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. While subjects predicted the binary outcomes of compound lotteries, I measure their values of signals for the outcome (Study 1) and the values of lotteries they played (Study 2) in varying sizes of the signal space. Results show that the size of the signal space was positively correlated with the elicited value of the signals, but not the value of the equivalent lotteries. These experimental findings cannot be explained by leading theoretical frameworks. In general, preference for a larger signal space suggests users find a five-star rating system more attractive than a binary recommendation system.

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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 has often been overlooked in the literature. In the context of information acquisition, the size of the signal space denotes the number of possible signals. In many cases, theorists have assumed that the signal space equals the action space when discussing the size of the signal space (Spence, 1973; Kamenica and Gentzkow, 2011). 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 and implications of models relying on this assumption could be limited if the receiver prefers a larger signal space. This paper investigates whether individuals have a preference for the size of the signal space, independent of 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 receives a utility of 1 for investing in the good company or for not investing in the bad company, and a utility of 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 the two signals with equal probability: "invest" or "not invest." If his signal is "invest," the probability that 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.

company is good is 70% ($Pr(G|\text{"}invest\text{"}) = 0.7$). If his signal is "not invest," the probability that the company is good is 30% ($Pr(G|\text{"}not\ invest\text{"}) = 0.3$). Since the number of possible signals sent from Advisor A is 2, the size of his signal space is 2.

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. Since the number of possible signals he will send is 5, the size of his signal space is 5.

If the investor is an expected utility maximizer, she only considers the signal accuracy of the advisor, which is defined by the "winning" probability when receiving the signal. For instance, if the investor receives and follows the signal from Advisor A, her winning probability is 0.7 regardless of whether she receives "invest" or "not invest." Hence, Advisor A's signal accuracy is 0.7. Similarly, Advisor B's signal accuracy is also 0.7.[2] Therefore, if the investor maximizes expected utility, she will be indifferent between Advisors A and B.

However, there might be some possible reasons to prefer larger or smaller signal space. In certain environments, limiting the size of the signal space can restrict the attainment of optimal outcomes. For instance, in most standard sender-receiver literature, a small signal space size can lead to inefficient outcomes (Crawford and Sobel, 1982; Heumann, 2020). Hence, in these cases, a larger signal space allows better decision-making.

On the other hand, decision-makers might prefer a simpler environment—a smaller signal space—if the signals are too complicated to comprehend. For instance, workers might prefer receiving direct instructions on what to do rather than abstract signals from their boss, which require interpretation of the boss's intent. This preference could be attributed to complexity aversion, which demonstrates a tendency to prefer simpler lotteries over complex ones, even when the expected values are the same

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

(Huck and Weizsäcker, 1999; Sonsino et al., 2002; Halevy, 2007; Moffatt et al., 2015).

To investigate the preference for the size of the signal space, I conducted a lab experiment. In the experiment, the size of the signal space was independent of the efficiency of the outcomes: the signal accuracy of each signal was the same. Therefore, there is no theoretical reason to prefer a larger signal space. Additionally, since the experiment was designed to be simple and straightforward, there was no evidence of complexity aversion. However, the results surprisingly revealed a preference for larger signal space. The results suggest that the investor favors Advisor B over A due to the size of the 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 showed that subjects' willingness to pay for the signal increased as the size of the signal space increased, even with fixed signal accuracy. Therefore, subjects overpaid for the signals when the signal space was large, resulting in lower profits when purchasing signals from a larger signal space. 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.

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, I measured subjects' willingness to pay for playing each of the four lotteries from Study 1 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 lotteries with larger signal space more. 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, 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. [3] 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.

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 lotteries, there is no reason to pay more for a signal with a larger space, given the same signal accuracy. Halevy (2007) revealed that ambiguity neutrality and reduction of compound lotteries are tightly associated. Extending his finding to signal acquisition, the preference for a larger signal space should be correlated with ambiguity neutrality. However, this paper did not find a correlation.

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 valuable 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

[3] I will provide a detailed explanation In Section 5.

from a binary suggestion to a five-star rating, demand for the service will increase, even without improving the system's accuracy.

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) propose different values for different signals. Despite these differences, none of these models can adequately predict the systemic preference for signal space size and the behavioral differences observed between Study 1 and Study 2. This gap between theoretical models and the experimental evidence poses a substantial challenge for game theory.

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 consisted of two parts. Part 1 measured the value of signals in Study 1 or equivalent lotteries in Study 2, and Part 2 measured ambiguity attitudes using 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.[4]

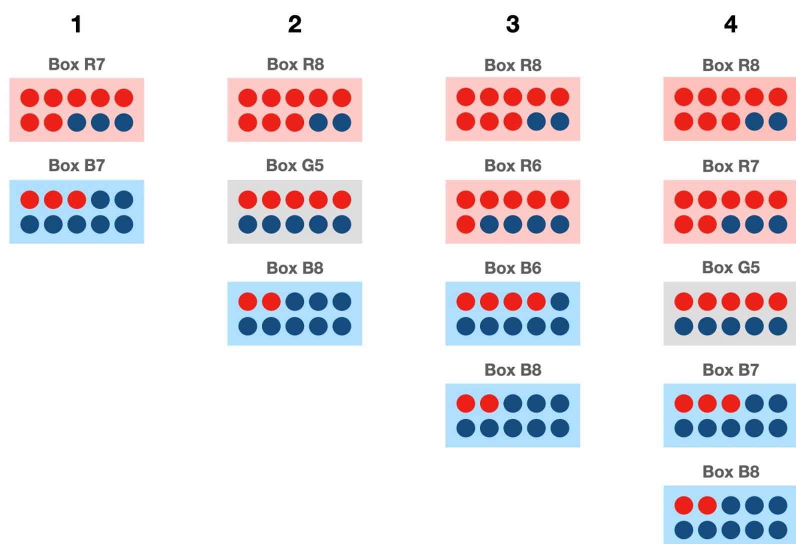

Figure 1: Four lotteries

Each box is denoted by Box Xn, where $X \in \{R, B, G\}$ and $n \in \{5, 6, 7, 8, 9\}$.[5] X and n represent the majority color of the balls in the box and the number of balls

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

[5] 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 $n = 10$.

in the box, respectively. For example, Box R7 has more red balls than blue balls, and the number of red balls is 7.[6] Note that there is no other Box Gn than Box G5 because Box G always contains 5 red balls and 5 blue balls.

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

[6] In the actual experiment, the boxes were referred to as Box R, Box B, Box G, Box RR (if there were multiple Box R in the same lottery), and Box BB (if there were multiple Box B in the same lottery). Numerical labels were deliberately avoided to encourage participants to rely more on intuition.

lottery was measured. Figure 2 shows the timeline of both studies.

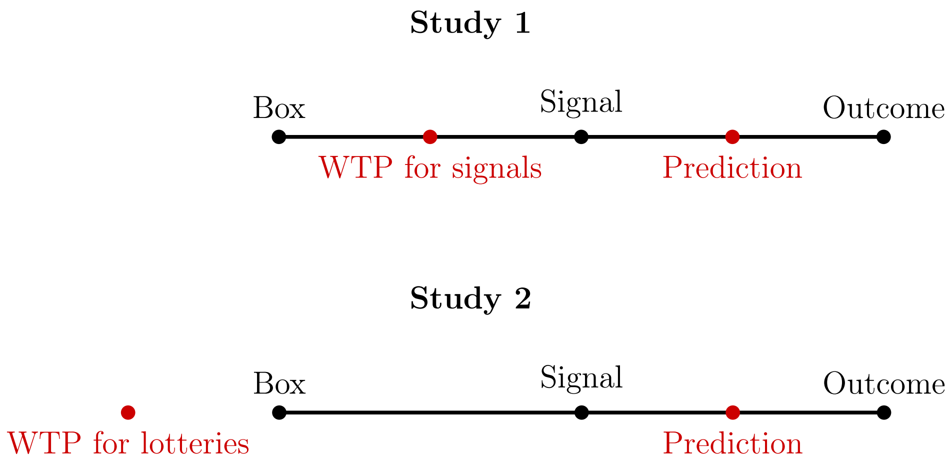

Figure 2: Timeline of studies

To measure the willingness to pay, I employed the Becker-DeGroot-Marschak (BDM) mechanism (Becker et al., 1964) in the format of a multiple price list. 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.

The major issue with the BDM mechanism is its difficulty, which can lead to biased results in some environments.[7] 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,

[7]See Noussair et al. (2004) for discussions about the biased results of the BDM.

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

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.[8] Specifically, 179 and 158 subjects participated in studies 1 and 2, respectively. Also, an additional 130 subjects 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.

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 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

[8] 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.

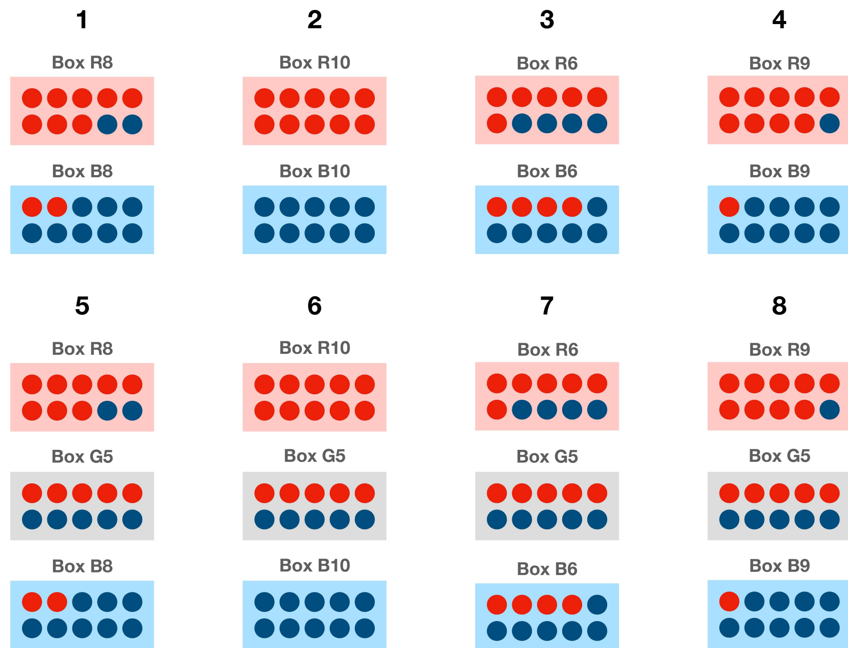

Figure 3: Lotteries in the robustness study

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*, and let $L_i^{signal}(c)$ denote lottery i *with the signal* purchased at a cost of c, where $c \geq 0$. Also, V_i represents the values of lotteries i, where $V_i^{signal}(0) \geq V_i^{prior}$. This implies that the value of the lottery with a signal is weakly better than the value of the lottery without a signal when the cost of the signal is free. There are two assumptions regarding the function $V(c)$.

Assumption 1. *$V(c)$ is a decreasing function of c.*

Assumption 2. *$V_i(c) \geq V_j(c)$ implies $V_i(c') \geq V_j(c')$.*

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

Assumption 1 implies that the value of the lottery with the signal decreases when the cost of the signal increases. Additionally, Assumption 2 suggests that if an individual prefers lottery i to lottery j when the cost is c, the preference remains unchanged when the cost changes to c'.

When c_i is the price for the signal for lottery i, the optimal price for the signal c_i^* is determined at the point where the value of lottery i with the signal is equal to the value of the lottery i without the signal. Therefore, the values of c_i^* and c_j^* can be obtained when $V_i^{signal}(c_i^*) = V_i^{prior}$ and $V_j^{signal}(c_j^*) = V_j^{prior}$ hold.

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

$$V_i^{signal}(c_i^*) = V_j^{signal}(c_j^*). \tag{2}$$

For simplicity, I will use the notation $V_i(c)$ instead of $V_i^{signal}(c)$ from now on. Consider a scenario where the submitted price for lottery i is greater than the price for lottery j, i.e., $c_i \geq c_j$. According to the Equation 2, we have $V_i(c_i) = V_j(c_j) = V^{prior}$. Additionally, Assumption 1 implies $V_i(c_i) \leq V_i(c_j)$, which leads to $V_j(c_j) \leq V_i(c_j)$. Assumption 2 indicates that $V_j(c) \leq V_i(c)$. Therefore, the following implication holds.

$$c_i^* \geq c_j^* \implies V_i(c) \geq V_j(c). \tag{3}$$

For example, let's suppose an individual is willing to pay 20 points for signal 1 (the signal in lottery 1) and 30 points for signal 2 (the signal in lottery 2). If both signals are priced equally at 15 points, she would prefer to purchase signal 2 instead of signal 1. Therefore, to simplify calculations, I will compare the values $V_i(c)$ and $V_j(c)$ whenever a comparison between c_i and c_j is necessary.

In Study 1, c_i was measured for $i \in 1, 2, 3, 4$. In Study 2, $L_i(0)$ was elicited for $i \in 1, 2, 3, 4$, since the signal was free ($c = 0$). The remaining part of this section describes how different theories under uncertainty predict these values.

3.1 Expected Utility

According to expected utility theory, the decision-makers assign a probability $p(s)$ to the state $s \in S$ to evaluate a lottery. Therefore, the expected utility of lottery i is given by

$$U_{EU}(L_i) = \sum_{s \in \mathrm{S}} p(s)u(L_i(s)). \tag{4}$$

The expected utility suggests that decision-makers are only interested in the expected values of lotteries, but are indifferent to the process of resolving uncertainty. They do not distinguish between lotteries that are simple, compound, or mean-preserving spreads of one another. Therefore, according to the expected utility model, individuals are indifferent between signals and between lotteries.

$$\begin{gathered} c_1 = c_2 = c_3 = c_4, \\ V_1(0) = V_2(0) = V_3(0) = V_4(0). \end{gathered} \tag{5}$$

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 in the space of second-order compound lotteries. Specifically, when they evaluate lottery i, there exists a second-order belief μ such that

$$U_{KMM}(L_i) = \sum_{\Delta(S)} \phi\Big(\sum_{s \in S} p(s) u(L_i(s))\Big)\mu(p), \tag{6}$$

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.

Suppose an individual evaluates the signal for lottery 1 using a recursive smooth ambiguity model. There are two possible outcomes in the first stage (second-order): the selected box is R7 or B7. In the second stage (first-order), the expected utility for both cases is $0.7u(100-c) + 0.3u(-c)$. Therefore, the evaluation of $L_1(c)$ 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 other 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 the second-order belief μ is subjective, KMM explained ambiguity aversion by the concavity of ϕ. If ϕ is concave, individuals will prefer Lottery X over Lottery Y when Y is a mean-preserving spread of X. 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,

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

Additional calculations (detailed in Appendix A.1) reveal the following preferences.

$$\begin{aligned} c_1 \geq & c_3 \geq c_2, \\ c_1 \geq & c_4 \geq c_2. \end{aligned} \tag{7}$$

As $L_i(0)$ represents a specific form of $L_i(c)$, the preference among $L_i(0)$ remains unchanged. Therefore, regardless of ambiguity attitude, KMM predicts consistent preferences between Study 1 and Study 2.

$$\begin{aligned} V_1(0) \geq & V_3(0) \geq V_2(0), \\ V_1(0) \geq & V_4(0) \geq V_2(0). \end{aligned} \tag{8}$$

When ϕ is convex, which implies ambiguity seeking, the opposite inequalities hold:

$$\begin{aligned} c_2 \geq & c_3 \geq c_1, & (9) \\ c_2 \geq & c_4 \geq c_1, \\ V_2(0) \geq & V_3(0) \geq V_1(0), & (10) \\ V_2(0) \geq & V_4(0) \geq V_1(0). \end{aligned}$$

3.3 Simulational Predictions from Other Models

3.3.1 Rank-Dependent Utility

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

$$U_{RDU}(x_1, p_1; x_2, p_2; \cdots; x_n, p_n) = u(x_1) + \sum_{i=2}^{n}[u(x_i) - u(x_{i-1})]f(\sum_{j=i}^{n} p_j), \tag{11}$$

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 pays out 100 with probability p and 0 with probability $1 - p$,

$$U(100, p; 0, 1 - p) = u(100)f(p). \tag{12}$$

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

$$CE(p) = CE(100, p; 0, 1 - p) = u^{-1}(u(100)f(p)). \tag{13}$$

Hence,

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

Similarly, the values of other lotteries with free signals are calculated as

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

The preferences between lotteries vary depending on the functional form of $f(p)$. Table 5 illustrates the simulated predictions of the RDU model with various concave functional forms.

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	$c_1 = c_2 = c_3 = c_4$	$V_1(0) = V_2(0) = V_3(0) = V_4(0)$
$log(p)$	$c_1 \geq c_3 \geq c_2 \geq c_4$	$V_1(0) \geq V_3(0) \geq V_2(0) \geq V_4(0)$
$ln(p)$	$c_1 \geq c_3 \geq c_2 \geq c_4$	$V_1(0) \geq V_3(0) \geq V_2(0) \geq V_4(0)$

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

3.3.2 Cumulative Prospect Theory

The first version of prospect theory, formulated by Kahneman and Tversky (1979), provided evidence of a systematic violation of expected utility theory. The authors presented an alternative theoretical model to explain this violation. Later, an extension of the original model called cumulative prospect theory was presented by

Kahneman and Tversky (1992), which incorporates 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

$$U_{CPT}(x_m, p_m; x_{m+1}, p_{m+1}; \cdots; x_0, p_0; \cdots; x_n, p_n) = \sum_{i=-m}^{n} \pi_i v(x_i), \tag{14}$$

where $v(\cdot)$ is a value function, which is an increasing function with $v(0) = 0$, and π is the decision weight. Kahneman and Tversky (1992) defined the value function as follows.

$$v(x) = \begin{cases} x^\alpha & \text{if } x \geq 0, \\ -\lambda(-x)^\beta & \text{if } x < 0, \end{cases} \tag{15}$$

where λ is a loss aversion parameter.

Decision weights π are defined by:

$$\begin{aligned} \pi_n^+ &= w^+(p_n), \\ \pi_{-m}^- &= w^+(p_{-m}), \\ \pi_i^+ &= w^+(p_i + ... + p_n) - w^+(p_{i+1} + ... + p_n),\ 0 \leq i \leq n-1, \\ \pi_i^- &= w^-(p_{-m} + ... + p_i) - w^-(p_{-m} + ... + p_{i-1}),\ 1-m \leq i \leq 0, \end{aligned} \tag{16}$$

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

$$w^+(p) = \frac{p^\gamma}{(p^\gamma + (1-p)^\gamma)^{1/\gamma}},\ w^-(p) = \frac{p^\delta}{(p^\delta + (1-p)^\delta)^{1/\delta}}. \tag{17}$$

To predict the preferences for c_i and $V_i(0)$ using CPT, I used the parameter values that were estimated from experimental data in Kahneman and Tversky (1992).

[9]According to a meta-analysis by Brown et al. (2022), the mean of the loss aversion coefficient λ

Table 6: Values of parameters from Kahneman and Tversky (1992)

Parameter	Meaning	Value
α	power for gains	0.88
β	power for losses	0.88
λ	loss aversion	2.25[9]
γ	probability weighting parameter for gains	0.61
δ	probability weighting parameter for losses	0.69

Additionally, I assumed the cost of the signal to be 20, which is the theoretically expected value when the decision-maker is a risk-neutral expected utility maximizer. Therefore, the preference between c_i is based on simulation results from $L_i(20)$. With these parameter values, CPT predicts the following preferences:

$$c_1 \geq c_3 \geq c_4 \geq c_2, \qquad (18)$$
$$V_1(0) \geq V_3(0) \geq V_4(0) \geq V_2(0).$$

To summarize the theoretical predictions for the value of signals in Study 1, none of the models predict a 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. Furthermore, none of the models predict 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.

from numerous empirical estimates is 1.97. I found that simulational results with $\lambda = 1.97$ do not change the preference between lotteries.

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. Regarding c_i, the theoretical predictions from the risk-neutral expected utility maximizer are 20 points for each lottery. Therefore, overall, the demand for signals exceeds the theoretical predictions. The most notable feature of the willingness to pay for the signal is the preference for a 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 linear regressions of the form:

$$y_{in} = \beta_0 + \beta_1|S|_i + \beta_2 AmbNeutral_n + \beta_3|S|_i * AmbNeutral_n + \epsilon_{in}. \tag{19}$$

$y_{i,n}$ is the value of either c_i or $V_i(0)$ for individual n, and $AmbNeutral_n$ is a dummy variable that indicates whether individual n is ambiguity neutral or not. Standard errors are clustered by subject.

The first three columns in Table 8 indicate a significant effect of the size of the signal space on the value of signals (F-test p-values < 0.001 for these columns). As the

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 ×		−0.20			0.16	
Ambiguity Neutrality		(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. $^{***}p < 0.01$, $^{**}\ p < 0.05$, $^{*}p < 0.1$.

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 subjects in Study 2 exhibited risk-averse behavior.

If 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.[10]) However,

[10] Note that risk-averse individuals are less likely to prefer purchasing the signal because they

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 Attitude	Study 1 Number	Study 1 Percentage	Study 2 Number	Study 2 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 $V_i(0)$.

prefer to play the simplest lottery, which is the lottery without the signal, as it has a 50% chance of winning or losing.

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 Payoffs and the Size of the Signal Space

This section examines if the preference for larger signal space harms the information buyers. Table 12 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 12: 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 13 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.

Table 13: 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.
***$p < 0.01$, ** $p < 0.05$, *$p < 0.1$.

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

4.5 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 14: 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 14 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 15: 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 15 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 4.5) 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 be willing to pay more to reveal uncertainty about the boxes. However, when they consider the value of the entire lottery, they realize that each lottery is identical, which means that they have the ability to reduce the complexity of 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 perspective 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 $Pr(G|\text{“}invest\text{”}) = 0.7 > 0.5$. In this case, her expected utility is

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

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

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

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

$$0.5u(\textit{signal=``invest''}) + 0.5u(\textit{signal=``not invest''})$$
$$= 0.5 * 0.7 + 0.5 * 0.7 = 0.7.$$

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

$$Pr(G|\textit{``must invest''}) = 0.8,$$
$$Pr(G|\textit{``invest''}) = 0.7,$$
$$Pr(G|\textit{``no opinion''}) = 0.5,$$
$$Pr(G|\textit{``not invest''}) = 0.3,$$
$$Pr(G|\textit{``never invest''}) = 0.2.$$

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

Hence, when Advisor B's signal is "must invest", the expected utility is

$$u(\textit{signal=``must invest''})$$
$$= 0.8u(INVEST, G) + 0.2u(INVEST, B)$$
$$= 0.8 * 1 + 0.2 * 0 = 0.8.$$

Similarly,

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

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

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

A.1.2 Expected Utility

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

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

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

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

A.2 Predictions with Signals

Table 16 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 16: 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 17 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 17: 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					

A.3 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.