ESSAYS IN BEHAVIORAL ECONOMICS AND DECISION THEORY

A Dissertation

by

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ABSTRACT

This dissertation comprises three chapters on behavioral economics and decision theory. Each chapter is independent.

In the first chapter, I present the first experimental evidence that information receivers exhibit a preference for a larger signal space, even when it does not affect signal accuracy. This preference for a larger signal space suggests that users are more attracted to a five-star rating system than a binary recommendation system.

The second chapter is about the timing of the resolution of uncertainty. We provide the first experimental examination of uncertainty resolution in the domain of ambiguity. Results show that individuals prefer early resolution of both risk and ambiguity, and these preferences are positively correlated.

In the last chapter, we examined a novel explanation for vaccine hesitancy: ambiguity aversion. Using a modified version of the Interactive Vaccination (I-Vax) Game from Bohm et al. (2016), we found that ambiguity-averse subjects were more likely to take the vaccination in general but were differentially less likely to take it in a treatment where there is ambiguity in the vaccination option.

DEDICATION

I am deeply grateful to everyone who has helped me start this journey.

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Contributors

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I. DOES THE SIZE OF THE SIGNAL SPACE MATTER?

I.1 Introduction

Signal transmission is an essential part of the literature on game theory, where 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. When discussing the size of the signal space, in many cases, theorists assume that the signal space equals the action space. They have shown that assuming an equivalence between the signal space and the action space is sufficient to find the equilibrium; therefore, a larger signal space is 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 the two signals with equal probability: "invest" or "not invest." If his signal is "invest," the probability that the company is good is 70% ($Pr(G|\text{"invest"}) = 0.7$). If his signal is "not invest," the probability that the company is good is 30% ($Pr(G|\text{"not invest"}) = 0.3$). 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

[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.

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. 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 provides the first empirical evidence that the size of the signal space matters in information acquisition. In Study 1, subjects in a lab experiment bet on the binary outcomes of four lotteries. Before betting, they can purchase a signal for each lottery. For each lottery, while the signal accuracy is identical, the size of the signal space varies from 2 to 5. I find that subjects’ willingness to pay for the signal increases as the size of the signal space increases, even though the signal accuracy is fixed. It is well-known that, in many cases, individuals prefer simpler situations when making decisions. In that sense, the preference for a larger signal space could be counterintuitive because a larger signal space generates a complicated environment.

A possible explanation for the preference for larger signal space would be that subjects mistakenly believe that larger signal space implies higher signal accuracy. I falsify this explanation in a second study. Study 2 measures the willingness to pay to play each of the four lotteries in Study 1. In Study 2, subjects always receive the signal in each lottery because the signal is free. Note that the environments in both studies are isomorphic. Therefore, if decision-makers think larger signal space implies higher signal accuracy, they should value more lotteries with larger signal space in Study 2. However, the result reveals that subjects no longer prefer the larger signal space; they are indifferent to the size of the signal space.

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 III.4.

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. (1) 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 (2; 3). 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 (4; 5; 1; 6). 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 (7), 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 (8). 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 I.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 (9), the rank-dependent utility model (10), and prospect theory (11; 12) 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 III.2 describes the experimental design and procedure. Section I.3 provides theoretical predictions of the results from various models. Section III.3 reveals experimental results, and Section III.4 concludes.

I.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 (13) questions.

I.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 I.1 illustrates the four lotteries.[2]

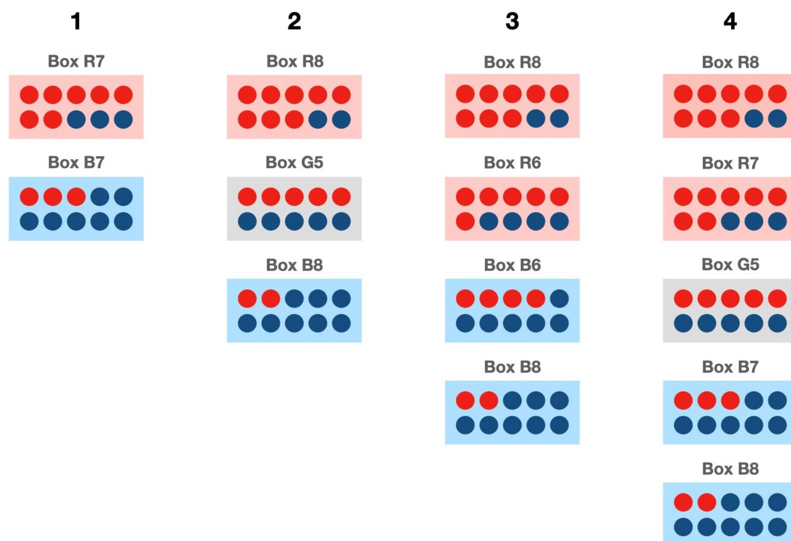


Figure I.1: Four lotteries

Each box is denoted by Box Xn, where $X \in \{R, B, G\}$ and $n \in \{5, 6, 7, 8, 9\}$.[3] 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 the number of red balls is 7.[4]

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

[3](14) 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 $n = 10$.

[4]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 subjects rely more on intuition.

In Study 1, subjects do not know which box was selected. However, before the prediction, subjects have a chance to "buy" a costly signal with their 100 endowment points. If they purchase a signal, the computer will tell them which box is selected. That signal increases their probability of winning but requires some cost, whether they win or lose.

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 subjects 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.

Study 2 measures the values of the four lotteries when the signals are free: before predicting the ball's color, subjects can observe which box is selected without the signal purchasing process. Note that the information structures of both studies are isomorphic. Hence, if a subject has a preference over the size of the signal space in Study 1, she will also have the same preference in Study 2. To quantify the values of the lotteries, I measured the subjects' willingness to pay to play each lottery. Figure I.2 shows the timeline of both studies.

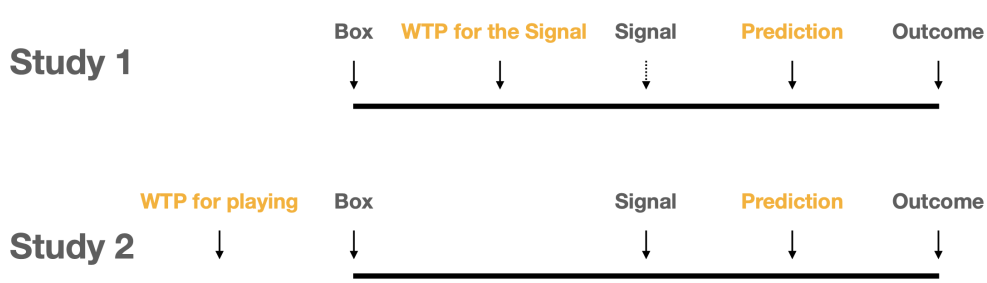


Figure I.2: Timeline of both studies

To measure the willingness to pay, the Becker-DeGroot-Marschak (BDM) mechanism (15) was used. In Study 1, subjects submit the values of the signals, which are the maximum points they can pay for each lottery. After submitting values for signals for all four lotteries, one of them is randomly selected. Then, a random number is generated between 1 and 100. The random number represents the price for the signal for the selected question in the selected lottery. If a subject's submitted value in the selected lottery is greater than the price, she can see the signal and pays the price. However, if the submitted value in the selected lottery is equal to or lower than the price, she does not receive the signal and pays nothing. After the signal is revealed or not revealed, subjects predict the color of the ball. Figure I.3 shows 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

Figure I.3: The BDM mechanism in Study 1

The procedure of the BDM in Study 2 is similar to that in Study 1 (See figure I.4). Before playing the lotteries, subjects are asked the maximum number of points they are willing to pay for playing each lottery. After submitting four values for four lotteries, one of the lotteries is randomly selected. Then, a random number between 1 and 100, representing a substitute prize, is generated. If the submitted value in the selected lottery is greater than the prize, a subject plays the lottery. Otherwise, she receives the prize without playing the lottery. If subjects play the lottery, they see which box is selected and predict the color of the ball from the selected 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

Figure I.4: The BDM mechanism in Study 2

The major issue with the BDM mechanism is its difficulty and the biased results in some environments.[5] To minimize the confusion, subjects were asked to submit their maximum willingness to pay for the signal instead of deciding between Option A and B 100 times. Also, before subjects submit their actual values, an example was illustrated of how the mechanism works when a specific value is submitted. Furthermore, even if the result is upward or downward biased, the biased result does not impair the primary purpose of the BDM mechanism, which is to compare preferences between signals and between lotteries, not to elicit their exact values.

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

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

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 measures $V_i^{signal}(0)$ for four lotteries. Suppose a subject values the signal for lottery i is

[5] See (16) and (17) for discussions about the biased results of the BDM.

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.

I.2.2 Part 2: Ellsberg Questions

After the elicitation of the value of signals, subjects' ambiguity attitudes were measured by two questions from (13). Ambiguity attitude is closely related to two-stage lotteries, especially to the ability to reduce compound lotteries (1; 18). (1) showed the strong association between ambiguity neutrality and reduction of compound lotteries. Since 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 is related 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 are asked to choose their preferred options between A & B and between C & D. Table III.1 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 I.1: Ellsberg questions

If a subject prefers A to B and D to C, there is no formulation of subjective probability that can rationalize the preference. This preference is interpreted to be a consequence of ambiguity aversion. After the rewards from Part 1 and Part 2 are determined, one of the parts is randomly selected. Subjects will get the points in the selected part. Each point is converted to 0.01 USD.

I.2.3 Procedural Details

467 subjects participated in experiments through Prolific, an online platform for recruiting research participants.[6] 179 and 158 subjects participated in studies 1 and 2, respectively. Also, another 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.

I.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.

[6](19) showed Prolific can be a reliable source of high-quality data. For details on the Prolific's subject pool, see (20). In both studies, only US subjects participated.

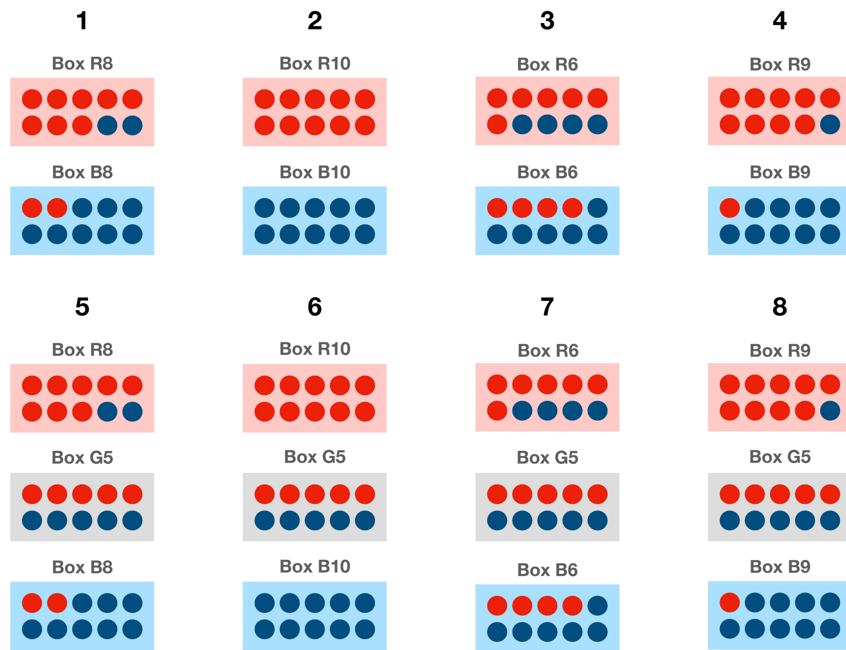


Figure I.5: Lotteries in the robustness study

The procedure of this study is identical to Part 1 in Study 1: 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 I.5 illustrates the lotteries in this study.

Table I.2: 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 I.2 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 understand the information framework of the signaling process, their demands for the signals will be in line with theoretical predictions.

I.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

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

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

where V_i denotes the value of lottery i.

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

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

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 I.4,

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

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.

I.3.1 Expected Utility

The expected utility of lottery i is given by

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

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.

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

I.3.2 Recursive Smooth Ambiguity Utility

The recursive smooth ambiguity model by (9) (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

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

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

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

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 for details) show the following preferences hold.

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

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.

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

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

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

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

I.3.3 Simulational Predictions from Other Models

I.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 (10; 21; 22). According to the RDU model, the utility of a lottery paying x_i with probability p_i is described as

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

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

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

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

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

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 I.3 illustrates simulational predictions of the RDU model based on different concave functions.

Table I.3: 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.

I.3.3.2 Prospect Theory

The first version of prospect theory was formulated by (11), providing evidence of a systemic violation of the expected utility theory. The authors presented an alternative theoretical model to explain the violation. Later, (12) (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

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

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.

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

where λ is a loss aversion parameter.

Decision weights π are defined by:

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

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

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

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 I.4: 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[7]
γ	probability weighting parameter for gains	0.61
δ	probability weighting parameter for losses	0.69

[7]According to a meta-analysis by (23), the mean of the loss aversion coefficient λ from numerous empirical esti-

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 values, CPT predicts the following preferences:

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

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.

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

I.4 Results

I.4.1 Preference for a Larger Signal Space

Table I.5: Elicited values for c_i and $V_i(0)$ with different size of signal space.

		Study 1		Study 2	
Lottery	$\lvert S\rvert$	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 I.5 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.

I did not find evidence for complexity aversion in lottery choice. According to (5), 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.

Table I.6: 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 I.6 illustrates the individual preferences between signals and lotteries. A larger proportion of subjects preferred the larger signal space in Study 1 ($c_4 \geq c_3 \geq c_2 \geq c_1$, but not $c_1 = c_2 = c_3 = c_4$) than in Study 2 ($V_4(0) \geq V_3(0) \geq V_2(0) \geq V_1(0)$, but not $V_1(0) = V_2(0) = V_3(0) = V_4(0)$). Also, a smaller proportion of subjects preferred the smaller signal space in Study 1 ($c_1 \geq c_2 \geq c_3 \geq c_4$, but not $c_1 = c_2 = c_3 = c_4$) than in 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 $V_1(0) = V_2(0) = V_3(0) = V_4(0)$)

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

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

$y_{i.n}$ 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 I.7: 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. ***$p < 0.01$, ** $p < 0.05$, *$p < 0.1$.

The first three columns in Table I.7 show 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:*** *When purchasing signals, the willingness to pay for the signal increases as the signal space size increases.*

Result 5 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*** *When the signal is free, subjects no longer prefer a larger signal space.*

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.

I.4.2 Ambiguity Attitudes

Table I.8: 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 I.9: 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 I.8 and I.9 respectively describe the ambiguity attitudes of subjects, and values of c_i and $V_i(0)$ conditional on different ambiguity attitudes. It can be easily seen that the overall patterns between the WTP for signals and lotteries are consistent even though the attitude towards ambiguity changes. The p-values of F-tests provide evidence that there is no effect of ambiguity attitude on c_i or $V_i(0)$.

The third row of Table I.7 verifies that ambiguity neutrality is independent of the preference for the size of the signal space. In (1), ambiguity neutrality is tightly related to the ability to reduce the compound lottery. However, the findings of this paper contradict these results.

Result 3. *Ambiguity neutrality is not related to the preference for the signal space size.*

I.4.3 Predictions with Signals

Table I.10 illustrates 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 implies that the subjects understood the information structure of the experiments. In both studies, the chi-square test and Fisher's exact test reject the null hypothesis that subjects randomly predicted. (p-values < 0.001 for both studies.)

Table I.10: 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 $= 0.000$					

Did subjects make better decisions when receiving signals from smaller or larger signal spaces? Table I.11 shows the correct decision rate with different signals. The correct decision is defined as whether the subject's prediction is consistent with the signal suggested after receiving Box R or Box B as a signal. Results show that the correct decision rate and the signal space size are not correlated. (Chi-square test p-value and Fisher's exact test p-value are approximately 0.513 and 0.672, respectively).

Table I.11: 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 $= 0.513$					

I.4.4 Payoffs and the Size of the Signal Space

This section investigates whether the preference for a larger signal space hurts information buyers. Table I.12 shows subjects' payoffs in points from Part 1 in both studies. Overall, profits were larger in Study 1 than in Study 2 because of the 100-point endowment in Study 1. In Study 1, subjects earned the highest profit on average when they played Lottery 1, the simplest lottery. In other words, they earned less profit when they played lotteries with larger signal space. However, this pattern disappeared when signals were free.

Table I.12: Payoffs from part 1

Lottery	Signal Space	Study 1			Study 2		
Selected	Size	Payoff	Std. Error	Number	Payoff	Std. Error	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 I.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 when the signal is free.

Table I.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 4. *Subjects earned less profit when purchasing signals from a larger signal space.*

The implication of Result 4 is that people overvalue signals when the signal space is large. Therefore, they submitted overpriced values for these signals, resulting in lower earnings.

I.4.5 Robustness Study

Results from the robustness study show that subjects understood the entire information structure, especially the accuracy of each signal. Subjects' submitted values for each lottery are consistent with the expected utility model.

Table I.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 I.14 reveals the submitted values of the willingness to pay for the signal in each lottery. What stands out in this table is that subjects valued the signals consistent with the theoretical prediction. Also, compared to the WTP for signals in Lotteries 1-4, subjects overpaid for signals in Lotteries 5-8 because of the effect of the signal space size. The chi-square test result rejects the null thesis that the willingness to pay for signals was randomly submitted (p-value< 0.001).

Table I.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 I.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.

I.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 I.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 (24)'s model of information and political regime change, the number of informative signals helps to overthrow the regime. Additionally, (25) 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 (26; 27; 28). 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.

II. PREFERENCES FOR THE RESOLUTION OF RISK AND AMBIGUITY

II.1 Introduction

Unlike discounted expected utility theory, many models of generalized recursive utility relax the assumption of a direct linkage between preferences of objective uncertainty and intertemporal substitutability (e.g., 29; 30; 31). Applications of these models explain a wide variety of anomalies regarding asset prices, trade, and inflation (see below). An added implication of these models is that many of them require agents to have a preference over when uncertainty is to be resolved, independent of instrumental concerns. Initial debates concerned whether such preferences were plausible, and, if plausible, whether people prefer early or late resolution of uncertainty. Experimental work is generally divided and elicitation of these preferences may be complicated by other factors (see 32; 33, for surveys).

As conventionally defined, "uncertainty" includes both elements of "risk" and "ambiguity" (34). The objective domain of uncertainty, risk, describes a situation where the result is not known, but the underlying probability could be theoretically, or empirically determined; the subjective domain of uncertainty, ambiguity, describes a situation where people do not know any basis for objective probability. Interestingly, all aforementioned experimental studies that elicit preferences for uncertainty resolution have focused entirely on the domain of risk. That is, a determination of preferences for early resolution of uncertainty is only finding preferences for early resolution of risk, without establishing individuals' preferences over the removal of ambiguity. By considering environments with subjective uncertainty exclusively, the theoretical studies of (35) and (36) examine uncertainty resolution where ambiguity is considered. Since these papers focus on the subjective domain of uncertainty, the models examined by them may explain strict preferences for ambiguity resolution, but not risk.

This current paper provides the first experimental elicitation of preferences of uncertainty resolution in the subjective domain as well as in the objective domain. We elicit separate preferences over ambiguity and risk resolution and examine their interrelation with ambiguity attitude. In particular, we find that a plurality of the subjects (47.4%) prefer early resolution of risk and a majority (63.7%) prefer early resolution of ambiguity, and the two preferences are positively correlated.

Controlling for risk resolution preference, being ambiguity seeking decreases the likelihood of preferring early resolution of ambiguity by 25.6 percentage points.

The examination this paper provides is important for two separate reasons, one theoretical and one methodological. The main (theoretical) reason is that there are a variety of models of generalized recursive utility, many with different implications about preferences towards the timing of risk resolution and ambiguity resolution. Scholars began using these models, because the best-fitting discounted expected utility models required unrealistic parameter values.[1] While this specific determination of what is "unrealistic" can be done through introspection, anecdotal observation, or study of actual data, as models become more complex, it becomes more difficult to determine what is "realistic" through the former two methods. Since these generalized recursive utility models have different implications on an individual's preference on risk and ambiguity resolution, this paper investigates the full reasonableness of these theoretical implications. At a basic level, certain models of generalized recursive utility can only account for uncertainty resolution in the form of risk resolution and some can only account for uncertainty resolution in the form of ambiguity resolution. More complex relations exist as well. While the mean subject holds a preference for the early resolution of ambiguity, variation in this preference is positively correlated with variation in the preference for risk resolution. Further, the attitude toward ambiguity affects this relationship. Conclusions drawn about the validity of such models must necessarily include an investigation of both preferences over risk resolution and ambiguity resolution.

To understand what features are important for a model to have strict and differential preferences for risk and ambiguity resolution, we review six representative recursive utility models that have been axiomatized by decision theorists and are commonly applied to field data: the discounted expected utility model, the generalized recursive utility model of (29), the recursive smooth ambiguity model of **(author?)** (9, 38) and (18), the generalized recursive maxmin expected utility model of (39), and the generalized recursive smooth ambiguity model of (40).[2] A deductive examination

[1]For instance, to explain the equity premium puzzle, the risk-aversion parameter would need to be implausibly large (37).

[2]In the paper, the term "recursive utility model" refers to both the canonical discounted expected utility model and the other five generalized recursive utility models. Models of generalized recursive utility have consequential implications in many applications in empirical macroeconomic and finance literature. For example, (41), (42), and (43) assume that a representative agent has (30) preference; (44) adopt the recursive smooth ambiguity model; **(author?)** (45, 46) follow a continuous-time version of the recursive maxmin expected utility model; (47) and (48) essentially adopt the model axiomatized by (39); (49) follow the generalized recursive smooth ambiguity model axiomatized

reveals that only the generalized recursive smooth ambiguity model of (40)—which allows for a three-way separation between the parameter of risk attitude, the parameter of ambiguity attitude, and the elasticity of intertemporal substitution—is consistent with our results. This observation highlights the importance of separating the three parameters in empirical applications.

A secondary (methodological) reason concerns measurement and identification. Until this study, there has been no experimental elicitation of individuals' preferences over the resolution of ambiguity. All previous experimental studies have used preferences of risk resolution as a proxy for the more general, uncertainty resolution. Depending on the correlations between preferences of risk resolution and ambiguity resolution, the conclusions of these studies may vary in their validity. For instance, if preferences of risk and ambiguity resolution are not perfectly correlated, the use of risk-resolution preferences as a proxy for the entirety of one's uncertainty-resolution preferences is problematic.

There have been several previous experimental studies on uncertainty resolution. (33) provides a thorough review, categorizing and summarizing findings in four distinct areas. Early studies surveyed participants on their preferences and did not incentivize choice (53; 54; 55; 56). Later studies incentivized choice but were potentially confounded by the fact that the information revealed is instrumental (57; 32; 58; 59; 60). That is, learning the information early may pose an additional benefit to an individual outside of these preferences. In both categories, the literature often, but not always, finds a preference for the early resolution of uncertainty. Along a related line of experimental literature, there have also been papers studying the association between a subject's attitudes towards ambiguity and compound lotteries (e.g., 1; 61).

Among the studies that do not provide instrumental information, studies that rely on multi-stage lotteries—where uncertainty has yet to be determined—generally find preferences for late or gradual resolution of uncertainty (i.e., 62). Studies that rely on information structures—where the uncertainty is determined but yet to be resolved for the subject—generally find preferences for early resolution of uncertainty (i.e., 63; 64; 65). (33) is the first to note this relationship and demonstrates this general result in a unified, non-instrumental framework. That is, she finds a

by (40). In spite of differences in modeling details, these calibrated models are able to better explain the equity premium, the risk-free rate, and/or the volatility puzzles among others, to different degrees. See also (50), (51), and (52) for further applications of generalized recursive utility models in explaining puzzles in international economics and inflation.

preference for early resolution with information structures and late resolution with isomorphic multi-stage lotteries.

There are several additional key features of our experimental design. Our experiment follows the general structure of **(author?)**'s in the risk domain, eliciting subjects' preference over uncertainty with non-instrumental information in information structure frames. We build upon the design in that we separately elicit risk and ambiguity resolution preferences. To the best of our knowledge, the latter has not previously been elicited. Secondly, we examine more than binary choices, which have been the focus of the literature to date. We also include gradual resolution of information options (non-skewed, positively-skewed, and negatively skewed) as well as early and late options. Positively skewness eliminates more uncertainty about the good state and negatively skewness is the opposite.[3] Hence, participants express preferences over larger choice sets.

This paper proceeds as follows. Section II.2 details the experimental design and procedures on the elicitation of risk resolution preference, ambiguity resolution preference, and ambiguity attitude. Section II.3 provides hypotheses to test the six theoretical models, and Section II.4 provides experimental results. Section II.5 reviews six representative recursive utility models and examines their implications on the preferences of risk resolution and ambiguity resolution. Lastly, Section II.6 concludes.

II.2 Experimental Design and Procedures

The experiment consists of two parts: the risk-resolution-preference elicitation part and the ambiguity-resolution-preference elicitation part. Each part utilizes four questions to elicit subject preferences on the timing of risk/ambiguity resolution, yielding eight questions in total. The order of the two parts and the questions within are randomly ordered for subjects in four ways comprising four separate, within-subjects treatments. Full details of the random ordering are explained in Section II.2.3.

II.2.1 Risk-Resolution-Preference Elicitation

In the risk-resolution-preference elicitation experiment, subjects participate in a two-period consumption process. In $t = 1$, subjects receive $\$10$ advance payment. In $t = 2$, a lottery is drawn and the additional payoff is realized. The lottery has 50% chance leading to a "high prize (\$22)"

[3](66) focus on an environment with (1) objective uncertainty and (2) gradual resolution options only.

and 50% chance leading to a "low prize ($4)" ex-ante, and thus subjects have the same prior belief at the beginning of $t = 1$: the overall probability of winning the high prize is 0.5.

An additional piece of information on the underlying probability of the lottery is realized at the end of $t = 1$. The additional information is either a piece of "good news" or "bad news." Upon receiving the news, subjects update their beliefs on the chance of receiving the "low prize" and the "high prize" in $t = 2$.

An information structure is a vector (p, q, r) satisfying the constraint that $pq + (1 - p)r = 0.5$, where the value p is the probability of receiving good news, q is the probability of winning the high prize conditional on receiving good news, and r is the probability of winning the high prize conditional on receiving bad news. Following (33), we impose the restriction that $pq + (1 - p)r = 0.5$ to ensure that the prior belief of winning a high prize is equal to 0.5. A general consumption process is shown in Figure 1.

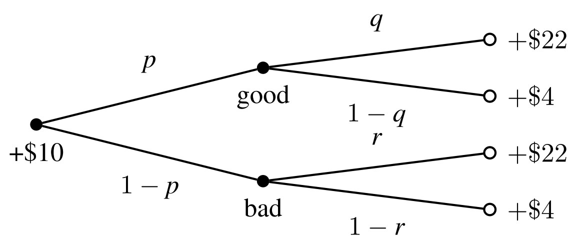


Figure II.1: A general consumption process in risk resolution experiment

In three separate questions, subjects are asked to select their most preferred information structure from a subset of options listed in Table II.1. The options are described as follows.

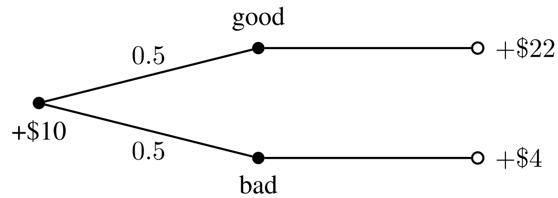
Under **One-Shot Early** option, all the risk is resolved in the first stage solely. To see this, if a subject receives good news, she will receive the high prize ($22) for sure ($q = 1$). Otherwise, she will receive the low prize ($4) for sure ($r = 0$). Hence, under One-Shot Early option, the consumption process shown in Figure II.1 can be simplified into Figure II.2(a).

Under the three Gradual options, risk is resolved gradually throughout two periods. Under the **Gradual (non-skewed)** information structure, good news and bad news are equally likely to arrive. Under the **Gradual (positively skewed)** information structure, the subject is more likely

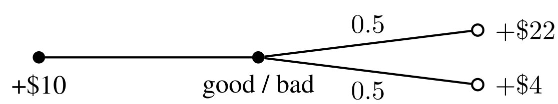
Options	Information Structure
One-Shot Early	p=0.5, q=1, r=0
Gradual (non-skewed)	p=0.5, q=0.75, r=0.25
Gradual (positively skewed)	p=0.2, q=0.9, r=0.4
Gradual (negatively skewed)	p=0.8, q=0.6, r=0.1
One-Shot Late	p=0.5, q=0.5, r=0.5

Table II.1: Options in risk resolution experiment

to receive bad news ($p = 0.2$). However, the good news is informative in the sense that the conditional probability of winning the high prize is very high upon receiving good news ($q = 0.9$). **Gradual (negatively skewed)** implies the opposite: the probability of receiving good news is high ($p = 0.8$), but the good news is not that informative ($q = 0.6$) compared to the good news under **Gradual (positively skewed)**. However, if a subject receives bad news, she has 90% chance to get the low prize.



(a) One-Short Early option (E)



(b) One-Short Late option (L)

Figure II.2: Information structures for early and late risk resolution options

The **One-Shot Late** option means risk is resolved all at once in the second stage. In this case, the news is useless, because regardless of the news she receives, her conditional winning probability remains the same ($q = r = 0.5$). Hence, one can simplify the consumption process as is illustrated in Figure II.2(b).

It is important to note that the choice of information structure does not affect the ex-ante probability of winning the high prize, which is equal to 0.5. Also, the choice of the information structure does not change the timing of the payment of the lottery, which takes place in $t = 2$.

There is a 30-minute lag after subjects receive a piece of news at the end of $t = 1$ and before they observe the realization of the lottery in $t = 2$. An inappropriate choice of time lag might cause an instrumental information issue. That means, subjects may *use* this information to adjust their future consumption, which implies that subjects' preference for early resolution might not be intrinsic. To prevent this potential issue, we implement a 30-minute lag between two stages where subjects will be occupied with another activity. To identify preferences for non-instrumental information, 30-minute is considered as a minimum, but substantial, time delay in existing studies (66; 33).

During the 30-minute lag, subjects participate in Raven's Progressive Matrices. The Raven test is one of the most widely used methods to measure abstract reasoning and analytic intelligence, by non-verbal multiple choice questions. Each question consists of a visual pattern with a missing piece, and the subjects are asked to pick the right element to fill in. Previous studies have found that people with high Raven test scores more accurately predict others' behavior (67), and update their beliefs with fewer errors (68). In our study, the main purpose of this test is to make subjects stay focused during the time delay. Our experiment consists of two parts and each part has the same 30-minute lag.

II.2.2 Ambiguity-Resolution-Preference Elicitation

The ambiguity-resolution-preference elicitation experiment is similar to the aforementioned risk-resolution experiment. Subjects are involved in a two-period consumption process. In $t = 1$, subjects receive the advance payment of $\$10$. In $t = 2$, a lottery is drawn and the payoff is realized. Subjects could earn a "high prize ($22)" or a "low prize ($4)" from this lottery. However, subjects do not know the winning probability of the lottery at the beginning of $t = 1$. Instead, subjects are given the following description:

> You will draw a ping pong ball out of a bag. The bag contains 60 ping pong balls, and each ball is either red or yellow. If you draw a red ping pong ball, then you will receive a high prize ($22). If you draw a yellow ball, then you will receive a low prize ($4). However, the precise composition of red ping pong balls versus yellow ones in the bag is unknown, although already determined. The only information now is that

> the proportion of red ping pong balls in the bag, denoted by **p**, can only be one of the following numbers: 10%, 40%, 60%, and 90%. So the probability for you to win the high prize is one of the following four numbers: 0.1, 0.4, 0.6, or 0.9.

As the proportion of each ball is unknown, at the beginning of $t = 1$, the probability of drawing each ball is unknown. Notice that it is not necessary that the case that 0.1, 0.4, 0.6, and 0.9 are drawn uniformly at random. At the end of $t = 1$, subjects receive a piece of news about the value of **p** from the ball they draw. Depending on the information structure, this news provides no information, partial information, or complete information about the winning probability.

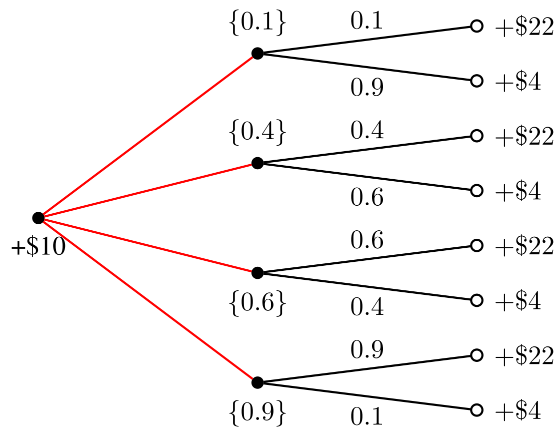
An information structure is a partition of the set $\{0.1, 0.4, 0.6, 0.9\}$. In three questions, subjects are asked to choose their most preferred option from a subset of the five alternatives listed in Table II.2.

Options	Information Structure
One-Shot Early	{0.1} {0.4} {0.6} {0.9}
Gradual (non-skewed)	{0.1, 0.4} {0.6, 0.9}
Gradual (positively skewed)	{0.1, 0.4, 0.6} {0.9}
Gradual (negatively skewed)	{0.1} {0.4, 0.6, 0.9}
One-Shot Late	{0.1, 0.4, 0.6, 0.9}

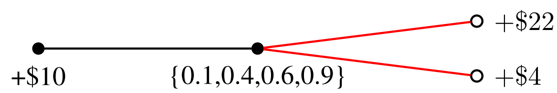
Table II.2: Options in ambiguity resolution experiment

One-Shot Early is the fully revealing information structure. If a subject chooses **One-Shot Early**, she will be informed of the exact winning chance **p** at the end of $t = 1$. Hence, ambiguity is resolved in $t = 1$. The consumption process has been summarized in Figure II.3(a). The red edges starting from the $t = 1$ node are realized with unknown probability. Conditional on a message that has been received, the black edges starting from the corresponding $t = 2$ node is realized with known probability.

The three information structures implied by the three Gradual options are partially revealing. If choosing **Gradual (non-skewed)**, the subject will either receive the message {0.1, 0.4} or {0.6, 0.9} at the end of $t = 1$ with unknown probability. If the winning chance is 0.1 or 0.4, she will receive the message {0.1, 0.4}. Otherwise, she will receive {0.6, 0.9}. A subject is not disclosed



(a) One-Shot Early option (E)



(b) One-Shot Late option (L)

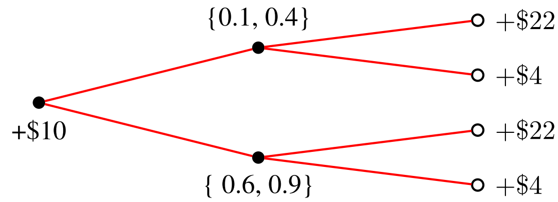
Figure II.3: Information structures for early and late ambiguity resolution options

the exact probability of the lottery upon receiving either message. Hence, ambiguity exists in both periods but is resolved gradually. The consumption process is illustrated in Figure II.4(a).

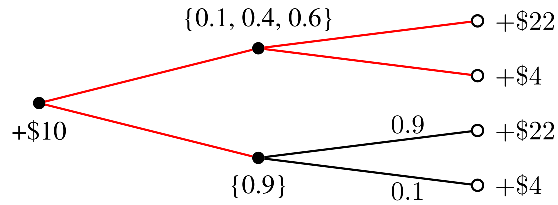
A subject choosing **Gradual (positively skewed)** option will either receive the message $\{0.9\}$ or $\{0.1, 0.4, 0.6\}$ at the end of $t = 1$. Hence, a subject will know if the true winning probability is 0.9 or not. Upon receiving $\{0.1, 0.4, 0.6\}$, the subject knows the winning probability in $t = 2$ is 0.1, 0.4, or 0.6, but she is not informed of the likelihood of each realization, and thus ambiguity still exists in $t = 2$. If $\{0.9\}$ is received, then ambiguity is dissolved immediately and only risk exists in $t = 2$. The consumption process is summarized in Figure II.4(b).

Similarly, under **Gradual (negatively skewed)**, one of the two messages will be realized at the end of $t = 1$: $\{0.1\}$ and $\{0.4, 0.6, 0.9\}$. It tells the individual whether the winning chance is 0.1 or not. We illustrate the process in Figure II.4(c).

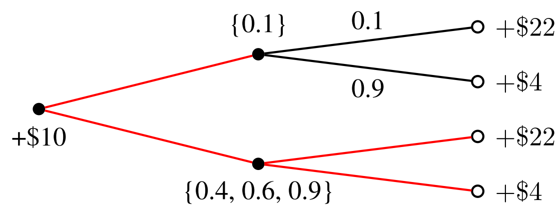
One-Shot Late leads to a non-revealing information structure. The only possible message received at the end of $t = 1$ conveys no new information and the subject knows that the value of **p** is 0.1, 0.4, 0.6, or 0.9. All uncertainty, including the value of **p** and the outcome, is resolved in $t = 2$. We illustrate this consumption process in Figure II.3(b).



(a) Gradual (non-skewed) option (G)



(b) Gradual (positively skewed) option (Gp)



(c) Gradual (negatively skewed) option (Gn)

Figure II.4: Information structures for three gradual ambiguity resolution options

The remaining steps are the same as in risk-resolution-preference elicitation experiment. Subjects encounter another set of questions from the Raven test during the 30-minute delay. After 30 minutes have elapsed, all risk and ambiguity are resolved.

II.2.3 Choice Set

The risk-resolution-preference/ambiguity-resolution-preference elicitation experiment utilizes four questions to determine subjects' preferences. The first three involve subjects picking their most preferred option from subsets of the five-option sets shown in Table II.1/Table II.2. The first question, denoted by RR1/AR1, is an unrestricted choice from the risk-resolution-preference/ambiguity-resolution choice set. The second question, denoted by RR2/AR2 removes the option "One-Shot Early" to eliminate the possibility that the subject's choice in the first question was due to a preference for simply one-shot resolution. The third question, denoted by RR3/AR3 removes the option "One-Shot Late." The last question, denoted by RRMPL/ARMPL, aims to measure the strength of preference for early resolution or late resolution by using the multiple price list. Each row presents a mini question that asks the subject to choose from two options "One-Shot Early + $\$x$" and "One-Shot Late + $\$y$." The values of x and y vary among different rows (see Figure II.5). For example, if a subject is indifferent to the timing of resolution, she will always choose the option with additional payment. However, if she strictly prefers early resolution, then she might give up some additional payment to choose one-shot early. These multiple price list questions rule out the potential problem that subjects are indifferent between One-Shot Early and One-Shot Late. Table II.3 provides a summary of these procedures.

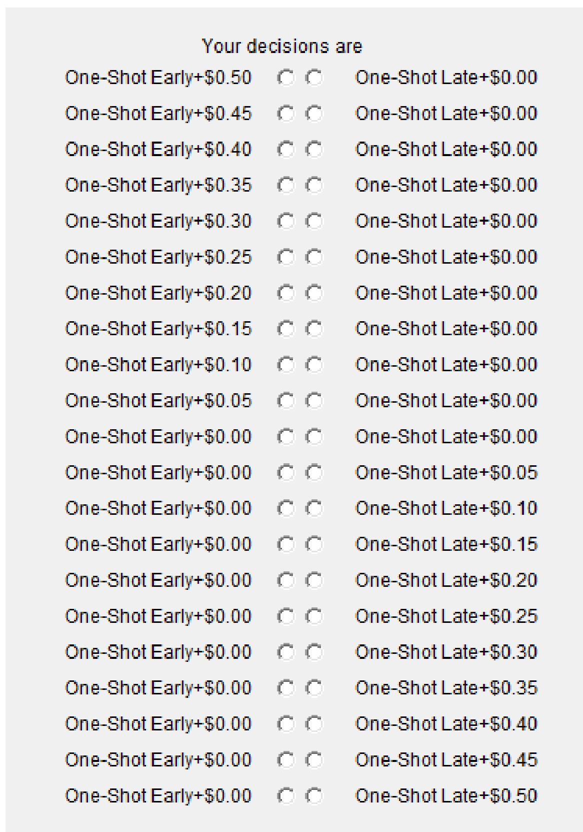


Figure II.5: Multiple price list questions

After finishing all four sections on risk resolution/ambiguity resolution, subjects receive news/messages based on their choices of information structures, conduct Raven's Progressive Matrices test for the

	Choices	Available Options	Description
RR	RR1	E, G, Gp, Gn, L	Unrestricted
	RR2	G, Gp, Gn, L	One-Shot Early is removed
	RR3	E, G, Gp, Gn	One-Shot Late is removed
	RRMPL	Multiple Price List Questions	
AR	AR1	E, G, Gp, Gn, L	Unrestricted
	AR2	G, Gp, Gn, L	One-Shot Early is removed
	AR3	E, G, Gp, Gn	One-Shot Late is removed
	ARMPL	Multiple Price List Questions	

Table II.3: Choice sets used in the experiment

next 30 minutes, and then the outcome is revealed. The ordering of the questions in the two elicitation tasks was partially randomized to reduce ordering effects. We randomize the order of decisions in four different ways.

Order 1. RR1, RR2, RR3, RRMPL; AR1, AR2, AR3, ARMPL

Order 2. RR1, RR3, RR2, RRMPL; AR1, AR3, AR2, ARMPL

Order 3. AR1, AR2, AR3, ARMPL; RR1, RR2, RR3, RRMPL

Order 4. AR1, AR3, AR2, ARMPL; RR1, RR3, RR2, RRMPL

II.2.4 Ellsberg Questions

Subjects also answered two (13) questions in the ambiguity-resolution-preference elicitation task section. Each subject has a small chance to receive an additional $10, depending on their answers to the questions. There are two reasons why these questions are necessary.

First, we need to elicit each subject's attitude toward ambiguity. Theoretically, ambiguity aversion may or may not affect the preference for early resolution depending on the theoretical model (see Section II.5). Hence, to know which model best explains the experimental results, it is essential to elicit the ambiguity attitude.

Another reason is to confirm that subjects are not using subjective expected utility (i.e., 69) in the ambiguity-resolution-preference elicitation task. If they use subjective belief in this task, the preference for resolution of ambiguity is no longer different from the preference for risk resolution. To make sure that ambiguity resolution questions and Ellsberg questions do not affect each other, Ellsberg questions are given to subjects after they have completed all ambiguity resolution questions, but before the revelation of the winning probability.

Subjects are given the following statement.

> Consider 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 balls are well mixed so that each individual ball is as likely to be drawn as any other. You will bet on the color that will be drawn from the bag.

Subjects are asked to choose their preferred options between A & B and between C & D. The four options are listed in Table II.4.

	Options
Option A	receiving a payment of $10, if a blue ball is drawn.
Option B	receiving a payment of $10, if a red ball is drawn.
Option C	receiving a payment of $10, if a blue ball or a yellow ball is drawn.
Option D	receiving a payment of $10, if a red ball or a yellow ball is drawn.

Table II.4: Subjective belief formation questions

A subject that prefers A to B and D to C demonstrates a traditional representation of ambiguity aversion. That is, there is no formulation of subjective probabilities that can rationalize this decision. We would thus infer the subject does not use subjective probabilities to make decisions under ambiguity.

II.2.5 Experimental Procedures

Subjects were 135 undergraduate students at Texas A&M University, recruited using the `econdollars.tamu.edu` website, a server based on ORSEE (70). Subjects sat at computer terminals and made decisions using zTree software (71). Sessions took place at the Experimental Research Laboratory at Texas A&M University from February to May 2021.

Subjects were fully informed about the procedure and the total time of the session at the beginning of the experiment. After the experiment concluded subjects were paid based on one randomly selected decision out of the eight that they made (see Table II.3). In addition, subjects have another chance to receive an additional $10 from the "bonus" question. The average payment for each participant was $23.33 including a $10 participation payment.

II.3 Hypotheses and Predictions

Table II.16 provides theoretical predictions of the six models studied in this paper. Each makes a distinct set of predictions about our experiment highlighted by the following hypotheses.

Hypothesis 3. *Subjects exhibit no preference for the resolution of risk. The answers provided in RR1–RR3 appear to be random. There is no preference for early or late resolution of risk demonstrated in RRMPL.*

A falsification of Hypothesis 3 would falsify the DEU, MEU and KMM models and provide differential support for the EZ, H, and HM models. Previous literature suggests Hypothesis 1 would be falsified.

Hypothesis 4. *Subjects will not exhibit ambiguity aversion in the Ellsberg task. Their responses will be in line with the use of subjective probabilities.*

A falsification of Hypothesis 4 would falsify the DEU and EZ model and provide differential support for the MEU, H, KMM, and HM models. Previous literature suggests Hypothesis 2 would be falsified.

Hypothesis 5. *Subjects will exhibit no preference for the resolution of ambiguity. The answers provided in AR1–AR3 will appear to be random. There is no preference for early or late resolution of ambiguity demonstrated in ARMPL.*

A falsification of Hypothesis 5 would falsify the DEU, MEU and H models and provide differential support for the EZ, KMM, and HM models. There is no precedent in previous literature to evaluate Hypothesis 3.

A rejection of all three hypotheses is only consistent with the HM model. That model allows subjects to exhibit preferences for early resolution of risk, preferences for early resolution of ambiguity, and ambiguity aversion.

II.4 Results

II.4.1 Risk Resolution and Ambiguity Resolution

Table II.5 shows the summary of the choices of risk resolution and ambiguity resolution. Consistent with previous literature, the modal response of subjects is the preference for early resolution of risk (64 of 135, 47.4%). A majority of subjects prefer the early resolution of ambiguity (86 of 135, 63.7%). The most commonly occurring combination of the two preferences is a preference for the early resolution of both risk and ambiguity (57 of 135, 42.2%).

		Ambiguity Resolution			
		Early	Gradual	Late	Total
Risk Resolution	Early	57	6	1	64
	Gradual	22	32	3	57
	Late	7	4	3	14
	Total	86	42	7	135
Chi-square test p-value ≈ 0.000					

Table II.5: Choices of risk resolution and ambiguity resolution

The statistical analysis supports that the preferences for risk resolution and ambiguity resolution are not randomly distributed. Both the chi-square test and Fisher's exact test reject the null hypothesis that these classifications are randomly distributed (both p-values < 0.001). Further, the preference for early resolution of ambiguity and early resolution of risk are positively correlated ($\rho \approx 0.5,$ p-value < 0.001). The combined result suggests both the existence of and a relationship between these two preferences.

Result 5. *The preferences most expressed by subjects in our data are preferences for the early resolution of both risk and ambiguity.*

Result 6. *Preferences for risk resolution and ambiguity resolution are positively correlated.*

The preceding results reject Hypothesis 3, that the preference for risk resolution does not exist. They also reject Hypothesis 5, that preference for ambiguity resolution does not exist.

II.4.2 Ambiguity Attitudes

Among 135 subjects, 63 (46.7%) were ambiguity averse, 60 (44.4%) were ambiguity neutral, and 12 (8.9%) were ambiguity seeking. A chi-square test rejects the null hypothesis of these results being randomly distributed at standard levels of significance ($p < 0.001$).

Result 7. *The ambiguity attitudes most expressed by subjects in our data are ambiguity aversion and ambiguity neutral.*

The existence of ambiguity aversion rejects Hypothesis 4. The combination of Results 5–7, falsifies all 3 hypotheses. Hence, among the six models, the HM model is the only model which is consistent with our experimental findings.

II.4.3 Relationship between Preference for Resolution and Ambiguity Attitude

In the remainder of this section, we further explore the observed relationship between the preference for risk resolution, the preference for ambiguity resolution, and ambiguity attitudes.

			Ambiguity Resolution			
			Early	Gradual	Late	Total
Ambiguity Averse	Risk Resolution	Early	28	2	0	30
		Gradual	12	11	1	24
		Late	4	2	3	9
		Total	44	15	4	63
Ambiguity Neutral		Early	24	4	0	28
		Gradual	10	16	2	28
		Late	3	1	0	4
		Total	37	21	2	60
Ambiguity Seeking		Early	5	0	1	6
		Gradual	0	5	0	5
		Late	0	1	0	1
		Total	5	6	1	12

Table II.6: Preferences for resolution of risk and ambiguity conditional on ambiguity attitudes

Table II.6 illustrates the choices of risk resolution and ambiguity resolution conditional on different ambiguity attitudes. As an implication of the HM model, Corollary 1, is composed of three parts:

1. If an ambiguity-averse subject prefers early resolution of risk, then she also prefers early resolution of ambiguity;
2. An ambiguity-neutral subject prefers early resolution of risk if and only if she prefers early resolution of ambiguity;
3. If an ambiguity-seeking subject prefers late resolution of risk, then she also prefers late resolution of ambiguity.

Concerning the first prediction, among 30 subjects who are ambiguity averse and prefer early resolution of risk, 28 (93.3%) also prefer early resolution of ambiguity vs. 58 out of 105 (55.2%) for the remaining subjects ($p < 0.001$, Fisher Exact Test). For the second prediction, among 28 subjects who are ambiguity neutral and prefer early resolution of risk, 24 (85.7%) also prefer early resolution of ambiguity vs. 62 of 107 (57.9%) for the remaining subjects ($p \approx 0.007$, Fisher Exact Test). Among 37 subjects who prefer early resolution of ambiguity and are ambiguity neutral, 24 (64.8%) also prefer early resolution of risk compared with 40 of 98 (40.1%) without that classification ($p \approx 0.02$, Fisher Exact Test). For the third prediction, only 1 subject is both ambiguity seeking and prefers the late resolution of risk – that subject prefers the gradual resolution of ambiguity. This last result is admittedly inconsistent with the model, but is based on a single subject decision. Taken together, we can conclude that our results are generally consistent with the HM model.

Result 8. *Conditional on different ambiguity attitudes, preferences for risk resolution and ambiguity resolution are correlated in a way consistent with Corollary 1 overall.*

We also investigate the marginal effect of ambiguity attitude on ambiguity resolution.

Table II.7 shows the preference for ambiguity resolution with different ambiguity attitudes. Among subjects with ambiguity averse and ambiguity neutral, 69.8% and 61.7% of them choose the early option in the ambiguity resolution task. This rate decreases among the group of ambiguity seekers: only 41.7% prefer early resolution of ambiguity.

To validate these observations, we utilize the logistic regression below:

$$P(y = 1) = F(b_1 x_1 + b_2 x_2), \tag{II.1}$$

		Ambiguity Resolution				
		Early	Gradual	Late	Total	Early %
Ambiguity Attitude	Averse	44	15	4	63	69.8%
	Neutral	37	21	2	60	61.7%
	Seeking	5	6	1	12	41.7%
	Total	86	42	7	135	63.7%

Table II.7: Preferences for resolution of ambiguity depending on ambiguity attitudes

where y is the binary dependent variable that equals 1 when a subject chooses the early option in the ambiguity resolution task, x_1 is a binary variable that equals 1 when a subject chooses the early option in the risk resolution task, and x_2 is a binary variable that equals 1 when a subject exhibits ambiguity seeking behavior on the Ellsberg task.

Marginal Effects on Choosing Early in AR			
	Marginal Effect	Standard Error	p-value
Early in RR	0.436	0.045	0.000
Ambiguity Seeking	-0.256	0.123	0.037

Table II.8: The average marginal effects in percentage points

Table II.8 shows marginal effects of the logistic regression model. Preferring early resolution of risk increases the likelihood of preferring early resolution of ambiguity by 43.6 percentage points (p-value < 0.001). Being ambiguity seeking decreases the likelihood of preferring early resolution of ambiguity by 25.6 percentage points (p-value ≈ 0.037).

Result 9. *A smaller proportion of ambiguity seeking subjects favor early resolution of ambiguity compared with those who are ambiguity neutral or ambiguity averse.*

II.4.4 Willingness to Pay

If someone is indifferent between early and late resolution, the switching point of the multiple price list questions will be 10 or 11. That means she only chooses the option with the additional payment and she does not want to give up any amount of money for any option. If someone prefers the early (late) resolution and is willing to pay some amount of money for her preferred option, the switching point will be greater (smaller) than 11 (10). Table II.9 provides the average switching points of each group.[4]

	Risk Resolution		Ambiguity Resolution	
Group	Number	Average Switching Point	Number	Average Switching Point
Early	54	11.7	81	12.6
Gradual	47	10.9	32	10.9
Late	13	8.3	5	9.4
Total	114	10.9	118	12.0

Table II.9: The average switching points of the multiple price list questions

The values of the switching points are correlated to the preference for the resolution of ambiguity. In both risk resolution and ambiguity resolution tasks, the average switching point of subjects who chose the gradual option is 10.9. It implies that on average, they were indifferent between early or late resolution of ambiguity.

The average switching point of the subjects who prefer early resolution of risk and ambiguity are 11.7 and 12.6, respectively. That means a large portion of them gave up some amount of payment to resolve the ambiguity earlier. Similarly, subjects who chose late resolution gave up the additional payment for the late resolution, considering the average switching points 8.3 and 9.4. The Cuzick non-parametric trend test across ordered groups reveals these differences are significant for both risk-resolution-preference and ambiguity-resolution-preference categorizations. (p-values < 0.001 in both cases.)

Result 10. *In both risk resolution and ambiguity resolution, subjects who prefer early or late resolution have a significantly greater willingness to pay for that respective resolution than subjects who choose gradual options.*

[4] Among 135 subjects, 21 (15.6%) and 17 (12.6%) exhibited multiple switching behavior in risk-resolution-preference elicitation questions and ambiguity-resolution-preference elicitation questions. We only use subjects who has a single switching point (114 (84.4%) and 118 (87.4%)) for our analysis.

II.4.5 Consistency

For each elicitation task, subjects answered three times with different sets of possible options (RR1-RR3 and AR1-AR3). We categorize subjects according to whether their choices are consistent with the weak axiom of revealed preference (WARP). Tables II.10 summarizes the classification.

		Ambiguity Resolution			
	Preference	Monotone	One-Shot	Inconsistent	Total
Risk Resoultion	Monotone	104	9	2	115
	One-Shot	8	9	0	17
	Inconsistent	3	0	0	3
	Total	115	18	2	135

Table II.10: Consistency of choices

When a subject's choices do not violate the weak axiom of revealed preference, we consider her preference is *monotone*. 104 of 135 subjects (77.0%) show monotone preferences for both the risk resolution and the ambiguity resolution tasks.

There are two other cases where choices violate the WARP. First, consider that a subject chooses One-Shot options across three choices, e.g., One-Shot Early in RR1, One-Shot Late in RR2, and One-Shot Early in RR3. She chooses One-Shot Early in RR1 not because she wants an earlier resolution as possible but because she prefers One-Shot resolution, whether early or late. We categorize these choices as the preference for *one-shot resolution.* 17 (12.6%) and 18 (13.3%) subjects preferred one-shot resolution in the risk resolution task and the ambiguity resolution task each.

When a subject chooses One-Shot Early in RR1, One-Shot Late in RR2, and Gradual in RR3, we consider her preference *inconsistent* because she neither prefers early, late or one-shot resolution. Only 3 (2.2%) and 2 (1.5%) subjects' choices are inconsistent.

We run the same logistic regression model in equation (II.1), but only with subjects whose preferences are monotone.

	Coefficients	Standard Error	p-value
Early in RR	2.67	0.59	0.000
Ambiguity Seeking	-1.53	0.80	0.057
LR chi-square test p-value $= 0.000$			

Table II.11: The result of logistic regression model with monotone subjects

Marginal Effects on Choosing Early in AR			
	Marginal Effect	Standard Error	p-value
Early in RR	0.471	0.060	0.000
Ambiguity Seeking	-0.269	0.134	0.045

Table II.12: The average marginal effects in percentage points with monotone subjects

Tables II.11 and II.12 show that the results are the same when using the whole population or the subjects whose preferences are monotone.

II.5 Theoretical Predictions

This section reviews six representative recursive utility models under uncertainty, including the discounted expected utility model (henceforth the DEU model) which is predominant in applied works, the generalized recursive utility model of (29), (30), and (31) (henceforth the EZ model), the recursive maxmin expected utility model of (72) and (73) (henceforth the MEU model), the recursive smooth ambiguity model of **(author?)** (9, 38) and (18) (henceforth the KMM model), the generalized recursive maxmin expected utility model of (39) (henceforth the H model), and the generalized recursive smooth ambiguity model of (40) (henceforth the HM model). When constant relative risk aversion ex-post utility functions are adopted, the models reviewed here can be easily described with three parameters: risk aversion parameter, ambiguity aversion parameter, and elasticity of intertemporal substitution, which make them particularly tractable in the macroeconomics and finance literature.[5]

[5](35) has provided a more complete review of recursive utility models with linear time aggregators and ambiguity aversion. A wide class of models reviewed there have been shown to capture preferences for early resolution of uncertainty in the subjective domain, e.g., the recursive smooth ambiguity model, the dynamic variational preference of (74), and the multiplier preference of (75). However, due to the linear time aggregators, these models cannot capture strict preferences for risk resolution. We hence only review the smooth ambiguity model as a representative one among this class.

These models differ from each other in two dimensions. First, they take two approaches to describe intertemporal substitution: to derive the ex-ante utility of a consumption process, the DEU, MEU, and KMM models use a linear aggregator to sum up the flow of utilities across different periods; the other three models adopt a non-linear aggregator. In addition, the models are based on three intratemporal decision-making criteria under uncertainty: the DEU model and the EZ model follow the subjective expected utility and do not support ambiguity aversion behaviors; the MEU model and the H model use the worst-case criterion to capture ambiguity aversion behaviors; the KMM model and the HM model permit a separation between ambiguity and ambiguity aversion and accommodate a richer class of ambiguity attitudes. We summarize the key differences of these models in Table II.13.

		Intratemporal Criterion		
		Expected Utility	Worst-case Scenario	Smooth Ambiguity
Intertemporal Aggregator	Linear	DEU	MEU	KMM
	Non-linear	EZ	H	HM

Table II.13: A summary of recursive utility models under uncertainty

For simplicity, we focus on two-period problems and finite state spaces in each period. Let S_1 and S_2 denote the state space in period 1 and period 2 respectively. Let $p \in \Delta(S_1 \times S_2)$ be a joint distribution over the state space and P be a set of such joint distributions representing ambiguity. Consistent with our experiment design, we assume for simplicity that the set of possible distributions P is finite. To define risk and ambiguity resolution, we focus on consumption processes that are constant in period 1 and s_2-dependent in period 2. Let H denote the set of all $h = (h_1, h_2)$, where $h_1 \in \mathbb{R}_+$ and $h_2 : S_2 \to \mathbb{R}_+$. The restriction allows us to focus on the informational value of s_1 without making it payoff-relevant.

For tractability, this paper assumes that utility functions are of the constant relative risk aversion form. In particular, define $u(x) \equiv \frac{x^\alpha}{\alpha}$, where $1-\alpha$ is the risk aversion parameter; define $v(x) \equiv \frac{x^\eta}{\eta}$, where $1-\eta$ is the ambiguity aversion parameter in the KMM and HM models; define $W(x, y) = (x^\rho + \beta y^\rho)^{\frac{1}{\rho}}$, where $\frac{1}{1-\rho}$ is the elasticity of intertemporal substitution in the EZ, H, and HM models, and β is the discount factor. Throughout the paper, we assume that α, η, $\rho \neq 0$ for the functions to be well-defined.

The DEU, MEU, and KMM models adopt linear time aggregators. The period-1 utility of a consumption process h after s_1 is realized is given by

$$V_1(h|s_1) = u(h_1) + \beta V_2(h|s_1) = \frac{h_1^{\alpha}}{\alpha} + \beta V_2(h|s_1),$$

where $V_2(h|s_1)$ is the continuation utility when s_1 is realized in period 1.

In the DEU model, the subject forms a unique subjective probability p over uncertainty and follows the expected utility to derive the continuation utility:

$$V_2(h|s_1) = \sum_{s_2 \in S_2} u(h_2(s_2))p(s_2|s_1) = \sum_{s_2 \in S_2} \frac{h_2^{\alpha}(s_2)}{\alpha} p(s_2|s_1).$$

In the MEU model, the decision maker believes that multiple distributions are relevant and evaluates a consumption process by considering the worst-case distribution. By adopting the prior-by-prior updating rule, the continuation utility is given by

$$V_2(h|s_1) = \min_{p \in P} \sum_{s_2 \in S_2} u(h_2(s_2))p(s_2|s_1) = \min_{p \in P} \sum_{s_2 \in S_2} \frac{h_2^{\alpha}(s_2)}{\alpha} p(s_2|s_1).$$

In the KMM model, a subject has a subjective second-order belief over potential probabilities and does not reduce compound lotteries. The continuation utility conditional on s_1 being observed in period 1 is given by

$$\begin{aligned} V_2(h|s_1) &= u \circ v^{-1}\Big(\sum_{p \in P} v \circ u^{-1}\big(\sum_{s_2 \in S_2} u(h_2(s_2))p(s_2|s_1)\big)\mu(p|s_1)\Big) \\ &= \Big(\sum_{p \in P}\big(\sum_{s_2 \in S_2} h_2^{\alpha}(s_2)p(s_2|s_1)\big)^{\frac{\eta}{\alpha}}\mu(p|s_1)\Big)^{\frac{\alpha}{\eta}}. \end{aligned}$$

When $\eta > \alpha$, i.e., when v is strictly less concave than u, the subject is ambiguity seeking. When $\eta < \alpha$, the subject exhibits ambiguity aversion, and in the limiting case that η goes to $-\infty$, the KMM model converges to the MEU model. When $\eta = \alpha$, the subject is ambiguity neutral and the model reduces to the DEU model.

The EZ, H, and HM models use a non-linear aggregator of the consumption today and the certainty equivalent of the continuation consumption. In particular, a subject's certainty equivalent in period 1, denoted by I_1, is given by

$$I_1(h|s_1) = W\big(h_1, I_2(h|s_1)\big) = \big(h_1^\rho + \beta I_2^\rho(h|s_1)\big)^{\frac{1}{\rho}},$$

where $I_2(h|s_1)$ is the certainty equivalent of continuation consumption conditional on s_1 being observed in period 1.

In the EZ model,

$$I_2(h|s_1) = u^{-1}\Big(\sum_{s_2\in S_2} u\big(h_2(s_2)\big)p(s_2|s_1)\Big) = \big(\sum_{s_2\in S_2} h_2^\alpha(s_2)p(s_2|s_1)\big)^{\frac{1}{\alpha}}. \tag{II.2}$$

In the H model,

$$I_2(h|s_1) = \min_{p\in P} u^{-1}\Big(\sum_{s_2\in S_2} u\big(h_2(s_2)\big)p(s_2|s_1)\Big) = \min_{p\in P}\big(\sum_{s_2\in S_2} h_2^\alpha(s_2)p(s_2|s_1)\big)^{\frac{1}{\alpha}}.$$

In the HM model,

$$\begin{aligned} I_2(h|s_1) =& v^{-1}\Big(\sum_{p\in P} v\circ u^{-1}\big(\sum_{s_2\in S_2} u(h_2(s_2))p(s_2|s_1)\big)\mu(p|s_1)\Big) \\ =& \Big(\sum_{p\in P}\big(\sum_{s_2\in S_2} h_2^\alpha(s_2)p(s_2|s_1)\big)^{\frac{\eta}{\alpha}}\mu(p|s_1)\Big)^{\frac{1}{\eta}}. \end{aligned}$$

We remark that the HM model is general. When $\alpha = \eta$, the HM model degenerates to the EZ model. When η approaches $-\infty$, the HM model converges to the H model. When $\alpha = \rho$, the HM model yields the KMM model as a special case, and the latter nests the DEU model and can approximate the MEU model in the limit.

In later sections, we mostly rely on the certainty equivalent expressions $I_1(h|s_1)$ and $I_2(h|s_1)$ rather than the continuation utility expressions $V_1(h|s_1)$ and $V_2(h|s_1)$. We denote $I_1(h|s_1)$ by $I_1[p](h|s_1)$ or $I_1[P](h|s_1)$ when necessary to highlight the ex-ante joint distribution p or the set of joint distributions P. Let $I_1[p](h)$ or $I_1[P](h)$ denote the ex-ante certainty equivalent of consumption process h before period-1 state is realized.

II.5.1 Risk Resolution

The literature has extensively studied preferences on the timing of risk resolution. In this section, we follow these papers and assume that the only uncertainty that arises in the environment is risk.

For each distribution q over S_2 with $|S_1| \geq |S_2|$, define a set $P(q) \equiv \{p \in \Delta(S_1 \times S_2) | p(s_2) = q(s_2), \forall s_2 \in S_2\}$, which is the set of all joint distributions over $S_1 \times S_2$ with marginal distributions over S_2 identical to q. Let $P^E(q) \subseteq P(q)$ be the set of all joint distributions $p \in P(q)$ that resolve risk early, i.e., p satisfies that $p(s_2|s_1) \in \{0, 1\}$ for all $s_1 \in S_1$ and $s_2 \in S_2$. Let $P^L(q) \subseteq P(q)$ be the set of all joint distributions $p \in P(q)$ that resolve risk late, i.e., p satisfies $p(s_2|s_1) = q(s_2)$ for all $s_1 \in S_1$ and $s_2 \in S_2$. Let $P^G(q) = P(q) \setminus (P^E(q) \cup P^L(q))$ denote all joint distributions that resolve risk gradually.

We consider the following example as an illustration.

Example 1. *Let S_1 be given by $\{s_1^1, s_1^2\}$ and S_2 be $\{s_2^1, s_2^2\}$. Consider a distribution over S_2, $q = (0.5, 0.5)$. In Table II.14, under each of the three joint distributions over $S_1 \times S_2$, the marginal distribution over S_2 is equal to q. Thus, from an ex-ante perspective, all three joint distributions are equally risky about the period-2 state.*

	s_2^1	s_2^2
s_1^1	0.5	0
s_1^2	0	0.5

(a) $p \in P^E(q)$

	s_2^1	s_2^2
s_1^1	0.3	0.2
s_1^2	0.2	0.3

(b) $p \in P^G(q)$

	s_2^1	s_2^2
s_1^1	0.25	0.25
s_1^2	0.25	0.25

(c) $p \in P^L(q)$

Table II.14: Three joint distributions with different timings of risk resolution

In Table II.14(a), upon receiving s_1, the subject knows the s_2 that will be realized. Thus, the period-2 risk is resolved early. In Table II.14(c), receiving each s_1 leads to the same posterior belief about which s_2 will be realized, and thus period-2 risk is resolved late. In Table II.14(b), the period-1 state s_1 is neither fully uninformative nor fully informative about which s_2 will be realized, and thus partially, or gradually, resolves period-2 risk.

Definition 1. *1. A subject is indifferent towards the timing of risk resolution if $I_1[p](h) = I_1[p'](h)$ for all $h \in H$, $q \in \Delta(S_2)$, and $p, p' \in P(q)$.*

2. A subject prefers early resolution of risk if she is not indifferent towards the timing of risk resolution, and $I_1[p](h) \geq I_1[p'](h)$ for all $h \in H$, $q \in \Delta(S_2)$, $p \in P^E(q)$, and $p' \in P(q)$.

3. A subject prefers late resolution of risk if she is not indifferent towards the timing of risk resolution, and $I_1[p](h) \geq I_1[p'](h)$ for all $h \in H$, $q \in \Delta(S_2)$, $p \in P^L(q)$, and $p' \in P(q)$.

According to the well-known result of (30), a subject with the EZ preference prefers early resolution of risk if $\alpha < \rho$, prefers late resolution of risk if $\alpha > \rho$, and is indifferent towards the timing of risk resolution if $\alpha = \rho$.

When the only uncertainty that arises in the environment is risk, since the H model and the HM model reduce to the EZ model, preferences towards the timing of risk resolution in the H model and the HM model can be characterized in the same way as in the EZ model. Also, when there is no ambiguity, the MEU model and the KMM model reduce to the DEU model which is essentially the EZ model with $\alpha = \rho$. Hence, a subject is indifferent toward the timing of risk resolution in the MEU/KMM/DEU model.

II.5.2 Ambiguity Resolution

We consider a notion of ambiguity resolution with a partition structure. Let Q be a finite set of possible period-2 distributions over S_2, which captures period-2 ambiguity from an ex-ante view, such that $|Q| = |S_1|$.[6] Let $\mathcal{Q}$ be a partition of Q: a period-1 state informs the subject of an element of $\mathcal{Q}$, i.e., a subset of possible period-2 distributions. Hence, when the partition is the finest one $\mathcal{Q}^E$, any period-1 state resolves period-2 ambiguity early by identifying the unique period-2 distribution. Similarly, the coarsest partition $\mathcal{Q}^L$ corresponds to late resolution of ambiguity, and any other partition $\mathcal{Q}^G$ corresponds to gradual resolution.

To compare ex-ante payoffs a subject receives under different timings of ambiguity resolution, i.e., from different partitions of Q, we construct a set of joint distributions over $S_1 \times S_2$ for each partition $\mathcal{Q}$, denoted by $P[\mathcal{Q}](Q)$. This set can be understood as possible beliefs over $S_1 \times S_2$ from an ex-ante perspective. As an illustration, we look at the following example.

[6] We restrict Q to be finite and to satisfy $|Q| = |S_1|$ so that it is feasible to fully resolve ambiguity in period 1 by having a one-to-one relationship between states in S_1 and distributions in Q.

Example 2. *Let S_1 be given by $\{s_1^1, s_1^2, s_1^3, s_1^4\}$ and S_2 be $\{s_2^1, s_2^2\}$. Let $Q = \{q^1 = (0.1, 0.9), q^2 = (0.4, 0.6), q^3 = (0.6, 0.4), q^4 = (0.9, 0.1)\}$ represent possible period-2 distributions over S_2 from an ex-ante perspective. Table II.15 shows three sets of joint distributions over $S_1 \times S_2$. The second set of joint distributions, $P[\mathcal{Q}^G](Q)$, is generated by Let $\mathcal{Q}^G = \{\{q^1, q^2\}, \{q^3, q^4\}\}$. Again, $\mathcal{Q}^E$ and $\mathcal{Q}^L$ are the finest and coarsest partitions of Q respectively.*

	s_2^1	s_2^2
s_1^1	0.1	0.9
s_1^2	0	0
s_1^3	0	0
s_1^4	0	0

	s_2^1	s_2^2
s_1^1	0	0
s_1^2	0.4	0.6
s_1^3	0	0
s_1^4	0	0

	s_2^1	s_2^2
s_1^1	0	0
s_1^2	0	0
s_1^3	0.6	0.4
s_1^4	0	0

	s_2^1	s_2^2
s_1^1	0	0
s_1^2	0	0
s_1^3	0	0
s_1^4	0.9	0.1

(a) $P[\mathcal{Q}^E](Q)$

	s_2^1	s_2^2
s_1^1	0.05	0.45
s_1^2	0.05	0.45
s_1^3	0	0
s_1^4	0	0

	s_2^1	s_2^2
s_1^1	0.2	0.3
s_1^2	0.2	0.3
s_1^3	0	0
s_1^4	0	0

	s_2^1	s_2^2
s_1^1	0	0
s_1^2	0	0
s_1^3	0.3	0.2
s_1^4	0.3	0.2

	s_2^1	s_2^2
s_1^1	0	0
s_1^2	0	0
s_1^3	0.45	0.05
s_1^4	0.45	0.05

(b) $P[\mathcal{Q}^G](Q)$

	s_2^1	s_2^2
s_1^1	0.025	0.225
s_1^2	0.025	0.225
s_1^3	0.025	0.225
s_1^4	0.025	0.225

	s_2^1	s_2^2
s_1^1	0.1	0.15
s_1^2	0.1	0.15
s_1^3	0.1	0.15
s_1^4	0.1	0.15

	s_2^1	s_2^2
s_1^1	0.15	0.1
s_1^2	0.15	0.1
s_1^3	0.15	0.1
s_1^4	0.15	0.1

	s_2^1	s_2^2
s_1^1	0.225	0.025
s_1^2	0.225	0.025
s_1^3	0.225	0.025
s_1^4	0.225	0.025

(c) $P[\mathcal{Q}^L](Q)$

Table II.15: Three sets of joint distributions with different timings of ambiguity resolution

For each partition $\mathcal{Q}$ above, we can label the elements of $P[\mathcal{Q}](Q)$, from left to right, by p^1 to p^4 respectively. Elements of $P[\mathcal{Q}](Q)$ have a one-to-one correspondence with those in Q: upon receiving any $s_1 \in S_1$ that occurs with positive probability under $p^k \in P[\mathcal{Q}](Q)$, the updated belief of p^k over S_2 coincides with q^k, i.e., $p^k(\cdot|s_1) = q^k(\cdot) \in \Delta(S_2)$ for all $k \in \{1, 2, 3, 4\}$ and $s_1 \in S_1$ such that $p^k(s_1) > 0$.

Suppose a subject's ex-ante ambiguous beliefs over $S_1 \times S_2$ are given by Table II.15(a). When

$s_1^k \in S_1$ is realized, the only joint distribution in $P[\mathcal{Q}^E](Q)$ generating s_1^k with positive probability is p^k, and the subject knows that the true distribution over S_2 is q^k immediately. In this sense, receiving a period-1 state resolves ambiguity about period-2 distribution early.

Suppose a subject's ex-ante ambiguous beliefs over $S_1 \times S_2$ are given by Table II.15(c). Since all other five models are either special cases of the HM model or can be approximated by the HM model, we assume there is a second-order belief μ over Q. Given μ, let $\tilde{\mu}$ be a second-order belief over $P[\mathcal{Q}^L](Q)$ whose marginal distribution over Q is consistent with μ, i.e., $\tilde{\mu}(q^k) = \mu(q^k)$ for $k \in \{1, 2, 3, 4\}$. Due to the one-to-one correspondence between $P[\mathcal{Q}](Q)$ and Q, the only consistent $\tilde{\mu}$ must satisfy $\tilde{\mu}(p^k) = \mu(q^k)$ for $k \in \{1, 2, 3, 4\}$. Now, we verify that knowing period-1 state s_1 does not provide any information on period-2 distribution. Given $s_1 \in S_1$, the posterior belief for $q^k \in Q$ to be the true period-2 distribution is equal to

$$\frac{\sum_{p \in P[\mathcal{Q}^L](Q)\, s.t.\, p(\cdot|s_1) = q^k} \tilde{\mu}(p) \cdot p(s_1)}{\sum_{p \in P[\mathcal{Q}^L](Q)} \tilde{\mu}(p) \cdot p(s_1)} = \frac{\tilde{\mu}(p^k) \cdot p^k(s_1)}{\sum_{p \in P[\mathcal{Q}^L](Q)} \tilde{\mu}(p) \cdot p(s_1)} = \frac{\mu(q^k) \cdot 0.25}{0.25} = \mu(q^k),$$

which is independent of $s_1 \in S_1$ and coincides with the prior. Hence, we say $P[\mathcal{Q}^L](Q)$ resolves ambiguity late (i.e., does not resolve ambiguity in period 1).

In Table II.15(b), for any $\mu \in \Delta(Q)$, the only $\tilde{\mu} \in \Delta(P[\mathcal{Q}^G](Q))$ whose marginal distribution over Q is consistent with μ must satisfy that $\tilde{\mu}(p^k) = \mu(q^k)$ for $k \in \{1, 2, 3, 4\}$. Upon receiving any $s_1 \in \{s_1^1, s_1^2\}$, one can immediately see that the true period-2 distribution q must be in $\{q^1, q^2\}$. Moreover, one can derive from $\tilde{\mu}$ that the posterior belief that q^1 or q^2 is the correct period-2 distribution is equal to $\mu(q^1|\{q^1, q^2\})$ or $\mu(q^2|\{q^1, q^2\})$ respectively, which is independent of $s_1 \in \{s_1^1, s_1^2\}$. We can hence claim that elements of $\{s_1^1, s_1^2\}$ are equivalent – the information of both states is that the set of possible period-2 distributions is $\{q^1, q^2\}$. If $s_1 \in \{s_1^3, s_1^4\}$ is received, the information is that the set of possible period-2 distributions is $\{q^3, q^4\}$. The set of joint distributions $P[\mathcal{Q}^G](Q)$ hence gradually resolves ambiguity (i.e., partially resolves ambiguity in period 1).

We remark on two features of $P[\mathcal{Q}](Q)$. First, its elements have a one-to-one correspondence with elements of Q in the following sense: (1) each joint distribution in $P[\mathcal{Q}](Q)$ can only lead to one posterior belief in Q, regardless of the period-1 state observed, and (2) different joint distributions in $P[\mathcal{Q}](Q)$ have different posterior beliefs in Q. Second, for a general partition $\mathcal{Q}$, there may be multiple period-1 states leading to the same set of possible period-2 distributions: these states are equivalent informationally. The number of these equivalent classes is equal to the cardinality of $\mathcal{Q}$. Different equivalent classes of states in S_1 inform the subject of different elements of $\mathcal{Q}$.

We define the preferences towards the timing of ambiguity resolution as follows.

Definition 2. 1. *A subject is indifferent towards the timing of ambiguity resolution if* $I_1\big[P[\mathcal{Q}](Q)\big](h) = I_1\big[P[\mathcal{Q}'](Q)\big](h)$ *for any finite set* $Q \subseteq \Delta(S_2)$*,* $h \in H$*, partitions* $\mathcal{Q}$ *and* $\mathcal{Q}'$ *of* Q*, and* $\mu \in \Delta(Q)$*.*

2. *A subject prefers early resolution of ambiguity if she is not indifferent towards the timing of ambiguity resolution, and* $I_1\big[P[\mathcal{Q}^E](Q)\big](h) \geq I_1\big[P[\mathcal{Q}](Q)\big](h)$ *for any finite set* $Q \subseteq \Delta(S_2)$*,* $h \in H$*, partition* $\mathcal{Q}$*, and* $\mu \in \Delta(Q)$*.*

3. *A subject prefers late resolution of ambiguity if she is not indifferent towards the timing of ambiguity resolution, and* $I_1\big[P[\mathcal{Q}^L](Q)\big](h) \geq I_1\big[P[\mathcal{Q}](Q)\big](h)$ *for any finite set* $Q \subseteq \Delta(S_2)$*,* $h \in H$*, partition* $\mathcal{Q}$*, and* $\mu \in \Delta(Q)$*.*

Below we characterize preferences for ambiguity resolution in the six representative recursive utility models. We begin with the HM model first.

Proposition 1. *In the HM model, a subject prefers early resolution of ambiguity (resp. prefers late resolution of ambiguity or is indifferent towards the timing of ambiguity resolution) if* $\eta < \rho$ *(resp.* $\eta > \rho$ *or* $\eta = \rho$*).*

Proposition 1 shows that the preference for timing of ambiguity resolution is determined by two key factors: ρ and η. Recall the conclusion on risk resolution: α and ρ determine the preference for timing of risk resolution in the HM model.

In view of the two results, we can find the following connections between preferences towards the timing of risk resolution and ambiguity resolution.

Corollary 1. *In the HM model,*

1. *if an ambiguity-averse subject prefers early resolution of risk, then she also prefers early resolution of ambiguity;*

2. *an ambiguity-neutral subject prefers early resolution of risk (resp. prefers late resolution of risk, or is indifferent towards the timing of risk resolution) if and only if she prefers early resolution of ambiguity (resp. prefers late resolution of ambiguity, or is indifferent towards the timing of ambiguity resolution);*

3. *if an ambiguity-seeking subject prefers late resolution of risk, then she also prefers late resolution of ambiguity.*

Although the H model can be viewed as a limiting case of the HM model with $\eta \to -\infty$, the following result shows that the H model does not accommodate strict preferences towards the timing of ambiguity resolution.

Proposition 2. *In the H model, a subject is indifferent towards the timing of ambiguity resolution.*

As the DEU model is equivalent to the HM model with $\alpha = \rho = \eta$, the KMM model is equivalent to the HM model with $\alpha = \rho$, the EZ model is equivalent to the HM model with $\alpha = \eta$, and the MEU model is equivalent to the H model with $\alpha = \rho$, we have the following four corollaries.

Corollary 2. *In the DEU model, a subject is indifferent towards the timing of ambiguity resolution.*

Corollary 3. *In the KMM model, a subject prefers early resolution of ambiguity (resp. prefers late resolution of ambiguity, or is indifferent towards the timing of ambiguity resolution) if $\eta < \alpha$ (resp. $\eta > \alpha$, or $\eta = \alpha$).*

Corollary 4. *In the EZ model, a subject prefers early resolution of ambiguity (resp. prefers late resolution of ambiguity, or is indifferent towards the timing of ambiguity resolution) if $\alpha < \rho$ (resp. $\alpha > \rho$, or $\alpha = \rho$).*

Corollary 5. *In the MEU model, a subject is indifferent towards the timing of ambiguity resolution.*

II.5.3 Summary of Predictions

Table II.16 shows the summary of theoretical implications from each model. The first column means that the EZ, H, and HM models accommodate non-indifference in the timing of risk

	Risk Resolution	Ambiguity Resolution	Ambiguity Attitude
DEU			
MEU			✓
KMM		✓	✓
EZ	✓	✓	
H	✓		✓
HM	✓	✓	✓

Table II.16: Theoretical predictions from six models

resolution under some parameter values. The second column implies the KMM, EZ (with subjective beliefs), and HM models support non-indifference in the timing of ambiguity resolution under some parameter values. The last column shows that the MEU, KMM, H, and HM models can be used to explain non-neutral ambiguity attitudes. Hence, among these models, only the HM model can simultaneously accommodate strict preferences towards the timing of risk resolution and ambiguity resolution, as well as non-neutral ambiguity attitudes. Moreover, among the six models, the HM model is the only one that allows differential strict preferences in the timing of risk resolution and in the timing of ambiguity resolution.

II.6 Conclusion

Models of generalized recursive utility provide alternatives to the standard discounted expected utility model. They are quite useful in explaining various financial and macroeconomic anomalies that cannot be explained by the discounted expected utility model without highly dubious parameter choices. An implication of models of generalized recursive utility is a preference towards the timing of uncertainty resolution. Since these empirical estimations do not directly elicit preferences for the resolution of uncertainty, a natural question is whether it is reasonable to believe individuals have such preferences. A large number of experimental studies have found such preferences. However, all have looked at preferences over risk resolution, neglecting whether individuals have preferences over ambiguity resolution. Since different models make different assumptions about the two preferences, it is not clear to what extent models of generalized recursive utility are supported by solely findings based on risk-resolution preferences.

Our study provides the first experimental elicitation of preferences over ambiguity resolution, in addition to eliciting these preferences along with risk-resolution preferences. We also find that these two preferences are positively correlated, and the attitude toward ambiguity affects this relationship. If an individual prefers early resolution of risk, she is 43.6 probability points more likely to prefer early resolution of ambiguity. If she is ambiguity seeking, she is 25.6 probability points less likely to prefer early resolution of ambiguity.

We review six representative models of recursive utility that are widely used in the macroeconomics and finance literature. Most of these theoretical models of recursive utility, including the EZ model and the KMM model, are not consistent with these results. The totality of our findings is consistent with only one model, the generalized recursive smooth ambiguity models of (40).

III. VACCINATION DECISIONS AND AMBIGUITY AVERSION

III.1 Introduction

Vaccination is considered to be one of the greatest public health achievements. A high vaccination uptake rate is necessary to reduce the prevalence of vaccine-preventable diseases (VPD), including cholera, Ebola, diphtheria, or COVID-19. However, many people still have refused or hesitated to take the vaccine (76; 77; 78; 79; 80; 81). Surveys assess that the estimates of Americans' vaccine hesitancy about COVID-19 are between 25-34%. (81).

The World Health Organization (WHO) defined vaccine hesitancy as "the delay in acceptance or refusal of vaccination despite the availability of vaccination services." We focus on the former (delay) not the latter (refusal). This study provides experimental evidence that the "wait and see" attitude toward vaccines could be related to one of the psychological barriers: ambiguity aversion.

Due to its construction, vaccine development inevitably lags behind the emergence of new infectious diseases. Even in the most successful cases, such as with COVID-19, there is typically a one-year lag. Therefore, it is often the case that the risk of the virus becomes known while the potential side effects of the vaccine are not yet disclosed. Therefore, according to (13), the virus represents a known risk, while the vaccine may appear ambiguous. In this case, a "Wait and see" strategy may be simply waiting for the uncertainty associated with the side effect of the vaccine to become fully known. Concerns over the Janssen (Johnson & Johnson) COVID-19 vaccine could be examples (FDA, April 2021).

There is plenty of literature on how ambiguity affects medical decisions. (82) reveal individuals are more pessimistic in medical decisions under ambiguity than under risk. (83) theoretically show that the probability of side effects and the efficacy of the vaccine reduces the take-up rate of ambiguity averse individuals. (84) finds ambiguity about the outcomes of childhood immunization is an important factor in parental vaccine hesitancy. (85) reveal communicating scientific uncertainty about VPD risk and vaccine effectiveness leads to ambiguity aversion.

Our study employs the Interactive Vaccination (I-Vax) Game framework from (86) to observe interactive vaccination decisions. In addition to the standard I-Vax game (No Ambiguity treatment), we have added a new treatment where there is ambiguity in the side effects of the vaccine

(Ambiguity treatment).

We found that vaccination decisions are tightly associated with ambiguity. First, participants in the Ambiguity treatment are less likely to get vaccinated than those in the No Ambiguity treatment. The presence of ambiguity makes the vaccination option less appealing to them. Further, our results indicate that participants' attitudes towards ambiguity impact their vaccination decisions. Specifically, participants who are averse (seeking) to ambiguity are less (more) likely to choose to get vaccinated. Moreover, our study found that participants who are averse to (seeking) ambiguity are also less (more) likely to opt for vaccination in the Ambiguity treatment compared to the No Ambiguity treatment.

The rest of the paper is structured as follows: Section III.2 presents the experimental design and procedure. Section III.3 reports experimental results, and Section III.4 provides the concluding remarks.

III.2 Experimental Design

III.2.1 I-VAX Game

We used Interactive Vaccination (I-Vax) Game from (86) as the basic framework. They found individuals react to the interactive incentive structure and make strategic vaccination decisions. We used two versions of the I-Vax Game as two treatments: No Ambiguity treatment, which is identical to the standard I-Vax Game of (86), and Ambiguity treatment. 120 subjects participated in No Ambiguity treatment, and another 120 subjects participated in Ambiguity treatment.

III.2.1.1 No Ambiguity Treatment

In the standard I-Vax Game, participants play in groups of 12 over 20 rounds. In each round, they are endowed with 100 points and decide whether to get vaccinated or not. Their payoff of each round depends on their own decision and other group members' decisions.

Each vaccinated participant pays a fixed cost $c^{fixed} = 5$. Also, vaccinated participants might occur a side effect, with a probability of $p_1 = 0.3$. In the case of the side effect, the point loss would be $21, 36, 51$ with probabilities of $0.5, 0.4, 0.1$. Figure III.1 shows each consequence and its probability.

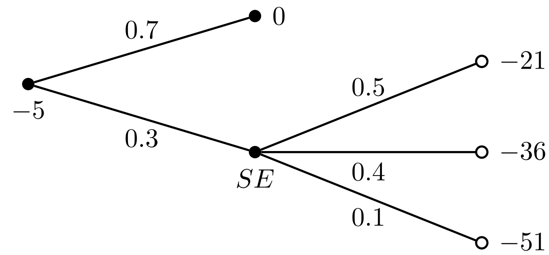


Figure III.1: Consequences and probabilities of vaccination

On the other hand, each unvaccinated participant could get a disease for each round. The probability of having the disease (p_0) depends on the number of other participants in her group who get vaccinated: The greater the number of vaccinated people, the lower the probability of point loss for unvaccinated participants. (See Figure III.2.) In the case of the disease, the point loss would be 35, 60, 85 with probabilities of 0.5, 0.4, and 0.1 each.

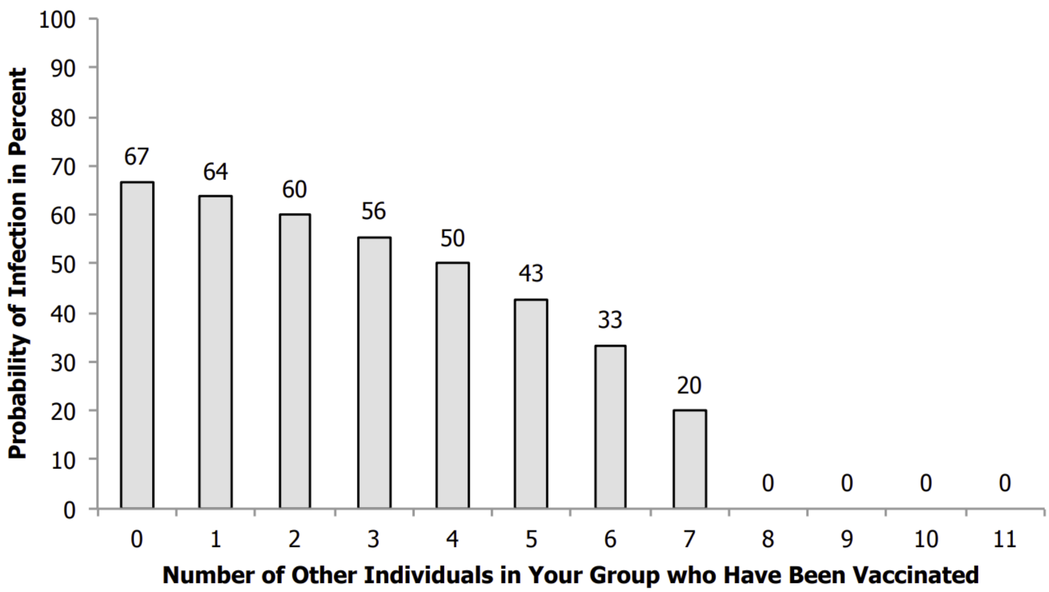


Figure III.2: How p_0 is determined based on other participants' decisions

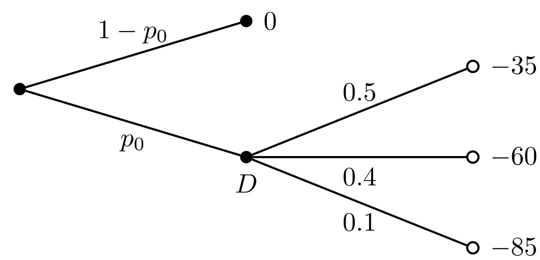


Figure III.3: Consequences and probabilities without vaccination

III.2.1.2 Ambiguity Treatment

In addition to the standard I-Vax setting, we added additional treatment, where ambiguity exists in the vaccination option. The possible consequences and probabilities of the side effect are different from the standard I-Vax Game, while other features are identical.

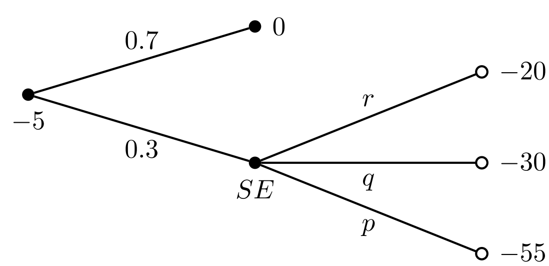


Figure III.4: Consequences and probabilities of vaccination

In this treatment, the values of p, q, r are unknown. The only restriction about these parameters is $p < 0.5$. This restriction leads to the important feature of the design, which is that the side effect under vaccination first-order stochastically dominates the disease without vaccine.[1]

III.2.2 Social Value Orientation (SVO)

To measure preference for allocation between herself and others, we use social value orientation (SVO) slider measure (87). Participants make 6 allocation decisions of decomposed games,

[1]Consider SE', a lottery that yields -35 with a probability of 0.5 and -55 with a probability of 0.5. The worst distribution of SE is better than $(p, q, r) = (0.5, 0.5, 0)$ since $p < 0.5$. Hence, SE first-order stochastically dominates SE'. Also, we can consider $D' = (-35, 0.5; -60, 0.5)$, which first-order stochastically dominates D. If there is no time discount, $D' = SE'$. Hence, SE first-order stochastically dominates D.

allocating points between themselves and an unknown participant. Responses for 6 decisions yield a single angle index, classifying the participant as prosocial, individualistic, or competitive.

III.2.3 Ambiguity Attitude

We elicited ambiguity attitudes by using two questions from (13).

> 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.

Participants chose their preferred options between A & B and between C & D. Table III.1 shows the 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 III.1: Ellsberg questions

If the submitted choices are A and D, the preference is considered to be a consequence of ambiguity aversion. Also, B and C represent ambiguity seeking preference, and the others choices show ambiguity neutral.

III.2.4 Vaccination Attitude

After finishing SVO slider tasks, I-Vax Game, and Ellsberg questions, participants were asked about their attitude towards vaccination. First, we measured participants' general attitudes toward vaccination. They submit a value of a 100-point bipolar slider item from $1 =$ completely against vaccination to 100 = completely for vaccination. Also, we measure their attitudes toward COVID-19 vaccine. The possible answer to the question "What is your attitude towards the COVID-19 vaccination?" varies from 1 = very negative to 5 = very positive.

Finally, we conducted a demographic survey (age, gender, and subject).

III.2.5 Procedure

240 subjects completed 20 sessions (10 Ambiguity Treatment and 10 No Ambiguity Treatment) from May to September 2022 in Texas A&M Economic Research Laboratory, recruited on a database using ORSEE (70). All experiments were implemented with z-Tree (71). Each session takes 30 minutes on average, and the average earnings were $18.87, including $10 show-up payment.

III.2.6 Hypotheses

First, we hypothesize the treatment effect: the vaccine take-up rate is lower in Ambiguity treatment because there is ambiguity in the vaccination option.

Hypothesis 6. *Participants are more likely to take the vaccine in No Ambiguity Treatment than in Ambiguity treatment*

Furthermore, we hypothesize that ambiguity affects vaccination decisions, and its effect is heterogeneous in treatment.

Hypothesis 7. *Ambiguity averse (seeking) participants are more (less) likely to take the vaccine.*

Hypothesis 8. *Ambiguity averse (seeking) participants are less (more) likely to take the vaccine in Ambiguity treatment than in No Ambiguity treatment.*

III.3 Results

III.3.1 Vaccination Decisions

Figure III.5 shows the overall vaccination rate in both treatments. The average vaccination rate is 0.527 for No Ambiguity treatment and 0.497 for Ambiguity treatment. The difference of 0.030 is statistically significant (the p-value is 0.059).

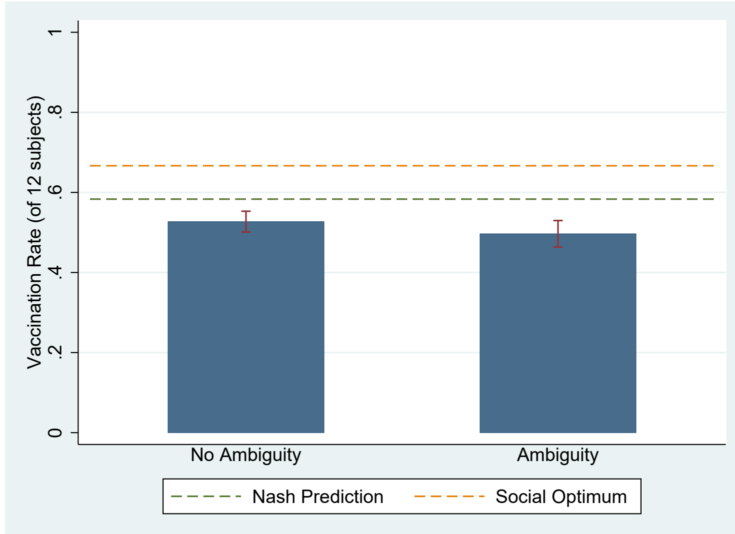


Figure III.5: Vaccination rates by treatment

Result 11. *Participants are less likely to choose the vaccination in Ambiguity treatment than in No Ambiguity treatment.*

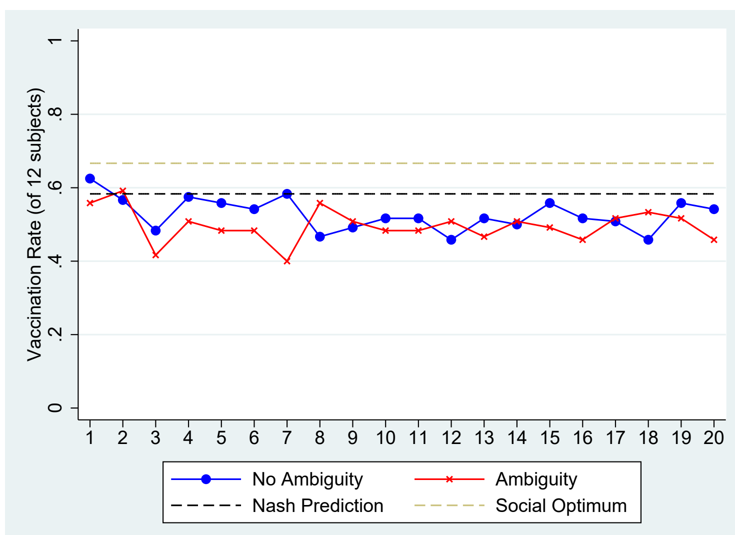


Figure III.6: Overall Vaccination Rates

Figure III.6 illustrates each treatment's vaccination rates over rounds. For periods 1-10, the average vaccination rate of No Ambiguity treatment and Ambiguity treatment is 0.540 and 0.499 each, and the difference is 0.041 (p-value is less than 0.05). On the other hand, for periods 11-20, where the average rate is 0.513 and 0.494 each, the difference shrinks to 0.019 (p-value is around 0.4).

III.3.2 Ambiguity and Vaccination

Results from the Ellsberg question show 125 participants (52.1%) show ambiguity aversion, 87 participants (36.2%) show ambiguity neutral, and 28 participants (11.7%) show ambiguity seeking preference. Table III.2 presents vaccination decisions depending on ambiguity attitude. We found that participants' vaccination rate is related to ambiguity attitude. (The p-values of both the Chi-square test and Fisher's exact test are 0.000.)

Ambiguity Attitude	Vaccination	No Vaccination
Averse	41.8%	58.2%
Neutral	49.6%	50.4%
Seeking	54.4%	45.6%
chi-square $p = 0.000$		

Table III.2: Ambiguity attitudes and vaccination decisions

Result 12. *Ambiguity averse (seeking) participants are less (more) likely to take the vaccine.*

Figure III.7 displays how ambiguity attitude is related to vaccination decisions in each treatment. In No Ambiguity treatment, preference for ambiguity is negatively correlated to vaccination decision: ambiguity-averse (ambiguity-seeking) participants were less (more) likely to take the vaccine.

On the other hand, in Ambiguity treatment, the preference/dislike for ambiguity offsets the relation. For example, ambiguity-seeking participants are basically less likely to want to take the vaccine. However, since there is an ambiguity in the vaccine in Ambiguity treatment, the vaccination option becomes more attractive to them. On the contrary, ambiguity-averse participants are more likely to take the vaccine. However, because of ambiguity in the vaccine, they find the vaccination option less attractive in Ambiguity treatment compared to No Ambiguity treatment.

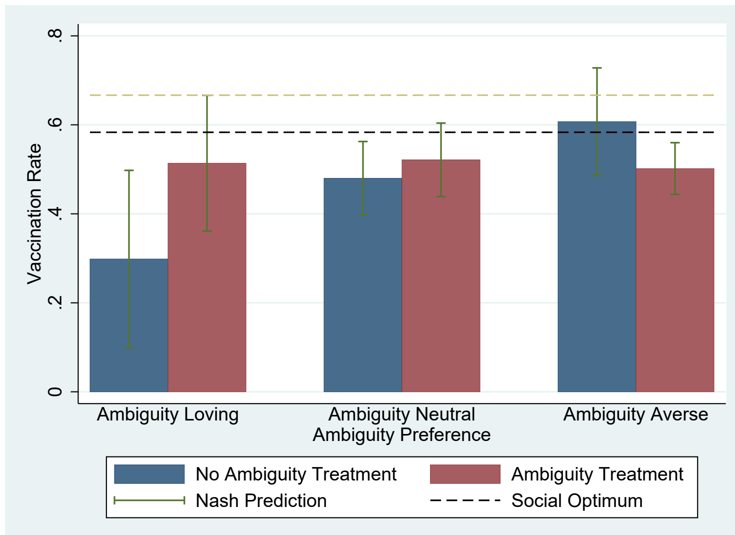


Figure III.7: Vaccination rates by ambiguity attitude in different treatments

Result 13. *Ambiguity averse (seeking) participants are less (more) likely to take the vaccine in Ambiguity treatment than in No Ambiguity treatment.*

III.3.3 Social Value Orientation (SVO)

We use SVO slider measure (87) to elicit the magnitude of concern for others. Given the angles of idealized SVO types, altruists would have angles greater than $57.15°$; prosocials would have angles between $22.45°$ and $57.15°$; individualists would have angles between $-12.04°$ and $22.45°$; and competitive types would have an angle less than $-12.04°$.

III.3.4 Vaccination Attitude

Most of the participants have shown a positive attitude towards both COVID vaccination, with an average score of 78.1 out of 100, and general vaccination, with an average score of 3.97 out

Table III.3: The percentage of individuals that were assigned to the SVO Slider Measure.

	(87)		(86)	Our Results
Prosocial	58	64	69	70
Individualistic	39	34	31	27
Competitive	3	2	0	3
Total	100	100	100	100

of 5. Moreover, the results of the chi-square test indicate a strong correlation between these two preferences (chi-square p-value is 0.000).

Additionally, 86.7% of participants received the COVID-19 vaccine, and the vaccine uptake rate was found to be significantly associated with both general vaccine attitude and COVID-19 vaccine attitude (with p-values of 0.000 for both chi-square tests). Table III.4 indicates that there is no significant relationship between ambiguity attitudes and the COVID-19 vaccination decision.

Ambiguity Attitude	Vaccinated	Not Vaccinated	Overall
Averse	108 (86.4%)	17 (13.6%)	125 (52.1%)
Neutral	77 (88.5%)	10 (11.5%)	87 (36.3%)
Seeking	23 (82.1%)	5 (17.9%)	28 (11.7%)
chi-square $p \approx 0.684$.			

Table III.4: Ambiguity attitudes and COVID-19 vaccination

III.3.5 Vaccination Decisions as a Strategic Interaction

To explain the rationale behind vaccination decisions formally, we used the following mixed effects model.

$$Pr(a = 1) \sim \textit{fixed effects} + (1|subject) + (1|round) + (1|group) + \varepsilon$$

Participants might change their vaccination decision strategically in response to the number of others' decisions. To test this hypothesis, we put a dummy variable RelVacc. This variable is 1 if the relative fraction of participants who got vaccinated were above the Nash equilibrium in the previous round and 0 otherwise. Model 1 in Table III.5 includes treatment (0 = No Ambiguity, 1 = Ambiguity), ambigutiy attitude (0 = ambiguity averse or ambiguity neutral, 1 = ambiguity seeking), and RelVacc as the predictors of the vaccination decisions (0 = non-vaccination, 1 = vaccination).

The results indicate that participants in the Ambiguity treatment were significantly less likely to get vaccinated than those in the No Ambiguity treatment (Result 11). Additionally, participants' attitude towards ambiguity significantly predicted their vaccination decisions. Ambiguity-seeking participants were less likely to get vaccinated (Result 12). Furthermore, the results indicate that RelVacc also predicted vaccination decisions, but not significantly. Specifically, when the fraction of participants who chose vaccination was above the Nash equilibrium, the vaccination rate decreased in the following round.

In Model 2, we include participants' social value orientation classification as an additional predictor (0 = prosocial, 1 = proself). The results show that although the effect of ambiguity attitude decreases slightly, it remains significant. However, the previously significant treatment effect disappears. Instead, this model indicates a significant interaction effect between ambiguity attitude and SVO classification, such as the attitude having a significant positive effect on proself.

Table III.5: Mixed effect models predicting vaccination decisions by the relative fraction of players who got vaccination in the previous round (reference: fraction vaccinated below Nash equilibrium), experimental treatment (reference: No Ambiguity Treatment), social value orientation (reference: prosocial), and general attitude towards vaccination.

Predictor	Model 1		Model 2	
	B	SE	B	SE
(Intercept)	0.556***	0.131	0.548***	0.029
Treatment: Ambiguity (A)	−0.056**	0.020	−0.009	0.0317
Ambiguity Seeking (B)	−0.232***	0.072	−0.224**	0.0750
RelVacc: above NE (C)	−0.028	0.023	−0.139	0.028
SVO: proself (D)			0.023	0.082
A * B	0.217*	0.099	0.078	0.114
A * C	0.019	0.283	0.020	0.039
A * D			−0.161†	0.089
B * C	0.058	0.051	0.044	0.055
B * D			0.433**	0.140
C * D			−0.042	0.035
A * B * C	−0.084	0.688	−0.050	0.0827
A * B * D			0.046	0.000
A * C * D			N/A	N/A
B * C * D			−0.039	0.087
A * B * C * D			N/A	N/A
Observations (subjects/rounds/groups)	4560(240/19/20)			

Note that there are only 19 rounds considered in the analyses (rounds 2–20) because the first feedback was given after round 1. ***$p < 0.001$, ** $p < 0.01$, *$p < 0.05$. $^{\dagger}p < 0.1$

III.4 Conclusion

In this study, we investigated the relationship between ambiguity and vaccination decisions. Our results demonstrate that the presence of ambiguity reduces the likelihood of vaccination, with participants in the Ambiguity treatment being less likely to get vaccinated than those in the No Ambiguity treatment. We also found that participants who are averse to ambiguity are less likely to opt for vaccination, indicating that attitudes towards ambiguity play a crucial role in vaccination decisions. Furthermore, we found that ambiguity averse participants are less likely to choose to get vaccinated in the Ambiguity treatment than in the No Ambiguity treatment. These findings highlight that information about the side effect could impact people's willingness to get vaccinated.

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