Signal Space Puzzle: Bigger is (Not Always) Better*

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Abstract

This paper examines whether the value of an informative signal varies with the size of the signal space, representing the number of possible signals. In our experiment, subjects either make a signal purchasing decision (SPD) while predicting the binary outcomes of compound lotteries or make a lottery purchasing decision (LPD) while the lottery includes a free signal regarding the outcome. We tested four distinct lotteries, each associated with varying signal space sizes, yet maintaining identical informational value across signals. Our findings revealed a fascinating dichotomy: in SPD, subjects are willing to pay more for a signal from a larger signal space, whereas in LPD, their willingness to pay for a lottery is not associated with the size of the signal. To explain experimental findings, we introduce a novel theoretical framework that integrates loss aversion with the uncertainty regarding a variable of their interests, represented by Shannon's entropy. In SPD, individuals are interested in the signal itself, so they are more willing to resolve the uncertainty of the signal within the larger signal space. In LPD, individuals are interested in the final outcome of a lottery, so they are more willing to buy a lottery ticket that includes signals with significantly more information than a coin toss.

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1 Introduction

Signal transmission is an essential part of the literature on game theory, in which a vast amount of theoretical and empirical research has been conducted. However, the desirable size of the signal space has often been overlooked in the literature. In the context of information acquisition, the size of the signal space denotes the number of possible signals. In many cases, theorists have assumed that the signal space equals the action space when discussing the size of the signal space (Spence, 1973; Kamenica and Gentzkow, 2011). They have shown that assuming an equivalence between the signal space and the action space is sufficient to find the equilibrium, making a larger signal space unnecessary. This assumption has been taken for granted, but its validity and implications of models relying on this assumption could be limited if the receiver prefers a larger signal space. This paper investigates whether individuals have a preference for the size of the signal space, independent of signal accuracy.

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

To reduce uncertainty about the investment decision, she is considering hiring a financial advisor with more knowledge of the company. There are two advisors she is considering: Advisor A and Advisor B. They both provide informative signals to the investor. Advisor A will send the investor one of the two signals with equal probability: "invest" or "not invest." If his signal is "invest," the probability that the

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

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

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

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

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

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

[2] See Section A.1 for detailed calculations.

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

To investigate the preference for the size of the signal space, we conducted a lab experiment. In the experiment, the size of the signal space was independent of the efficiency of the outcomes: the signal accuracy of each signal was the same. Therefore, there is no theoretical reason to prefer a larger signal space. Additionally, since the experiment was designed to be simple and straightforward, there was no evidence of complexity aversion. However, the results surprisingly revealed a preference for larger signal space. The results suggest that the investor favors Advisor B over A due to the size of the signal space.

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

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

With the innovative design that allows us to isolate the effects of signal space size while controlling for the informational content of the signals, we found interesting results in two distinct experimental contexts. In the Signal Purchasing Decision (SPD), subjects consistently displayed a preference for larger signal spaces, suggesting that they value the complexity of the signal space itself, beyond the practical utility of the information provided. However, in the Lottery Purchasing Decision (LPD), where subjects could opt out of the lottery, this preference for larger signal spaces disappeared. This indicates that subjects' willingness to engage with lager signal spaces is context-dependent and highlights the nuanced ways in which the decision making environment shapes their valuation of information. Our design thus uncovered key behavioral patterns that vary with the decision context, providing new insights into how individuals perceive and value the size of signal spaces.

Our second key contribution is the proposal of a new theoretical mechanism to explain the behavioral differences observed in the SPD and LPD experiments. While traditional expected utility theory explains decision making based on the instrumental value of information, it cannot fully account for the divergence in preferences observed between the two settings. To address this, we introduce a framework that incorporates loss aversion and Shannon's entropy to model the intrinsic value of information.

In the SPD, where subjects focus on determining which box contains the ball, they seem to value the reduction of uncertainty associated with larger signal spaces. This leads to a preference for larger signal space, as they help resolve uncertainty regarding the box. In contrast, in the LPD, where subjects focus on the color of the ball and can opt out of the lottery, subjects are more concerned with signals that significantly increase their chances of success. As a result, signals that do not offer a substantial improvement over a 50:50 chance are seen as less valuable, and the preference for larger signal spaces diminishes. By integrating these factors, our framework provides a more complete understanding of how and why preferences for signal complexity vary between different decision making contexts, offering a more comprehensive explanation for the observed results.

This paper proceeds as follows. Section 2 offers an overview of the experimental design, explaining how we isolate the effect of signal space size while keeping the informational content constant. Section 3 outlines the theoretical predictions and hypotheses based on classical expected utility theory. Section 4 presents the empirical results from both the SPD and LPD experiments, emphasizing key behavioral differences and demonstrating that expected utility theory fails to account for the observed data. Section 5 introduces the alternative theoretical framework, detailing how intrinsic information value is modeled by incorporating both loss aversion and Shannon's entropy. It then demonstrates how this mechanism successfully accounts for the data from both the SPD and LPD experiments, offering a comprehensive explanation for the observed behavioral differences. Finally, Section 6 explores related theories and examines how they connect to our findings.

2 Experimental Design

There are four lotteries, which are illustrated in Figure 1. For each lottery, multiple boxes are present, each containing ten balls colored either red or blue. The process involves the computer randomly choosing one box, ensuring each has an equal chance of being selected. Following this selection, a ball is randomly drawn from the chosen box. Subjects are prompted to forecast the color of the ball to be drawn prior to its selection. Successful predictions are rewarded with 100 points, with each point being equivalent to 0.01 USD.

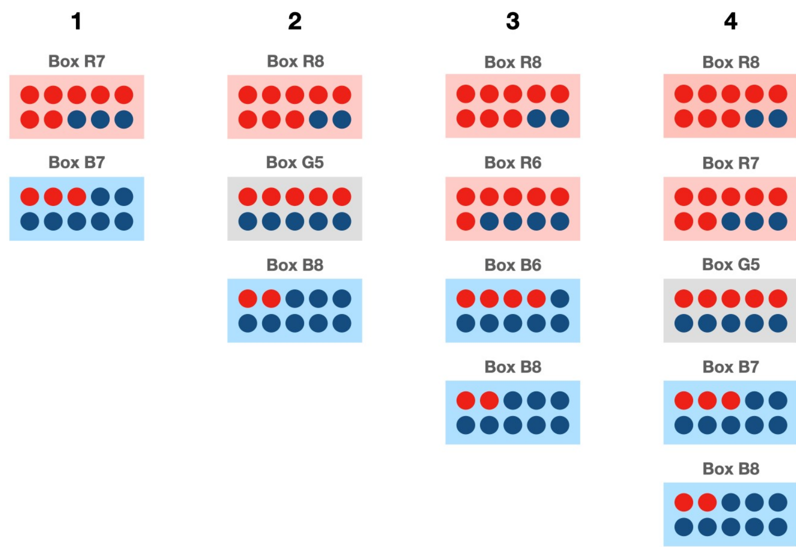

Figure 1: Four lotteries

Each box is labeled as Box Xn, where $X \in \{R, B, G\}$ and $n \in \{5, 6, 7, 8, 9\}$.[3] Here, X signifies the predominant color of the balls contained within the box, and n indicates the total count of balls of that color. For instance, Box R7 contains a majority of red balls, specifically seven red balls.[4] Note that Box G5 is the sole instance of Box Gn, as Box G invariably holds five red balls and five blue balls, maintaining an equal distribution between the two colors.

2.1 Signal Purchasing Decision and Lottery Purchasing Decision

Subjects were assigned to either the Signal Purchasing Decision (SPD) or the Lottery Purchasing Decision (LPD). While both decisions shared the same framework

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

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

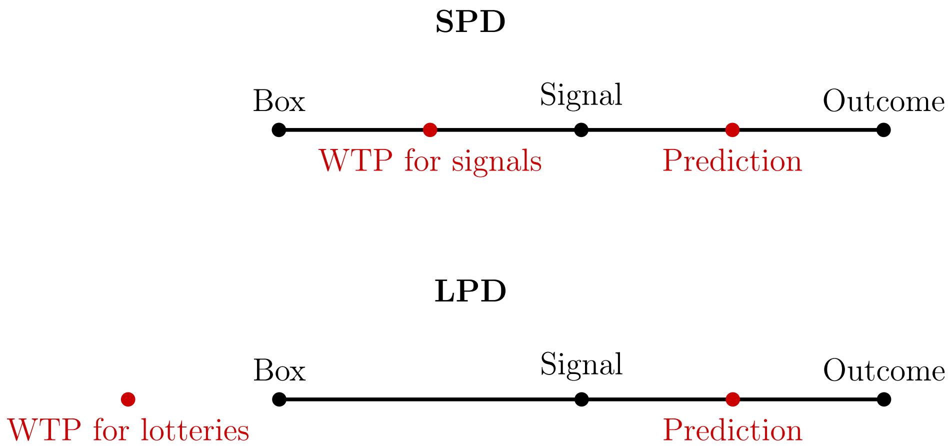

Figure 2: Timeline of studies

described above, the questions asked were different.

In the Signal Purchasing Decision (SPD), prior to making their predictions, participants were given the opportunity to "purchase" a costly signal using their 100 endowment points. If a subject opted to buy a signal, the computer would disclose the selected box. For instance, consider Lottery 2, which features three boxes: Box R8, Box G5, and Box B8. If Box R8 is chosen at random, subjects, without buying the signal, would have a 50% chance of winning regardless of betting on red or blue, due to the equal distribution of 15 red and 15 blue balls across the boxes. However, if they decide to purchase the signal and are informed that Box R8 was selected, their chances of winning increase to 80% if they bet on red, following the signal "Box R8."

In the Lottery Purchasing Decision (LPD), the focus shifted from assessing the value of the signals for the four lotteries to evaluating the value of the four lotteries themselves, with the signals provided at no cost. Specifically, subjects were tasked with indicating their willingness to pay to participate in each lottery. Prior to making their color prediction, subjects were informed about which box had been selected. The sequence of events for both studies is illustrated in Figure 2.

To gauge willingness to pay, we utilized the Becker-DeGroot-Marschak (BDM) mechanism (Becker et al., 1964), adopting a multiple price list format. The structure of the BDM questions is outlined in Table 1. In the SPD, subjects specified the

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

Table 1: The BDM mechanism in the SPD

maximum number of points they were willing to spend to purchase a signal for each lottery.[5] Upon specifying their valuation for signals across all four lotteries, one lottery was randomly chosen. Subsequently, a random number ranging from 1 to 100 was generated to denote the signal's price for the chosen lottery. Should a subject's stated value for the lottery exceed the set price, she was granted access to the signal upon payment of the specified price. Conversely, if her value was equal to or below the price, she was denied the signal without any cost. Following the disclosure or withholding of the signal, subjects proceeded to predict the ball's color.

The BDM procedure in the LPD mirrored that of the SPD, as illustrated in Table 2. Before engaging with the lotteries, subjects were instructed to declare the maximum number of points they were willing to allocate for the opportunity to play each lottery. Following the submission of their valuations for all four lotteries, one lottery was chosen at random. Subsequently, a random number ranging from 1 to

[5]The major issue with the BDM mechanism is its difficulty, which can lead to biased results in some environments. See Noussair et al. (2004) for discussions about the biased results of the BDM. To minimize the confusion, subjects were asked to indicate their maximum willingness to pay for the signal, rather than making 100 choices between Option A and B. Additionally, before subjects made their actual decision, an example was provided to illustrate how the mechanism works when a specific value was submitted. Furthermore, even if the results biased, whether upward or downward, it does not undermine the primary purpose of the BDM mechanism in this paper, which is to compare preferences between signals and between lotteries, rather than to elicit their exact values.

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

Table 2: The BDM mechanism in the LPD

100 was generated to act as a potential substitute reward. If a subject's bid for the selected lottery exceeded this substitute prize, she was allowed to participate in the lottery. Conversely, if her bid was equal to or less than the substitute reward, she received the prize and did not participate in the lottery. Subjects who proceeded to play the lottery were informed about the selected box and then asked to predict the color of the drawn ball.

2.2 Procedural Details

One of the decisions the subjects made was randomly selected, and they earned points based on the outcome of that decision. Each point was equivalent to 0.01 USD.

A total of 467 subjects participated in the experiments through Prolific, which is an online platform for recruiting research participants.[6] Specifically, 179 and 158 subjects participated in the SPD and the LPD, respectively. Also, an additional 130 subjects participated in a robustness study, which is discussed below. On average, subjects spent 10 minutes and earned $3.32, including a $2.20 base payment.

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

3 Theoretical Considerations and Hypotheses

A critical aspect of this experiment is the diversity in the quantity of boxes present in each lottery, which directly translates to the varying number of available signals: Lottery 1 features 2 boxes, Lottery 2 comprises 3, Lottery 3 includes 4, and Lottery 4 encompasses 5 boxes. Notably, despite these differences, from an ex-ante perspective, the value of information remains constant across all lotteries. The value of information, in this context, is defined by the difference between the expected utility for a subject who has acquired the signal and the expected utility for the subject who has not. This phenomenon is rationalized through expected utility theory, which posits that the value derived from obtaining information (or signals, in this case) is essentially the utility gain from making a more informed decision versus a less informed one. This theory suggests that while the availability of signals varies, the intrinsic value of being better informed does not fluctuate across different scenarios, as long as the informational content of the signals remains constant.

3.1 Expected Utility

According to expected utility theory, the decision-makers assign a probability $p(\omega)$ to the state $\omega \in \Omega$ to evaluate a lottery.

$$U_{EU}(L_i) \equiv E(u(L_i)) = \sum_{\omega \in \Omega} p(\omega) u(L_i|\omega) = 0.5 \times u(100).$$

In this context, ω represents the color of the drawn ball. Importantly, from an ex-ante perspective, the expected utility of lottery i with a signal $s_i \in S_i$, which indicates the selected box, aligns with the expected utility without the signal. The expected utility, considering the signal, can be expressed as:

$$U_{EU}(L_i|S_i) \equiv E_{s_i}[E(u(L_i|\omega, s_i)|s_i)] = \sum_{\omega \in \Omega} \sum_{s_i \in S_i} p(\omega|s_i) u(L_i|\omega, s_i) = 0.7 \times u(100) \;\; \forall i$$

This formulation demonstrates that, irrespective of from which a signal is provided, the expected utility for any given lottery remains constant. This equality underscores the theoretical premise that the size of the signal space does not alter the expected utility of participating in the lottery, assuming the signal's information content is fully integrated into the decision-making process.

Therefore, according to the expected utility theory, in our experiment, the value of information $VOI(S_i)$ is defined as

$$VOI(S_i) \equiv U_{EU}(L_i|S_i) - U_{EU}(L_i) = 0.2 \times u(100) \tag{1}$$

and constant at 20 for any lottery L_i for the risk-neutral expected utility maximizer.

From this theory we can have two different hypotheses. In the SPD, the focus was on assessing subjects' willingness to pay for the signal. Should the value of information solely dictate the signal's worth, then the willingness to pay across all four lotteries would be uniform. When $V(S_1|L_1)$ represents the value of signal S_i for lottery L_i, we hypothesize:

Hypothesis 1. *The size of the signal space does not affect the willingness pay for the signal:* $V(S_1|L_1) = V(S_2|L_2) = V(S_3|L_3) = V(S_4|L_4)$.

In the LPD, the valuation of lottery i with a cost-free signal, was measured. Let's denote the value as V_i. According to expected utility theory, this value corresponds to the expected utility of lottery i with a free signal s_i, expressed as $V_i \equiv U_{EU}(L_i|S_i) = U_{EU}(L_i) + VOI(S_i)$, as inferred from Equation (1). If a subject deems the signal for lottery i more valuable than that for lottery j, suggesting $VOI(S_i) > VOI(S_j)$, it naturally follows that she would also rate lottery i more highly than lottery j, indicated by $V_i > V_j$. Given that, under the expected utility theory, the value of information (VOI) for signal s_i equates to p_i, we arrive at the following hypothesis:

Hypothesis 2. *The ranking among* $V(L_i|S_i)$ *is aligned with the ranking among* $V(S_i|L_i)$*:* $V(L_i|S_i) > V(L_j|S_j) \Leftrightarrow V(S_i|L_i) > V(S_j|L_j)$.

4 Results

4.1 Preference for a Bigger Signal Space

Lottery	$\lvert S\rvert$	SPD $V(S_i\lvert L_i)$	SPD Number	LPD $V(L_i\lvert S_i)$	LPD 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 3: Elicited values for $V(S_i|L_i)$ and $V(L_i|S_i)$ with different sizes of signal space.

Table 3 presents the values of the signal for each lottery ($V(S_i|L_i)$) and the value of each lottery given a signal ($V(L_i|S_i)$), both expressed in points. The term $|S|$ denotes the size of the signal space.

A striking observation is subjects' increased willingness to pay for signals associated with larger signal spaces in the SPD, indicating a clear preference for larger signal spaces in this context. In contrast, in the LPD, the size of the signal space appears to have no significant impact on the valuation of equivalent lotteries. The Cuzick non-parametric trend test results show that the size of the signal space is significant in the SPD ($p = 0.005$) but not in the LPD ($p = 0.574$).

Table 4 presents the results of the regression analysis. The first two columns show a significant impact of signal space size on the willingness to pay for signals, denoted as $V(S_i|L_i)$, with F-test p-values below 0.001. This suggests that as the signal space size increases, so does the willingness to pay for the signal. Consequently, we can state Result 1, which rejects Hypothesis 1.

Result 1. ***(Preference for Larger Signal Space)*** *The willingness pay for signal increases with the size of signal space.*

	Dependent Var: $V(S_i\|L_i)$		Dependent Var: $V(L_i\|S_i)$	
	(1)	(2)	(3)	(4)
Signal Space Size	1.934***	1.934***	0.160	0.160
	(0.395)	(0.395)	(0.502)	(0.502)
Constant	21.218***	21.218***	50.978***	50.978***
	(1.650)	(0.988)	(1.798)	(1.255)
Observations	716	716	632	632
Individual Fixed Effect	No	Yes	No	Yes
R-Squared	0.010	0.046	0.000	0.000

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

Table 4: The effect of the size of signal space on the value of the signal space and the lottery

On the other hand, columns (3)-(4) of Table 4 show that the size of the signal space does not affects the value of lotteries, denoted as $V(S_i|L_i)$.[7] This result rejects Hypothesis 2.

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

4.2 Understanding Information Value: Insights from a Robustness Check

One explanation is that subject may not understand the value of information of the compounded lotteries in our experiment. To check this, we conduct a robustness study with lotteries with different values of information.

The procedure of this study was identical to Part 1 of the SPD, where subjects were asked to submit their willingness to pay for signals in different lotteries. However, to verify if subjects understood the value of information in different lotteries, we utilized eight different lotteries with varying values of information, as depicted in Figure 3. If subjects correctly understood the framework, they would be more willing to pay for

[7] F-test p-values are 0.7502, 0.7504, and 0.7502 for each column.

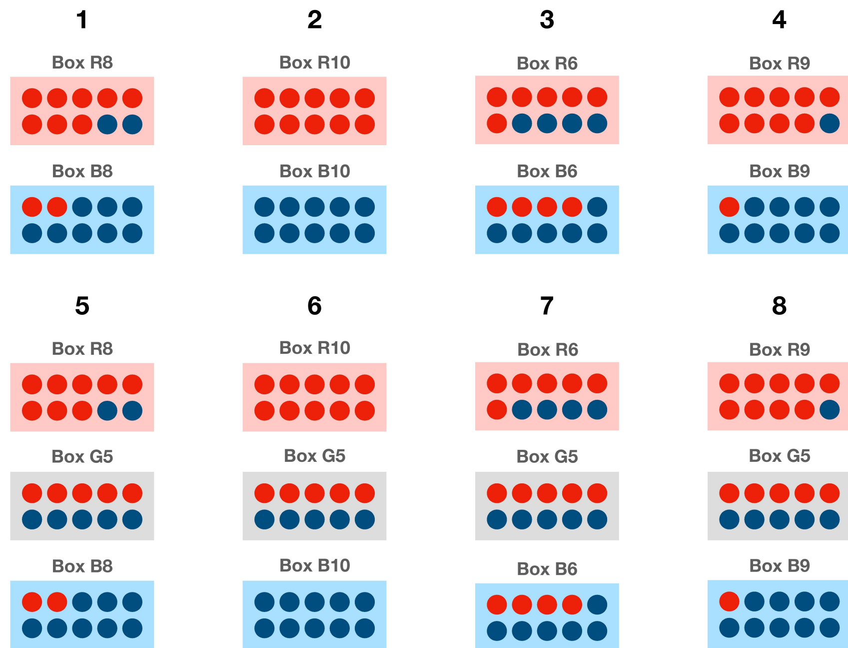

Figure 3: Lotteries in the robustness study

a signal with a higher value of information.

Table 5 summarizes the details of the lotteries and displays the submitted values for the willingness to pay for the signal in each lottery, p_i. 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 fourth column represents the values of information of lotteries, $VOI(S_i)$'s, which are served as the theoretical prediction for the willingness to pay of a risk-neutral utility maximizer. The submitted values on the fifth column, p_i's, indicate that subjects had a thorough understanding of the information structure, particularly the value of information. Consistent with theoretical predictions, subjects valued the signals with a higher value of information more.

Additionally, in comparison to the WTP for signals in Lotteries 1-4, subjects overpaid for signals in Lotteries 5-8 due to the effect of the signal space size. The

Questions	Signal Space Size	Winning Prob With Signals	$VOI(S_i)$	p_i
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 5: Theoretical prediction for $VOI(S_i)$ and WTP

chi-square test result rejects the null hypothesis that the willingness to pay for signals was submitted randomly (p-value < 0.001).

	Dependent Var: p_i			
	(1)	(2)	(3)	(4)
$VOI(S_i)$	0.251***	0.273***	0.251***	0.273***
	(0.065)	(0.067)	(0.065)	(0.067)
Signal Space Size		1.505		1.505
		(1.062)		(1.062)
Constant	22.322***	17.969***	22.322***	17.969***
	(1.982)	(3.719)	(1.751)	(3.613)
Observations	1040	1040	1040	1040
Individual Fixed Effect	No	No	Yes	Yes
R-Squared	0.020	0.020	0.045	0.047

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

Table 6: The effect of the value of information on WTP

The regression results presented in Table 6 further indicate that subjects have a thorough understanding of the value of information in the robustness study. The first row of the table suggests that the submitted WTP values, p_i's, are positively correlated with the theoretical predictions $VOI(S_i)$, which represent the value of information for a risk-neutral individual in the expected utility model.[8]

Therefore, we can fairly conclude that the behavior observed in the baseline studies is not due to a misunderstanding of the signaling structure related to compounded lotteries. Subjects appeared rational enough to understand the value of information clearly and adjusted their willingness to pay accordingly.

Thus, the explanation for the preference for a larger signal space in the SPD remains unclear. Furthermore, the reason why this preference disappears in the LPD also remains elusive. These considerations lead us to new conjectures.

5 Alternative Mechanism

So far, we have established that subjects care about something other than the expected utility or the value of information. In particular, the willingness to pay for a signal in the SPD is positively associated with the size of the signal space. Interestingly, however, this relationship does not hold in the LPD. To explain subjects' behavior in both designs, we may need another measure.

Here, we introduce new conjectures and alternative theoretical frameworks to explain the subjects' behavior in our baseline studies. Apart from the classical expected utility theory and the value of information calculated by the theory, our new conjectures are based on the presumption that subjects care about the intrinsic or non-instrumental value of information.

We do not intend to suggest that subjects are indifferent to the instrumental value of information, which is grounded in expected utility theory. On the contrary, as demonstrated in Section 4.2, subjects exhibit a clear and accurate understanding of the instrumental value of information. This indicates that they are fully capable

[8]Interestingly, the second row of the table suggests that the size of the signal space has no significant effect on the submitted value in the robustness study, although the estimates remain positive, consistent with our baseline studies. This may be because the size of the signal space in the robustness study varies only slightly, from 2 to 3, compared to the baseline studies where it varies from 2 to 5.

of evaluating information based on its utility in decision-making processes and its ability to reduce uncertainty, as posited by expected utility theory.

However, our argument extends beyond this foundational understanding. We contend that subjects are not solely motivated by the instrumental aspects of information. In addition to considering how information might improve their decisions or reduce uncertainty, subjects also appear to value the intrinsic qualities of information. By intrinsic value, we refer to the inherent worth that individuals assign to information regardless of its direct usefulness in achieving better outcomes. This suggests that information might be pursued or appreciated for reasons unrelated to its practical utility, such as satisfying curiosity, or gaining insight for its own sake.

This broader interpretation aligns with recent studies in neuroscience and psychology, which show that individuals are often driven by a desire to acquire knowledge beyond its immediate instrumental benefits. For instance, Bennett et al. (2016) and Gottlieb and Oudeyer (2018) show that individuals are motivated by more than just the practical utility of information. Kobayashi and Hsu (2019) demonstrate that decision-making is influenced by non-instrumental motives in addition to instrumental ones. Furthermore, Lau et al. (2020) reveal that people exhibit 'pure curiosity' about information, and the brain regions activated by this curiosity are the same as those involved in hunger.

By integrating these insights, we propose that subjects in our studies might be influenced by an intrinsic desire for information, driven by curiosity or other non-instrumental values. This framework can help explain the observed behaviors in the SPD and the LPD, where the size of the signal space seems to impact the willingness to pay for signals differently. This approach moves beyond traditional expected utility models to encompass a broader understanding of human information-seeking behavior.

5.1 Conjectures

We first conjecture that subjects naturally pose different questions when making decisions in these two studies. In the SPD, when deciding whether to purchase a signal that provides information regarding the box the ball is in, they may ask themselves which box the ball is likely in, thereby focusing primarily on the uncertainty regarding the box.

In the LPD, on the other hand, when deciding whether to purchase a lottery concerning the color of the ball, they may ask which ball is likely to be chosen, thus concentrating mainly on the uncertainty regarding the ball.

To measure this uncertainty, we use Shannon's entropy. Shannon's entropy quantifies the uncertainty of a random variable, providing a mathematical measure of unpredictability or information content. Here's how Shannon's entropy is defined:

$$H(X) = -\sum_x p(x) \log p(x)$$

We summarize the above argument as in the following conjecture.

Conjecture 1 (Shannon's entropy)**.** *The subject's willingness to pay for a signal in the SPD is associated with the uncertainty of box B_i, measured by $H(B_i)$, for any lottery i. On the other hand, the subject's willingness to pay for a lottery in the LPD is associated with the uncertainty of ball Q_i, measured by $H(Q_i)$, for any lottery i.*

We can utilize Shannon's entropy to measure the intrinsic value of information by examining the reduction in uncertainty of a random variable X due to the knowledge of another variable Y. This reduction can be quantified as Mutual Information. The mathematical formulation is as follows:

$$\begin{aligned}
I(X;Y) =& H(X) - H(X|Y) \\
=& \left(-\sum_x p(x)\log p(x)\right) - \left(-\sum_y p(y)H(X|Y=y)\right) \\
=& \sum_y p(y)\left[H(X) - H(X|Y=y)\right] \\
=& \sum_x \sum_y p(x,y)\log\frac{p(x,y)}{p(x)p(y)}
\end{aligned}$$

In this framework, the value of information is interpreted as the reduction in uncertainty when moving from a scenario without the signal to one with the signal. Mutual information quantifies this reduction by comparing the reference point, which is the state of uncertainty without the signal, to the updated state with the signal.

Now, it is natural to ask if subjects take any signal as a gain. In other words, we ask where is the natural reference point for subjects to evaluate the intrinsic value of information. We argue that it depends on the variable of interest.

In the SPD, as conjectured in 1, subjects consider which box the ball is likely in when deciding whether to purchase a signal while playing a lottery. Their attention is primarily focused on the identity of the box, B_i. Therefore, any signal that provides information about which box the ball is chosen from is perceived as a gain. This is because it reduces the uncertainty regarding the box, aligning with the subject's primary goal of identifying the box where the ball is located.

In the LPD, on the other hand, subjects focus on determining the color of the ball when deciding whether to participate in a lottery with a free signal. While evaluating the intrinsic value of the free signal, they have the option to opt out of the lotteries, thereby securing the status quo with no risk. As a result, only a signal that significantly improves the winning probability beyond a 50:50 chance would be perceived as a gain. Such an improvement in winning odds increases the intrinsic value of the lottery, thereby raising the subject's willingness to pay for it.

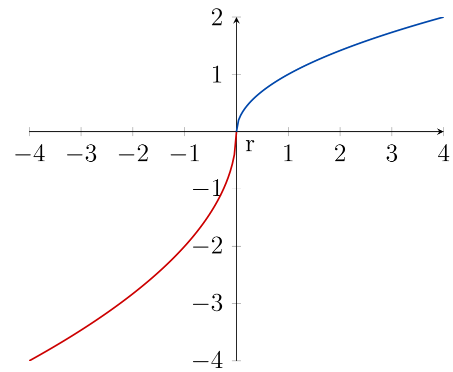

Figure 4: Value of uncertainty reduction

Consequently, the reference point for the subject becomes higher than the basic 50:50 odds, meaning that signals offering marginal or no improvement over 50:50 would be perceived as a loss. For instance, in our context, a signal from box G5, which does not raise the winning probability beyond 50:50, might be viewed as a loss rather than a gain, making it less appealing in terms of intrinsic value. Therefore, only signals that offer a substantial advantage, relative to this higher reference point, would effectively increase the subject's willingness to pay.

This nuanced view incorporating both Shannon's entropy and loss aversion provides a more comprehensive explanation of the subjects' decision-making processes in different experimental setups.

We model the reduction in uncertainty about a variable X given information about another variable Y, incorporating loss aversion, as follows:

$$v(Y|X,r) = \begin{cases} (r(X) - H(X|Y))^{\rho} & \text{if } H(X|Y) \leq r(X) \\ \lambda(-(r(X) - H(X|Y))^{\rho} & \text{if } H(X|Y) > r(X), \end{cases}$$

where $r(X)$ is the reference level of uncertainty on X and $H(X|Y)$ is the uncertainty of X given Y. Here, ρ is the parameter that captures the curvature of the value function, reflecting the diminishing sensitivity to changes in uncertainty, while λ represents the loss aversion coefficient, indicating the higher weight given to losses compared to gains. This framework captures how individuals evaluate reductions in uncertainty when they have intrinsic motivations, emphasizing the disproportionate aversion to information that increases uncertainty beyond their reference point. This model also highlights how individuals may overvalue reductions in uncertainty when it falls below the reference level and react strongly against increases in uncertainty when it exceeds that level.

Now we have the following conjecture:

Conjecture 2 (Intrinsic Value of Information, IVOI)**.** *The subject's willingness to pay is associated with the the expected value of uncertainty reduction given the reference point* r*,* $\hat{v}(S_i|X, r)$*. We call this the Intrinsic Value of Information with Loss Aversion.*

In the SPD, the variable X is the chosen box, B_i for the lottery i.

$$
\begin{aligned}
H(B_1) = -2\left(\frac{1}{2}\log\frac{1}{2}\right) < H(B_2) = -3\left(\frac{1}{3}\log\frac{1}{3}\right) < H(B_3) < H(B_4) \\
H(B_i|S_i) = -\left(1\log 1\right) = 0
\end{aligned}
$$

As argued above, the reference point for L_i in SPD is the uncertainty without the information, $H(B_i)$. Therefore,

$$
\begin{aligned}
\hat{v}(S_i|B_i, r) &\equiv \sum_{s_i} p(s_i)\left[r(B_i) - H(B_i|S_i = s_i)\right]^{\rho} \\
&= \sum_{s_i} p(s_i)\left[H(B_i) - H(B_i|S_i = s_i)\right]^{\rho}
\end{aligned}
$$

Then, we get the following order for the intrinsic value of information, IVOI:

$$
\hat{v}(S_1|B_i, 0) < \hat{v}(S_2|B_i, 0) < \hat{v}(S_3|B_i, 0) < \hat{v}(S_4|B_i, 0)
$$

This order reflects the increasing value of information as the uncertainty of the chosen box B_i increases. The calculation shows how the intrinsic value of information is higher for lotteries with greater initial uncertainty, given that the reduction in uncertainty (from the reference point $H(B_i)$) is more significant. This aligns with the conjecture that subjects' willingness to pay is associated with the expected value of uncertainty reduction.

In the LPD, the random variable X is the chosen ball, Q_i for lottery i.

$$H(Q_i) = -2\left(\frac{1}{2}\log\frac{1}{2}\right) = 1 \text{ for all } i.$$

$$H(Q_1|S_1) = -2\left((.7 \times .5)\log(.7 \times .5) + (.3 \times .5)\log(.3 \times .5)\right)$$

For the subjects in the LPD, any signal that leads to a lower uncertainty than 50:50 odds is considered a gain. Therefore, the reference point $r(Q_i)$ should be less than $H(Q_i) = 1$.

$$\hat{v}(S_i|Q_i, r) \equiv \sum_{s_i} p(s_i)\left[r(Q_i) - H(Q_i|S_i = s_i)\right]^{\rho}$$

By taking $r(Q_i) = 0.99$, we get the following order in a large set of parameter values:

$$\hat{v}(S_2|Q_i, .99) < \hat{v}(S_4|Q_i, .99) < \hat{v}(S_3|Q_i, .99) < \hat{v}(S_1|Q_i, .99) \tag{2}$$

This ordering reflects the intrinsic value of information in the LPD scenario, considering the reference point for uncertainty reduction. By setting the reference point slightly below the maximum entropy, we capture the subjects' preference for signals that significantly reduce uncertainty.

5.2 Empirical Evidence

Table 7 shows whether our framework aligns with the experimental results. $IVOI_{SPD}$ and $IVOI_{LPD}$ represent the intrinsic value of information for the SPD and LPD, respectively, as defined in the previous section. As mentioned above, the order of

$IVOI_{SPD}$ is identical to the size of the signal space. As shown in Table 4, the value of the signal in the SPD ($V(S_i|L_i)$) is significantly positively correlated with the size of the signal space. Therefore, not surprisingly, it is also significantly positively correlated with $IVOI_{SPD}$, but not correlated with $IVOI_{LPD}$.

	Dependent Var: V($S_i|L_i$)		Dependent Var: V($L_i|S_i$)	
	(1)	(2)	(3)	(4)
$IVOI_{SPD}$	1.933***	1.933***	0.675	0.675
	(0.414)	(0.414)	(0.525)	(0.525)
$IVOI_{LPD}$	-0.002	-0.002	1.287**	1.287**
	(0.464)	(0.464)	(0.545)	(0.545)
Constant	21.224***	21.224***	46.473***	46.473***
	(2.214)	(1.784)	(2.577)	(2.164)
Observations	716	716	632	632
Individual Fixed Effect	No	Yes	No	Yes
R-Squared	0.010	0.046	0.004	0.012

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

Table 7: The effect of the IVOI on the value of the signal space and the lottery

On the other hand, the regression results show that the value of the lottery in the LPD ($V(L_i|S_i)$) is significantly correlated with $IVOI_{LPD}$, but not with $IVOI_{SPD}$. These results demonstrate that our framework aligns well with the experimental findings.

6 Discussions

6.1 Ambiguity Attitude

Since subjects encounter several compounded lotteries in our experiments, one may question whether their evaluation of these lotteries, which deviates from expected utility theory, could be attributed to ambiguity neutrality as suggested by Halevy

(2007).[9] To answer the question, we measure the ambiguity attitude of the subjects.

Following the assessment of signal values, subjects' attitudes towards ambiguity were measured using two inquiries inspired by Ellsberg (1961). The notion of ambiguity aversion is intricately linked to the concept of two-stage lotteries, especially concerning the capability to simplify compound lotteries (Halevy, 2007; Seo, 2009). Halevy (2007) demonstrated a significant correlation between ambiguity neutrality and the simplification of compound lotteries. Given that a predilection for either a larger or smaller signal space could be seen as an inability to simplify compound lotteries, this examination aids in elucidating the connection between ambiguity attitudes and preferences regarding the size of signal space.

We measure ambiguity attitudes by using the questions from Ellsberg (1961)

The task is outlined as follows.

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

Subjects were prompted to select their preferred option from pairs A and B, as well as C and D. The specifics of these four choices are depicted in Table 8.

	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 8: Ellsberg questions

If a subject exhibits a preference for option A over B and for option D over C, it indicates a set of choices that cannot be rationalized through any subjective proba-

[9] Halevy (2007) proposes that ambiguity neutrality is strongly associated with the ability to simplify compound lotteries.

bility formulation. Such a pattern of preference is typically interpreted as indicative of ambiguity aversion.

To examine these relationships formally, linear regression models of the following structure are utilized:

$$y_{in} = \beta_0 + \beta_1 |S|_i + \beta_2 AmbNeutral_n + \beta_3 |S|_i * AmbNeutral_n + \epsilon_{in}. \tag{3}$$

Here, $y_{i,n}$ represents the value assigned to either p_i or V_i by individual n, while $AmbNeutral_n$ is a dummy variable that indicates whether individual n is ambiguity neutral or not. Standard errors are clustered by subject.

Ambiguity Attitude	SPD Number	SPD Percentage	LPD Number	LPD 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 9: Ambiguity attitudes

Attitude	$V(S_1\|L_1)$	$V(S_2\|L_2)$	$V(S_3\|L_3)$	$V(S_4\|L_4)$	$V(L_1\|S_1)$	$V(L_2\|S_2)$	$V(L_3\|S_3)$	$V(L_4\|S_4)$
Averse	22.8	23.8	24.4	29.9	55.7	47.7	49.5	55.8
Neutral	23.8	26.9	24.9	29.2	50.7	48.8	50.8	50.8
Seeking	25.5	28.7	26.5	31.4	54.2	52.9	55.8	52.2
Total	23.6	25.9	24.9	29.8	52.9	48.9	51.0	52.7
F-test p-value	0.8142				0.5988			

Table 10: The submitted values of $V(S_i|L_i)$ and $V(L_i|S_i)$ for different ambiguity attitudes

Table 9 and Table 10 respectively describe the ambiguity attitudes of subjects, and the values of $V(S_i|L_i)$ and $V(L_i|S_i)$ conditional on different ambiguity attitudes. The overall patterns of the willingness to pay for signals and lotteries remain consistent

	Dependent Var: $V(S_i\|L_i)$			Dependent Var: $V(L_i\|S_i)$		
	(1)	(2)	(3)	(4)	(5)	(6)
Signal Space Size	1.934***	2.030***	1.934***	0.160	0.077	0.160
	(0.395)	(0.551)	(0.395)	(0.502)	(0.727)	(0.502)
Ambiguity Neutrality		0.862			-2.698	
		(3.326)			(3.607)	
Signal Space Size × Ambiguity Neutrality		-0.203			0.156	
		(0.792)			(1.006)	
Constant	21.218***	20.809***	21.218***	50.978***	52.412***	50.978***
	(1.650)	(2.154)	(0.988)	(1.798)	(2.661)	(1.255)
Observations	716	716	716	632	632	632
Individual Fixed Effect	No	No	Yes	No	No	Yes
R-Squared	0.010	0.010	0.046	0.000	0.003	0.000

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

Table 11: The effect of the size of signal space and ambiguity neutrality on the value of the signal space and the lottery

across different ambiguity attitudes. The F-tests' p-values indicate that there is no significant effect of ambiguity attitude on $V(S_i|L_i)$ or $V(L_i|S_i)$.

The third row of Table 11 confirms that the preference for the size of the signal space is independent of ambiguity neutrality. This finding contrasts with the results reported in Halevy (2007), where ambiguity neutrality is strongly linked to the ability to reduce compound lotteries.

6.2 Cumulative Prospect Theory

One may wonder if the cumulative prospect theory explains the subjects behavior in our experiments.

The first version of prospect theory, formulated by Kahneman and Tversky (1979), provided evidence of a systematic violation of expected utility theory. The authors presented an alternative theoretical model to explain this violation. Later, an extension of the original model called Cumulative Prospect Theory (CPT) was presented by Kahneman and Tversky (1992), which incorporates rank-dependence in probability weighting.

To measure the preferences for $V(S_i|L_i)$ and $V(L_i|S_i)$ using CPT, we used the parameter values that were estimated from experimental data in Kahneman and Tversky (1992).[10]

Table 12: Values of parameters from Kahneman and Tversky (1992)

Parameter	Meaning	Value
α	power for gains	0.88
β	power for losses	0.88
λ	loss aversion	2.25[11]
γ	probability weighting parameter for gains	0.61
δ	probability weighting parameter for losses	0.69

Additionally, we assumed the cost of the signal to be 20, which is the expected value of information when the decision-maker is a risk-neutral expected utility maximizer. With these parameter values, CPT predicts the following orders:

$$\begin{aligned} &V(S_1|L_1) \geq V(S_3|L_3) \geq V(S_4|L_4) \geq V(S_2|L_2), \\ &V(L_1|S_1) \geq V(L_3|S_3) \geq V(L_4|S_4) \geq V(L_2|S_2). \end{aligned} \tag{4}$$

Since CPT primarily accounts for the instrumental value of information, it predicts the same order of preferences in both the SPD and LPD setups. This limitation suggests that CPT, by itself, cannot fully explain the different behaviors observed in subjects across these two experimental designs.

However, the CPT-based order of $V(L_i|S_i)$, which is relevant for the LPD scenario, aligns with the order derived from the intrinsic value of information we presented

[10] We use the same functional forms as Kahneman and Tversky (1992). For details, see Appendix E.

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

earlier in Inequality (2). The reason for this alignment is that, in our conjecture, the key question subjects are considering in the LPD is related to the color of the ball, which ties directly to the instrumental value of the information, as predicted by expected utility theory or CPT.

Thus, when loss aversion is applied to the calculation of the intrinsic value of information—specifically in relation to the color of the chosen ball—it yields a result similar to applying Cumulative Prospect Theory to the evaluation of a lottery outcome tied to the ball's color. This is a natural outcome because, in both cases, the core evaluation revolves around the same key uncertainty (the color of the ball), whether framed as an intrinsic or instrumental concern. The overlap of the questions subjects ask in the LPD—about the color of the ball—aligns these two theoretical approaches, making the results of CPT and IVOI with loss aversion in this specific context quite similar.

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A Omitted Calculations

A.1 Investor Example

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

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

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

0.5. In this case, her expected utility is

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

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

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

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

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

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

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

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

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

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

Similarly,

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

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

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

A.2 Expected Utility

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

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

B Predictions with Signals

Table 13 shows subjects' prediction decisions after the signal stage. The majority of subjects followed the signal when their signal was informative (Box R or Box B). This suggests that the subjects comprehended the information structure of the experiments. In both studies, the chi-square test and Fisher's exact test indicate that the null hypothesis of random prediction by subjects can be rejected. (p-values < 0.001 for both studies.)

Table 13: Predictions with signals

	Predictions	Box R	Box B	Box G	No Signal
SPD	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%)
LPD	Red	37 (94.9%)	4 (11.1%)	8 (72.7%)	N/A
	Blue	2 (5.1%)	32 (88.9%)	3 (27.3%)	N/A
Chi-square test p-value = 0.000					

The purpose of Table 14 is to investigate whether the signal space size influences the prediction decisions. The correct decision rate is defined as whether the subject's prediction aligns with the signal suggested after receiving Box R or Box B as a signal. Results show that there is no correlation between the correct decision rate and the signal space size. (Chi-square test p-value and Fisher's exact test p-value are approximately 0.513 and 0.672, respectively).

Table 14: 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					

C Complexity Aversion

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

D Payoffs and the Size of the Signal Space

This section examines if the preference for larger signal space harms the information buyers. Table 15 displays the subjects' payoffs in points from Part 1 in both studies. The profits were larger in the SPD than in the LPD due to the 100-point endowment in the SPD. According to the table, in the SPD, the highest average profit was earned by the subjects who played the simplest lottery, Lottery 1. This indicates that they gained a lower profit when they played lotteries with larger signal spaces. However, this pattern was not observed when valuing the lotteries in the LPD.

		SPD			LPD		
Lottery	|S|	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 15: Payoffs from Part 1

Table 16 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 the SPD has a significant effect: purchasing signals from larger signal spaces negatively affected payoffs.

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

The implication of the results is that subjecs tend to overvalue signals when the signal space is larger, causing them to submit overpriced values for these signals and ultimately resulting in lower earnings.

	Dependent variable: Payoffs in SPD		Dependent variable: Payoffs in LPD	
	(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.
***$p < 0.01$, ** $p < 0.05$, *$p < 0.1$.

Table 16: Determinants of the payoffs

E Functional Forms of Cumulative Prospect Theory

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

$$U_{CPT}(x_m, p_m; x_{m+1}, p_{m+1}; \cdots; x_0, p_0; \cdots; x_n, p_n) = \sum_{i=-m}^{n} \pi_i v(x_i), \tag{5}$$

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

$$v(x) = \begin{cases} x^{\alpha} & \text{if } x \geq 0, \\ -\lambda(-x)^{\beta} & \text{if } x < 0, \end{cases} \tag{6}$$

where λ is a loss aversion parameter.

Decision weights π are defined by:

$$
\begin{aligned}
\pi_n^+ &= w^+(p_n), \\
\pi_{-m}^- &= w^+(p_{-m}), \\
\pi_i^+ &= w^+(p_i + ... + p_n) - w^+(p_{i+1} + ... + p_n),\ 0 \leq i \leq n-1, \\
\pi_i^- &= w^-(p_{-m} + ... + p_i) - w^-(p_{-m} + ... + p_{i-1}),\ 1-m \leq i \leq 0,
\end{aligned}
\tag{7}
$$

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

$$w^+(p) = \frac{p^\gamma}{(p^\gamma + (1-p)^\gamma)^{1/\gamma}},\ w^-(p) = \frac{p^\delta}{(p^\delta + (1-p)^\delta)^{1/\delta}}. \tag{8}$$