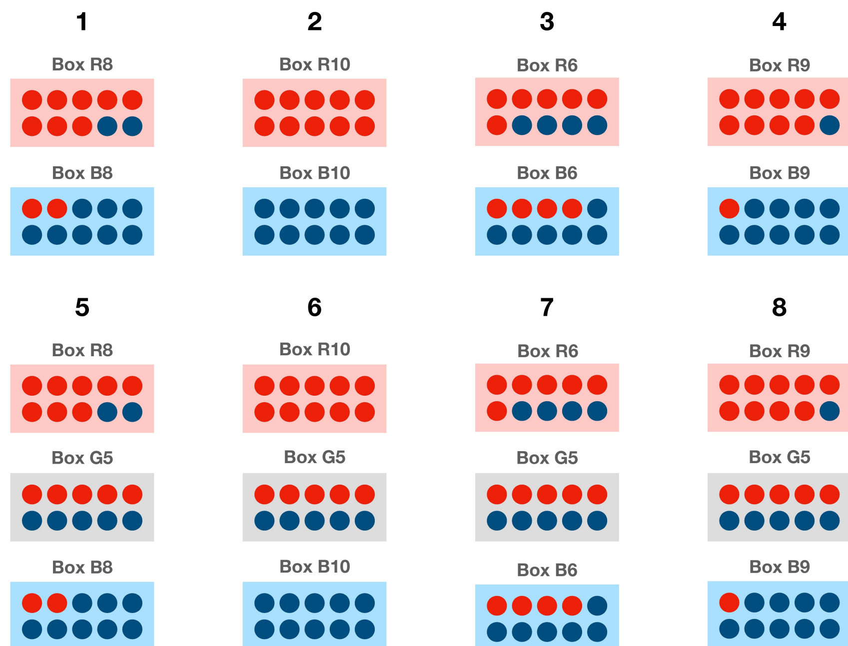

Figure 3: Lotteries in the robustness study

The procedure of this study was identical to Part 1 of Study 1, where subjects were asked to value signals in uncertain lotteries. To investigate subjects' understanding, the values of signals for eight lotteries were measured. The signal of each lottery provides a different winning probability. If subjects understood this information acquisition framework correctly, they would be more willing to pay for a signal with a higher winning probability. Figure 3 illustrates the lotteries in this study.

Table 4: Summary of lotteries in the robustness study

Questions	Signal Space Size	Signal Accuracy	Predictions
1	2	0.80	30
2	2	1.00	50
3	2	0.60	10
4	2	0.90	40
5	3	0.70	20
6	3	0.83	33.3
7	3	0.57	6.7
8	3	0.77	26.7

Table 4 summarizes the details of the lotteries. Lotteries 1-4 have two boxes, Box Rn and Box Bn, where $n \in \{5, 6, 7, 8, 9, 10\}$. Hence, the size of the signal space is 2. Also, since Lotteries 5-8 have three boxes, Box Rn, Box Gn, and Box Bn, the size of the signal space is 3 for these lotteries. The signal accuracy, which is the winning probability with the signal of each lottery, is described in the third column. The fourth column shows the theoretical prediction when the decision-maker is a risk-neutral utility maximizer. If subjects understood the information framework of the signaling process, their demands for the signals would be in line with theoretical predictions.

3 Theoretical Predictions

Let L_i^{prior} denote lottery i without the signal. Also, $L_i^{signal}(p)$ is lottery i with a signal with the cost c. Suppose an individual's willingness to pay for the signal for lottery i is greater than or equal to her willingness to pay for the signal for lottery j: $c_i \geq c_j$, where c_i denotes the elicited price for the signal for lottery i. The values of c_i and c_j

are determined by

$$V_i^{signal}(c_i) = V_i^{prior}, \tag{2}$$

$$V_j^{signal}(c_j) = V_j^{prior}, \tag{3}$$

where V_i denotes the value of lottery i.

Since $V_i^{prior} = V_j^{prior}$,

$$V_i^{signal}(c_i) = V_j^{signal}(c_j). \tag{4}$$

For simplicity of notation, I denote $V_i(c)$ instead of $V_i^{signal}(c)$ from now on. Note that $L_i(x)$ is a decreasing function of x. Hence, under the equation 4,

$$c_i \geq c_j \implies V_i(c) \geq V_j(c), \tag{5}$$

where $0 \leq c \leq \max(c_i, c_j)$. For example, suppose a subject's willingness to pay for signal 1 (the signal in lottery 1) is 20, and that for signal 2 (the signal in lottery 2) is 30. She will be happier to purchase signal 2 for a price of 15 than to purchase signal 1 for a price of 15. Hence, for calculation simplicity, I will compare $V_i(c)$ and $V_j(c)$ when a comparison between c_i and c_j is needed.

Study 1 measured c_i for $i \in \{1, 2, 3, 4\}$. Also, Study 2 elicited $L_i(0)$ for $i \in \{1, 2, 3, 4\}$ because the signal is free ($c = 0$). The remaining part of this section describes how different theories under uncertainty predict the two values in different lotteries.

3.1 Expected Utility

The expected utility of lottery i is given by

$$U_{EU}(L_i) = \sum_{s \in S} p(s)u(s). \tag{6}$$

The expected utility indicates that decision-makers are only interested in the expected values of lotteries but indifferent to the uncertainty resolution process. They do not care whether one lottery is a simple, compound, or a mean-preserving spread of the other lottery. Therefore, according to the expected utility model, subjects are indifferent between signals for lotteries, as well as between values of lotteries after receiving those signals.

$$\begin{aligned} c_1 = c_2 = c_3 = c_4, \\ V_1(0) = V_2(0) = V_3(0) = V_4(0). \end{aligned} \tag{7}$$

3.2 Recursive Smooth Ambiguity Utility

The recursive smooth ambiguity model by Klibanoff et al. (2005) (KMM, hereafter) suggests a theoretical utility model involving a second-order belief. KMM assumes that the decision-makers have a subjective expected utility on the space of second-order compound lotteries. For each f, there exists a second-order belief μ such that

$$U_{KMM}(f) = \sum_{\Delta(S)} \phi\Big(\sum_{s \in S} p(s)u(f(s))\Big)\mu(p), \tag{8}$$

where μ is a second-order subject belief, Δ is the set of possible first-order objective lotteries, and ϕ is a monotone function evaluating the expected utility associated with first-order beliefs.

For example, when purchasing a signal for L_1, there are two possible outcomes in the first stage (second-order): R7 or B7. In the second stage (first-order), the expected utility is $0.7u(100-c)+0.3u(-c)$ for both cases. Therefore, the evaluation of L_1 is given by

$$\begin{aligned}U_{KMM}(L_1(c)) &= \frac{1}{2}\phi(0.7u(100-c)+0.3u(-c))+\frac{1}{2}\phi(0.7u(100-c)+0.3u(-c))\\ &= \phi(0.7u(100-c)+0.3u(-c))\end{aligned}$$

Similarly, the values of lotteries are evaluated as

$$\begin{aligned}U_{KMM}(L_2(c)) &= \frac{2}{3}\phi(0.8u(100-c)+0.2u(-c))+\frac{1}{3}\phi(0.5u(100-c)+0.5u(-c)),\\ U_{KMM}(L_3(c)) &= \frac{1}{2}\phi(0.8u(100-c)+0.2u(-c))+\frac{1}{2}\phi(0.6u(100-c)+0.4u(-c)),\\ U_{KMM}(L_4(c)) &= \frac{2}{5}\phi(0.8u(100-c)+0.2u(-c))+\frac{2}{5}\phi(0.7u(100-c)+0.3u(-c))\\ &\quad+\frac{1}{5}\phi(0.5u(100-c)+0.5u(-c)).\end{aligned}$$

When μ is subjective, KMM explained ambiguity aversion by the concavity of ϕ: if Lottery Y is a mean-preserving spread of Lottery X, then individuals prefer X to Y because of their second-order subjective probability (μ). Since $L_3(c)$ is a mean-preserving spread of $L_1(c)$, decision-makers prefer $L_1(c)$ to $L_3(c)$:

For easier computation, let's define $U(\alpha)$ as,

$$U(\alpha)\equiv \alpha u(100-c)+(1-\alpha)u(-c).$$

Then,

$$\begin{aligned}U_{KMM}(L_1(c)) &= \phi(0.7u(100-c)+0.3u(-c))\\ &= \phi(U(0.7))\\ &\geq \frac{1}{2}\phi(U(0.8))+\frac{1}{2}\phi(U(0.6))\\ &= U_{KMM}(L_3(c)).\end{aligned}$$

A few more steps of calculations (See Appendix A.1 for details) show the following preferences hold.

$$
\begin{aligned}
c_1 \geq & c_3 \geq c_2, \\
c_1 \geq & c_4 \geq c_2.
\end{aligned} \tag{9}
$$

Since $L_i(0)$ is a specific form of $L_i(c)$, the preference among $L_i(0)$ does not change. Hence, regardless of the ambiguity attitude, KMM predicts consistent preferences between Study 1 and Study 2.

$$
\begin{aligned}
V_1(0) \geq & V_3(0) \geq V_2(0), \\
V_1(0) \geq & V_4(0) \geq V_2(0).
\end{aligned} \tag{10}
$$

When ϕ is convex, implying ambiguity seeking, the opposite inequality holds.

$$
\begin{aligned}
c_2 \geq & c_3 \geq c_1, \\
c_2 \geq & c_4 \geq c_1,
\end{aligned} \tag{11}
$$

$$
\begin{aligned}
V_2(0) \geq & V_3(0) \geq V_1(0), \\
V_2(0) \geq & V_4(0) \geq V_1(0).
\end{aligned} \tag{12}
$$

3.3 Simulational Predictions from Other Models

3.3.1 Rank-Dependent Utility

The rank-dependent utility (RDU) model suggested a probability weighting approach based on the order of rank for the outcomes (Quiggin, 1982; Segal, 1987, 1990). According to the RDU model, the utility of a lottery paying x_i with probability p_i is described as

$$U_{RDU}(x_1,p_1;x_2,p_2;\cdots;x_n,p_n)=u(x_1)+\sum_{i=2}^{n}[u(x_i)-u(x_{i-1})]f(\sum_{j=i}^{n}p_j), \tag{13}$$

where $x_1 \leq x_2 \leq x_3 \cdots \leq x_n,\ f:[0,1]\to[0,1],\ f(0)=0$ and $f(1)=1$. For the simple lottery that gives 100 with probability p and 0 with probability $1-p$,

$$U(100,p;0,1-p)=u(100)f(p). \tag{14}$$

Suppose its certainty equivalent is $CE(p)$, then

$$CE(p)=CE(100,p;0,1-p)=u^{-1}(u(100)f(p)). \tag{15}$$

Hence,

$$U_{RDU}(L_1(0))=u(CE(0.7))=u(100)f(0.7).$$

Similarly, values of four lotteries with signals are calculated as

$$\begin{aligned}
U_{RDU}(L_1(0)) &= u(100)f(0.7),\\
U_{RDU}(L_2(0)) &= u(100)f(0.5)+[u(100)(f(0.8)-f(0.5))]f(\frac{2}{3}),\\
U_{RDU}(L_3(0)) &= u(100)f(0.6)+[u(100)(f(0.8)-f(0.6))]f(\frac{1}{2}),\\
U_{RDU}(L_4(0)) &= u(100)f(0.5)+[u(100)(f(0.7)-f(0.5))]f(\frac{4}{5})\\
&\quad+[u(100)(f(0.8)-f(0.7))]f(\frac{2}{5}).
\end{aligned}$$

Preferences between lotteries vary depending on the functional form of $f(p)$. Table 5 illustrates simulational predictions of the RDU model based on different concave functions.

Table 5: Theoretical predictions by RDU

$f(p)$	Preferences between c_i	Preferences between $V_i(0)$
$p^{0.1}$	$c_2 \geq c_4 \geq c_3 \geq c_1$	$V_2(0) \geq V_4(0) \geq V_3(0) \geq V_1(0)$
$p^{0.5}$	$c_2 \geq c_4 \geq c_3 \geq c_1$	$V_2(0) \geq V_4(0) \geq V_3(0) \geq V_1(0)$
$p^{0.8}$	$c_2 \geq c_4 \geq c_3 \geq c_1$	$V_2(0) \geq V_4(0) \geq V_3(0) \geq V_1(0)$
p	$c_1 = c_2 = c_3 = c_4$	$V_1(0) = V_2(0) = V_3(0) = V_4(0)$
$log(p)$	$c_1 \geq c_3 \geq c_2 \geq c_4$	$V_1(0) \geq V_3(0) \geq V_2(0) \geq V_4(0)$
$ln(p)$	$c_1 \geq c_3 \geq c_2 \geq c_4$	$V_1(0) \geq V_3(0) \geq V_2(0) \geq V_4(0)$

Simulation results show that the RDU models with various functional forms of $f(p)$ do not predict the preference for larger signal space.

3.3.2 Prospect Theory

The first version of prospect theory was formulated by Kahneman and Tversky (1979), providing evidence of a systemic violation of the expected utility theory. The authors presented an alternative theoretical model to explain the violation. Later, Kahneman and Tversky (1992) (KT, henceforth) presented an extension of the original model, cumulative prospect theory, which adopted rank-dependence in probability weighting.

According to the cumulative prospect theory (CPT), the utility of a lottery paying x_i with probability p_i is described as

$$U_{CPT}(x_m, p_m; x_{m+1}, p_{m+1}; \cdots ; x_0, p_0; \cdots ; x_n, p_n) = \sum_{i=-m}^{n} \pi_i v(x_i), \tag{16}$$

where $v(\cdot)$ is a value function, which is an increasing function with $v(0) = 0$, and π is the decision weight. KT defined the value function as follows.

$$v(x) = \begin{cases} x^{\alpha} & \text{if } x \geq 0, \\ -\lambda(-x)^{\beta} & \text{if } x < 0, \end{cases} \tag{17}$$

where λ is a loss aversion parameter.

Decision weights π are defined by:

$$\begin{aligned}
\pi_n^+ &= w^+(p_n), \\
\pi_{-m}^- &= w^+(p_{-m}), \\
\pi_i^+ &= w^+(p_i + ... + p_n) - w^+(p_{i+1} + ... + p_n),\ 0 \le i \le n-1, \\
\pi_i^- &= w^-(p_{-m} + ... + p_i) - w^-(p_m + ... + p_{i-1}),\ 1-m \le i \le 0,
\end{aligned} \tag{18}$$

where w^+ and w^- are the following functions.

$$w^+(p) = \frac{p^\gamma}{(p^\gamma + (1-p)^\gamma)^{1/\gamma}},\ w^-(p) = \frac{p^\delta}{(p^\delta + (1-p)^\delta)^{1/\delta}}. \tag{19}$$

To predict the preferences for c_i and $V_i(0)$ by CPT, I used the parameter values from KT. They estimated the values from experimental data.

Table 6: Values of parameters from KT

Parameter	Meaning	Value
α	power for gains	0.88
β	power for losses	0.88
λ	loss aversion	2.25[8]
γ	probability weighting parameter for gains	0.61
δ	probability weighting parameter for losses	0.69

Also, I assume the cost of the signal is 20, which is the theoretically expected value when the decision-maker is a risk-neutral expected utility maximizer. Hence, the preference between c_i is from simulational results from $L_i(20)$. With these parameter

[8] According to a meta-analysis by Brown et al. (2022), the mean of the loss aversion coefficient λ from numerous empirical estimates is 1.97. I found that simulational results with $\lambda = 1.97$ do not change the preference between lotteries.

values, CPT predicts the following preferences:

$$c_1 \geq c_3 \geq c_4 \geq c_2, \tag{20}$$
$$V_1(0) \geq V_3(0) \geq V_4(0) \geq V_2(0).$$

Summarizing the theoretical predictions for the value of the signals in Study 1, no model predicts the preference for a larger signal space ($c_1 \geq c_2 \geq c_3 \geq c_4$).

Prediction 1. *Preference for a larger signal space does not exist.*

This prediction is consistent with Hypothesis 1. Also, no model predicts different preferences between c_i and $V_i(0)$, which is consistent with Hypothesis 2.

Prediction 2. *Preferences in both studies are identical.*

To summarize, theoretical predictions are aligned with the hypotheses: no theoretical models predict the preference for a larger signal space or inconsistent preferences.

4 Results

4.1 Preference for a Larger Signal Space

Table 7: Elicited values for c_i and $V_i(0)$ with different size of signal space.

		Study 1		Study 2	
Lottery	$\|S\|$	c_i	Number	$V_i(0)$	Number
1	2	23.6	179	52.9	158
2	3	24.9	179	48.9	158
3	4	25.8	179	51.0	158
4	5	29.8	179	52.7	158
Cuzick's test p-value		0.005		0.574	

Table 7 shows the submitted value for each signal (c_i) and each lottery given the signal ($V_i(0)$) in points. $|S|$ represents the size of the signal space. For c_i, the theoretical predictions from the risk-neutral expected utility maximizer are 20 points for each lottery. Hence, overall, the demand for signals is greater than the theoretical predictions. The most notable feature of the willingness to pay for the signal is the preference for larger signal space: the demand for the signal increases as the size of the signal space increases. However, in Study 2, the size of the signal space does not affect the value of equivalent lotteries.

To examine these relationships formally, I consider OLS regressions of the form:

$$y_{in} = \beta_0 + \beta_1 |S|_i + \beta_2 AmbNeutral_n + \beta_3 |S|_i * AmbNeutral_n + \epsilon_{in}. \tag{21}$$

$y_{i.n}$ is the value of c_i or $V_i(0)$ by individual n, $|S|_i$ is a dummy variable indicating whether individual n is ambiguity neutral or not.

Table 8: Determinants of the demand for signals and lotteries

	Dependent variable: c_i			Dependent variable: $V_i(0)$		
	(1)	(2)	(3)	(4)	(5)	(6)
Signal Space Size	1.93***	2.03***	1.93***	0.16	0.08	0.16
	(0.40)	(0.55)	(0.40)	(0.50)	(0.73)	(0.50)
Ambiguity Neutrality		1.06			−2.85	
		(3.77)			(4.37)	
Signal Space Size × Ambiguity Neutrality		−0.20			0.16	
		(0.79)			(1.01)	
Constant	19.28***	18.78***	19.28***	50.82***	52.34***	50.82***
	(1.87)	(2.50)	(1.38)	(2.18)	(3.20)	(1.76)
Subject fixed effect	No	No	Yes	No	No	Yes
Observations	716	716	716	632	632	632
R-squared	0.010	0.010	0.046	0.000	0.003	0.000
F-test p-value	0.0000	0.0001	0.0000	0.7502	0.8211	0.7502

Notes: Robust standard errors clustered by subject in parentheses. Columns (2) and (5) cannot include subject fixed effect because the ambiguity attitude is measured at the subject level. $^{***}p < 0.01$, $^{**}\ p < 0.05$, $^{*}p < 0.1$.

The first three columns in Table 8 indicate that the signal space size significantly affects the value of signals. (F-test p-values < 0.0001 for these columns.) When the size of the signal space increases, the willingness to pay for the signal also increases.

Result 1. ***Preference for Larger Signal Space:*** *Demand for the signal increases as the signal space size increases.*

Result 1 rejects Hypothesis 1. Also, columns (4)-(6) show that the signal space size no longer affects the value of lotteries when the signal is free. (F-test p-values are 0.7502, 0.7504, and 0.7502 for each column.) This result rejects Hypothesis 2.

Result 2. ***Inconsistent Preferences*** *The size of the signal space does not affect the value of equivalent lotteries.*

Since no theoretical model predicts the preference for larger signal space, the result falsifies Prediction 1. Also, no model predicts inconsistent preferences. Therefore, Predictions 1 and 2 are both falsified by the experimental results.

Table 9: Individual preferences among c_i and among $V_i(0)$.

	Study 1		Study 2	
Preference	Number	Percentage	Number	Percentage
Larger Signal Space	39	21.8%	17	10.8%
Indifferent	33	18.4%	28	17.7%
Smaller Signal Space	6	3.4%	15	9.5%
Others	101	56.4%	98	62.0%
Total	179	100.0%	158	100.0%

Table 9 illustrates the individual preferences between signals and lotteries. In Study 1, a larger proportion of subjects preferred the larger signal space ($c_4 \geq c_3 \geq c_2 \geq c_1$, but not $c_1 = c_2 = c_3 = c_4$) compared to Study 2 ($V_4(0) \geq V_3(0) \geq V_2(0) \geq V_1(0)$, but not $V_1(0) = V_2(0) = V_3(0) = V_4(0)$). Additionally, in Study 1, a smaller proportion of subjects preferred the smaller signal space ($c_1 \geq c_2 \geq c_3 \geq c_4$, but not

$c_1 = c_2 = c_3 = c_4$) compared to Study 2 ($V_1(0) \geq V_2(0) \geq V_3(0) \geq V_4(0)$, but not $V_1(0) = V_2(0) = V_3(0) = V_4(0)$). There is no proportional difference between the groups who showed indifference to signal space size ($c_1 = c_2 = c_3 = c_4$ or $V_1(0) = V_2(0) = V_3(0) = V_4(0)$).

4.2 Risk Attitudes

Suppose the utility function is given by $u(x) = x^{1-r}$. This specification implies that an individual is risk-averse for $r > 0$, risk-neutral for $r = 0$, and risk-seeking for $r < 0$. Based on the submitted values for the lotteries ($V_i(0)$) in Study 2, the estimated value of the risk parameter r is approximately 0.46, according to the expected utility model. This finding suggests that the subjects in Study 2 exhibited risk-averse behavior.

If the subjects in Study 1 had the same utility function with $r = 0.46$, then their submitted value for each signal (c_i) should have been 10.1. ($c_i < 20$ indicates risk-averse, $c_i = 20$ indicates risk-neutral, and $c_i > 20$ indicates risk-seeking.) However, the actual submitted values of c_i, whose average was 26.0, suggest that the individuals in Study 1 exhibited risk-seeking behavior.

Result 3. *Subjects displayed risk-seeking behavior when valuing signals, but were risk-averse when valuing equivalent lotteries.*

4.3 Ambiguity Attitudes

Table 10: Ambiguity attitudes

Ambiguity	Study 1		Study 2	
Attitude	Number	Percentage	Number	Percentage
Averse	72	40.2%	55	34.8%
Neutral	85	47.5%	84	53.2%
Seeking	22	12.3%	19	12.0%
Total	179	100.0%	158	100.0%

Table 11: The submitted values of c_i and $V_i(0)$ with different ambiguity attitudes

Attitude	c_1	c_2	c_3	c_4	$V_1(0)$	$V_2(0)$	$V_3(0)$	$V_4(0)$
Averse	22.8	23.8	24.4	29.9	55.7	49.5	47.7	55.8
Neutral	23.8	26.9	24.9	29.2	50.7	50.8	48.7	50.8
Seeking	25.5	28.7	26.5	31.4	54.2	55.8	52.9	52.2
Total	23.6	25.9	24.9	29.8	52.9	51.0	48.9	52.7
F-test p-value	0.8142				0.5988			

Table 10 and 11 respectively describe the ambiguity attitudes of subjects, and the values of c_i and $V_i(0)$ conditional on different ambiguity attitudes. The overall patterns of the willingness to pay for signals and lotteries remain consistent across different ambiguity attitudes. The F-tests' p-values indicate that there is no significant effect of ambiguity attitude on c_i or $V_i(0)$.

The third row of Table 8 confirms that the preference for the size of the signal space is independent of ambiguity neutrality. This finding contrasts with the results reported in Halevy (2007), where ambiguity neutrality is strongly linked to the ability to reduce compound lotteries.

Result 4. *Ambiguity neutrality is not related to the preference for the signal space size.*

4.4 Complexity Aversion

I did not find evidence for complexity aversion in lottery choice. According to Sonsino et al. (2002), a lottery's complexity is measured as the product of the number of rows and columns. Hence, in this environment, the number of boxes in the lottery indicates the complexity of the lottery. The results show that when the signal is free, the number of boxes — the size of the signal space — did not affect the values of playing the lotteries.

4.5 Predictions with Signals

Table 12 shows subjects' prediction decisions after the signal stage. The majority of subjects followed the signal when their signal was informative (Box R or Box B). This suggests that the subjects comprehended the information structure of the experiments. In both studies, the chi-square test and Fisher's exact test indicate that the null hypothesis of random prediction by subjects can be rejected. (p-values < 0.001 for both studies.)

Table 12: Predictions with signals

	Predictions	Box R	Box B	Box G	No Signal
Study 1	Red	16 (94.1%)	3 (15.8%)	12 (85.7%)	85 (65.9%)
	Blue	1 (5.9%)	16 (84.2%)	2 (14.3%)	44 (34.1%)
Study 2	Red	37 (94.9%)	4 (11.1%)	8 (72.7%)	N/A
	Blue	2 (5.1%)	32 (88.9%)	3 (27.3%)	N/A
Chi-square test p-value = 0.000					

The purpose of Table 13 is to investigate whether the signal space size influences the prediction decisions. The correct decision rate is defined as whether the subject's prediction aligns with the signal suggested after receiving Box R or Box B as a signal. Results show that there is no correlation between the correct decision rate and the signal space size. (Chi-square test p-value and Fisher's exact test p-value are approximately 0.513 and 0.672, respectively).

Table 13: Correct decision rate with each signal

Signal Received	s_1	s_2	s_3	s_4	Total
Correct	9 (81.8%)	3 (100.0%)	11 (84.6%)	9 (100.0%)	32 (88.9%)
Incorrect	2 (18.2%)	0 (0.0%)	2 (15.4%)	0 (0.0%)	4 (11.1%)
Total	11	3	13	9	36
Chi-square test p-value = 0.513					

4.6 Payoffs and the Size of the Signal Space

This section examines if the preference for larger signal space harms the information buyers. Table 14 displays the subjects' payoffs in points from Part 1 in both studies. The profits were larger in Study 1 than in Study 2 due to the 100-point endowment in Study 1. According to the table, in Study 1, the highest average profit was earned by the subjects who played the simplest lottery, Lottery 1. This indicates that they gained a lower profit when they played lotteries with larger signal spaces. However, this pattern was not observed when valing the lotteries in Study 2.

Table 14: Payoffs from part 1

Lottery Selected	Signal Space Size	Study 1 Payoff	Study 1 Std. Error	Study 1 Number	Study 2 Payoff	Study 2 Std. Error	Study 2 Number
1	2	160.9	7.1	48	71.6	6.2	32
2	3	141.6	7.5	50	80.0	4.5	43
3	4	140.9	7.0	46	67.0	6.2	40
4	5	142.0	8.2	35	72.8	5.4	43
Total		146.7	3.7	179	73.1	2.8	158

Table 15 reports the regression results to clarify whether and when signal space size affects the payoffs. Columns (1) and (3) reveal the effect of the signal space size on the payoffs. Results show that only Study 1 has a significant effect: purchasing signals from larger signal spaces negatively affected payoffs.

Columns (2) and (4) show the effect of playing the simplest lottery (Lottery 1). If a subject played more complex lotteries (Lotteries 2-4), her expected payoff was 19.4 points less than when playing Lottery 1 (F-test p-value is 0.0202). The result of Column (4) reveals that this pattern vanishes in Study 2.

Result 5. *Subjects earned less profit when purchasing signals from a larger signal space.*

The implication of Result 5 is that individuals tend to overvalue signals when the

Table 15: Determinants of the payoffs

	Dependent variable: Payoffs in Study 1		Dependent variable: Payoffs in Study 2	
	(1)	(2)	(3)	(4)
Signal Space Size	−6.12*		−1.17	
	(3.38)		(2.54)	
Simplest Lottery		19.44**		−1.79
		(8.29)		(6.86)
Constant	161.23***	141.46***	76.11***	73.44***
	(9.00)	(4.33)	(6.95)	(3.14)
Observations	716	716	632	632
R-squared	0.017	0.030	0.001	0.000
F-test p-value	0.0720	0.0202	0.6466	0.7946

Notes: Robust standard errors clustered by subject in parentheses.
***$p < 0.01$, ** $p < 0.05$, *$p < 0.1$.

signal space is larger, causing them to submit overpriced values for these signals and ultimately resulting in lower earnings.

4.7 Robustness Study

The results of the robustness study indicate that subjects had a thorough understanding of the information structure, particularly the accuracy of each signal. Subjects' submitted values for each signal are consistent with the expected utility model.

Table 16 displays the submitted values of the willingness to pay for the signal in each lottery. What is noteworthy in this table is that subjects valued the signals consistent with the theoretical prediction. Additionally, in comparison to the WTP for signals in Lotteries 1-4, subjects overpaid for signals in Lotteries 5-8 due to the effect of the signal space size. The chi-square test result rejects the null hypothesis that the willingness to pay for signals was submitted randomly (p-value < 0.001).

Table 16: Summary of results in the robustness study

Questions	Signal Space Size	Winning Prob With Signals	Predictions	WTP
1	2	0.80	30	24.1
2	2	1.00	50	38.0
3	2	0.60	10	24.8
4	2	0.90	40	37.8
5	3	0.70	20	28.4
6	3	0.83	33.3	34.7
7	3	0.57	6.7	23.7
8	3	0.77	26.7	30.8

Table 17: Determinants of the demand for signals

	Dependent variable: c_i			
	(1)	(2)	(3)	(4)
Predictions	0.25***	0.27***	0.25***	0.27***
	(0.07)	(0.07)	(0.07)	(0.07)
Signal Space Size		1.51		1.51
		(1.06)		(1.06)
Constant	22.32***	17.97***	22.32***	17.97***
	(1.98)	(3.72)	(1.75)	(3.61)
Subject fixed effect	No	No	Yes	Yes
Observations	1040	1040	1040	1040
R-squared	0.020	0.020	0.045	0.047

Notes: Robust standard errors clustered by subject in parentheses.
***$p < 0.01$, ** $p < 0.05$, *$p < 0.1$.

The results presented in Table 17 support the claim that subjects had a thorough understanding of the entire information structure, including the meaning of signal accuracy. Theoretical predictions based on the risk-neutral expected utility model are significantly related to the actual submitted values.

The second row of the table suggests that the signal space size has a positive effect on the demand for signals, but the effect is not statistically significant.

5 Conclusion

Economists have examined various environments where individuals purchase costly stochastic information. This article contributes to the literature by experimentally investigating the demand for signals with different signal space sizes. It provides the first empirical evidence of a preference for a larger signal space in the information acquisition process. Specifically, subjects preferred to receive a signal from a larger signal space, even when signal accuracy was fixed. Furthermore, an inconsistent preference pattern was observed, where the preference for the larger signal space disappeared when the value of equivalent lotteries was measured.

What is the behavioral reason for the preference for a larger signal space? One possible explanation is that subjects were confused and had a poor understanding of signal accuracy. However, this explanation is not plausible because the experimental design allowed subjects to easily calculate the signal accuracy. Additionally, the results of the robustness study (see Section 4.7) reject the argument that subjects were confused about understanding the signal accuracy.

Another explanation for the preference for a larger signal space is that subjects mistakenly believed that a larger signal space implies higher signal accuracy. In many cases, a larger number of signals implies more information. Numerous theoretical and experimental studies have shown a preference for frequent signals in various contexts. For instance, in Edmond (2013)'s model of information and political regime change, the number of informative signals helps to overthrow the regime. Additionally, Lee and Niederle (2015) demonstrated that more signals (virtual roses) increase the success rate of dates in the internet dating market. However, this explanation cannot account for the inconsistent preferences observed in Study 2. If subjects believed that signals from larger signal spaces were more accurate, they should have also valued the equivalent lotteries.

The third and most plausible explanation is based on curiosity or a myopic view. A contemporary definition of curiosity characterizes it as an intrinsic motivation to seek information, even when it has no instrumental value (Loewenstein, 1994; Oudeyer and Kaplan, 2007; Kidd and Hayden, 2015). In Study 1, suppose that subjects were focused on guessing the selected box rather than the color of the drawn ball. Without the signal, a lottery containing more boxes reduces the chance of choosing the "correct" box. Therefore, when a lottery has more boxes, subjects may pay more to reveal uncertainty about the boxes. However, when they value the entire lottery, they realize that each lottery is identical: they have the ability to reduce compound lotteries.

Imagine someone deciding whether or not to go to a restaurant. She makes her decision based on a five-star rating suggestion: she goes to the restaurant only when the rating is greater than 3. Since her choice is binary, this five-star system could be simplified to a binary suggestion. For example, the suggestion is “Go” if the rating is greater than 3, and “Don’t Go” otherwise In that case, the information about whether the restaurant’s rating is 4 or 5 has no instrumental value for her decision because she will go in either case. However, the view of curiosity suggests that she still wants to know this information, even if it has no practical value for her decision.

Several questions remain unanswered at present. This paper presents a preference for a larger signal space when the signal space size is between 2 and 5. However, the results do not confirm the optimal size of the signal space. It is possible that decision-makers would prefer a larger space even when the signal space is extremely large, or there may be a most preferred signal space size.

Another question is whether these results can be generalized to a non-binary action space or even a continuous one. The experimental design of this paper restricts the action space to binary. In reality, however, actions are not necessarily binary. Therefore, investigating whether the results of this paper still hold in a more generalized action space is also an interesting question. I hope future studies will answer these questions.

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A Appendix

A.1 Omitted Calculations

A.1.1 Investor Example

Suppose the investor gets a signal from Advisor A. The conditional probability that the company is good is given by

$$Pr(G|\text{“}invest\text{”}) = 0.7,$$
$$Pr(G|\text{“}not\ invest\text{”}) = 0.3.$$

Let *INVEST* or *NOT INVEST* denotes the investor's action. When the signal is "invest", then the investor will invest in the company, because $Pr(G|\text{"invest"}) = 0.7 > 0.5$. In this case, her expected utility is

$$\begin{aligned}
&u(\textit{signal}=\text{"invest"})\\
&= 0.7u(\textit{INVEST}, G) + 0.3u(\textit{INVEST}, B)\\
&= 0.7 * 1 + 0.3 * 0 = 0.7.
\end{aligned}$$

Otherwise, she will not invest because $Pr(G|\text{"not invest"}) = 0.3 < 0.5$. Her expected utility is given by

$$\begin{aligned}
&u(\textit{signal}=\text{"not invest"})\\
&= 0.3u(\textit{NOT INVEST}, G) + 0.7u(\textit{NOT INVEST}, B)\\
&= 0.3 * 0 + 0.7 * 1 = 0.7.
\end{aligned}$$

Therefore, the expected utility when receiving Advisor A's signal is

$$\begin{aligned}
&0.5u(\textit{signal}=\text{"invest"}) + 0.5u(\textit{signal}=\text{"not invest"})\\
&= 0.5 * 0.7 + 0.5 * 0.7 = 0.7.
\end{aligned}$$

Suppose the investor hires Advisor B. The conditional probability of the state is

$$\begin{aligned}
&Pr(G|\text{"must invest"}) = 0.8,\\
&Pr(G|\text{"invest"}) = 0.7,\\
&Pr(G|\text{"no opinion"}) = 0.5,\\
&Pr(G|\text{"not invest"}) = 0.3,\\
&Pr(G|\text{"never invest"}) = 0.2.
\end{aligned}$$

If the signal is “must invest” or “invest,” then the investor will invest because $Pr(G|\text{“}\textit{must invest}\text{”})) = 0.8 > 0.5$ and $Pr(G|\text{“}\textit{invest}\text{”})) = 0.7 > 0.5$. If the signal is “no opinion,” then she is indifferent between investing or not because $Pr(G|\text{“}\textit{no opinion}\text{”}) = 0.5$. She will not invest if the signal is “not invest” or “never invest” because $Pr(G|\text{“}\textit{not invest}\text{”}) = 0.3 < 0.5$ and $Pr(G|\text{“}\textit{never invest}\text{”})) = 0.2 < 0.5$.

Hence, when Advisor B’s signal is “must invest”, the expected utility is

$$\begin{aligned}
&u(\textit{signal}\text{=“}\textit{must invest}\text{”}) \\
&= 0.8u(INVEST, G) + 0.2u(INVEST, B) \\
&= 0.8 * 1 + 0.2 * 0 = 0.8.
\end{aligned}$$

Similarly,

$$\begin{aligned}
&u(\textit{signal}\text{=“}\textit{invest}\text{”}) = 0.7, \\
&u(\textit{signal}\text{=“}\textit{no opinion}\text{”}) = 0.5, \\
&u(\textit{signal}\text{=“}\textit{not invest}\text{”}) = 0.7, \\
&u(\textit{signal}\text{=“}\textit{never invest}\text{”}) = 0.8.
\end{aligned}$$

Hence, the expected utility of receiving a signal from Advisor B is

$$\begin{aligned}
&0.2u(\textit{signal}\text{=“}\textit{must invest}\text{”}) + 0.2u(\textit{signal}\text{=“}\textit{invest}\text{”}) + 0.2u(\textit{signal}\text{=“}\textit{no opinion}\text{”}) \\
&+ 0.2u(\textit{signal}\text{=“}\textit{not invest}\text{”}) + 0.2u(\textit{signal}\text{=“}\textit{never invest}\text{”}) \\
&= 0.2 * 0.8 + 0.2 * 0.7 + 0.2 * 0.5 + 0.2 * 0.7 + 0.2 * 0.8 = 0.7.
\end{aligned}$$

A.1.2 Expected Utility

When the cost of the signal is c, the expected utility of each lottery is,

$$\begin{aligned}
U_{EU}(L_1(c)) &= 0.7u(100-c) + 0.3u(-c) \\
U_{EU}(L_2(c)) &= \frac{2}{3}(0.8u(100-c) + 0.2u(-c)) + \frac{1}{3}(0.5u(100-c) + 0.5u(-c)), \\
U_{EU}(L_3(c)) &= \frac{1}{2}(0.8u(100-c) + 0.2u(-c)) + \frac{1}{2}(0.6u(100-c) + 0.6u(-c)), \\
U_{EU}(L_4(c)) &= \frac{2}{5}(0.8u(100-c) + 0.2u(-c)) + \frac{2}{5}(0.7u(100-c) + 0.3u(-c))) \\
&+ \frac{1}{5}(0.5u(100-c) + 0.5u(-c)).
\end{aligned}$$

Similarly,

$$\begin{aligned}
U_{EU}(L_1(0)) &= 0.7u(100) + 0.3u(-c) \\
U_{EU}(L_2(0)) &= \frac{2}{3}(0.8u(100)) + \frac{1}{3}(0.5u(100)), \\
U_{EU}(L_3(0)) &= \frac{1}{2}(0.8u(100)) + \frac{1}{2}(0.6u(100)), \\
U_{EU}(L_4(0)) &= \frac{2}{5}(0.8u(100)) + \frac{2}{5}(0.7u(100)) + \frac{1}{5}(0.5u(100)).
\end{aligned}$$

A.1.3 Recursive Smooth Ambiguity Preference

$V_1(c) \geq V_4(c)$ can be derived by the following procedure:

$$\begin{aligned}
U_{KMM}(L_1(c)) &= \phi(U(0.7)) \\
&\geq \frac{2}{5}\phi(U(0.8)) + \frac{2}{5}\phi(U(0.7)) + \frac{1}{5}\phi(U(0.5)) \\
&= U_{KMM}(L_4(c)).
\end{aligned}$$

Also, $V_3(c) \geq V_2(c)$:

$$\begin{aligned}
U_{KMM}(L_3(c)) &= \frac{1}{2}\phi(U(0.8)) + \frac{1}{2}\phi(U(0.6)) \\
&= \frac{1}{2}\phi(U(0.8)) + \frac{1}{2}\phi(\frac{1}{3}U(0.8) + \frac{2}{3}U(0.5)) \\
&\geq \frac{1}{2}\phi(U(0.8)) + \frac{1}{6}\phi(U(0.8)) + \frac{1}{3}\phi(U(0.5)) \\
&\geq \frac{2}{3}\phi(U(0.8)) + \frac{1}{3}\phi(U(0.5)) \\
&= U_{KMM}(L_2(c)).
\end{aligned}$$

Similarly, $V_4(c) \geq V_2(c)$:

$$\begin{aligned}
U_{KMM}(L_4(c)) &= \frac{2}{5}\phi(U(0.8)) + \frac{2}{5}\phi(U(0.7)) + \frac{1}{5}\phi(U(0.5)) \\
&= \frac{2}{5}\phi(U(0.8)) + \frac{2}{5}\phi(\frac{2}{3}U(0.8) + \frac{1}{3}U(0.5)) + \frac{1}{5}\phi(U(0.5)) \\
&\geq \frac{2}{5}\phi(U(0.8)) + \frac{4}{15}\phi(U(0.8)) + \frac{2}{15}\phi(U(0.5)) + \frac{1}{5}\phi(U(0.5)) \\
&= \frac{2}{3}\phi(U(0.8)) + \frac{1}{3}\phi(U(0.5)) \\
&= U_{KMM}(L_2(c)).
\end{aligned}$$