Preferences for Non-Instrumental Information and Skewness∗

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Abstract

We present experimental results from a broad investigation of intrinsic preferences for information. We examine whether people prefer negatively skewed or positively skewed information structures when they are equally informative, whether people prefer Blackwell more informative information structures, and how individual preferences over the skewness and the degree of information relate to one another. The wide scope of our investigation not only reveals new insights regarding intrinsic preferences for information, but as we show, also allows for testing of existing models in this domain. We find that models based on the framework of Kreps and Porteus (1978) and Caplin and Leahy (2001), are the most consistent with the data we observe.

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1 Introduction

Imagine having recently submitted a paper to a top journal. You are attending a conference where two of your previous mentors, Andy and Jim, are also present. You are considering asking them about their opinion on the fate of your paper at this journal. Neither can have any influence on the outcome, and you cannot make any changes to the paper, therefore their views are entirely non-instrumental at this time. They tend to have equally informative opinions, but differ in how they communicate them. Jim likes to be pretty certain of a good outcome before he gives you a thumbs up, whereas Andy gives a thumbs down only if he is quite certain of a bad outcome. Would you talk to either of your mentors at the conference? If so, which one would you prefer to talk to?

Psychologists have long recognized the desire to regulate anticipatory emotions, such as hope, anxiety and suspense, regarding an uncertain outcome in the future. Anecdotal evidence suggests that this desire may lead to a demand for information in the absence of an ability to act on that information, or to an avoidance of information even when information is useful.¹ For example, hopeful voters park themselves in front of the TV on election night, even though it costs them a good night’s sleep; and anxious patients with potential symptoms of a disease may put off taking a diagnostic test, even if it means to delay possible treatments. Consequently, the bulk of the work trying to understand preference for non-instrumental information in economics have focused on choices between information sources that vary in their timing of uncertainty resolution.

Importantly, an intrinsic preference for information may also dictate the kind of information people prefer to obtain. For example, certain information sources eliminate more uncertainty about the undesired outcome conditional on generating a bad signal, but are unlikely to generate a bad signal (i.e., they are negatively skewed, such as talking to Andy). Yet others eliminate more uncertainty about the desired outcome conditional on generating a good signal, but are unlikely to generate a good signal (i.e., they are positively skewed, such as talking to Jim).² How do individuals choose among such sources? Clearly, anticipatory emotions may also play a role in


²There has been some modeling of consumers who have a demand for skewed information structures; including Dillenberger and Segal (2015), Schweizer and Zech (2013) (2013), Caplin and Eliaz (2003), Eliaz and Spiegler (2006), Eliaz and Schotter (2010), and Muñainathan and Shleifer (2005) (our notion of skewness can also be thought of as a type of biased information). However, these applications disagree about what kind of skew individuals should prefer. Boiney (1993) and Eliaz and Schotter (2010) are the only two papers that explicitly test for positive versus negative skewed preferences.
these choices. Individuals who would like to preserve hope may prefer sources that lead to more confident beliefs regarding good outcomes at the expense of greater uncertainty regarding bad outcomes. For example, Caplin and Eliaz (2003) hypothesize that patients may opt for tests that are precise in ruling out the disease, but imprecise in ruling it in. On the other hand, individuals who want to minimize disappointment may instead opt for signals that are more accurate in predicting the bad outcomes at the expense of greater uncertainty regarding the good outcomes. Clearly, an understanding of preferences of over non-instrumental information is incomplete without an investigation of such tradeoffs.

In this paper, we present experimental results from a broad investigation of intrinsic preferences for information. In particular, we explore i) whether people prefer negatively skewed or positively skewed information structures when they are equally informative, ii) whether they prefer Blackwell more informative information structures, and iii) how individual preferences over the skewness and the degree of information relate to one another. Our experiment has several important features that address the common challenges in identifying preferences for non-instrumental information. First, preference election occurs in an environment where the information, by construction, cannot influence actions. Second, it ensures that the observed preferences are for information that impact subjects’ beliefs about future outcomes and their belief-utility, and not for information that shapes their self-perceptions, confidence or ego-utility. Third, it greatly reduces information processing cost of subjects to ensure that preferences reflect utility and not cognitive processing constraints. Finally, the experiment is designed to elicit preferences for information structures directly, rather than studying preferences over compound lotteries to make inferences over informational preferences.

The experimental design is detailed in Section 3. The experiment features one outcome of interest that has two states ordered in terms of payoffs: winning the lottery, which pays $10, or losing it, which pays $0. For each participant, the likelihood of winning is 50%. We determine the list of participants who won the lottery at the beginning of the experiment. Participants observe the process of determination, but not the outcomes. They know that the lottery outcome is fixed, and will eventually be revealed at the end of the experiment. During the experiment, participants are asked to make choices between information structures. All information structures generate one of two possible signals: good or bad, but they vary in how much and what kind of information uncertainty they resolve. At the time of choice, participants fully understand the probability with which each information structure can display a particular signal, and the posteriors they should have.

\footnote{Please see Hoffman (2011), El and Rao (2011), and Mobius et al. (2011) for examples where information of interest is about the action or characteristics of the subject, and Eliaz and Schotter (2010) for the case where confidence matters due to agency.}
after observing any given signal. After making their choices, participants see the signal generated by the information structure of their choice, and sit with the posterior beliefs based on this signal while working on hypothetical questions of unrelated nature before the winning ticket numbers are finally revealed.

Our contribution is three-fold. First, our investigation extends the scope of existing research on preferences over non-instrumental information by pursuing a more comprehensive understanding of these preferences. Second, exploring a wider range of non-instrumental information preferences allows us to carefully assess existing models in this domain. Third, in our experimental design, we utilize a novel and natural domain to test for information preferences by directly eliciting choices among information structures for a given prior. While there is a theoretical one to one mapping between compound lotteries and information structures, an empirical equivalence is not obvious. Directly eliciting preferences over information structures more closely reflects real-life decisions regarding information acquisition, and as we discuss below, can shed light on future theoretical work.

We present our experimental results in Section 4. They reveal a strong preference for positive skew over negative skew; in other words for ruling out more uncertainty about the desired outcome (and tolerating uncertainty about the undesired outcome) compared to ruling out more uncertainty about the undesired outcome (and tolerating uncertainty about the desired outcome). In our running example, these preferences suggest most of our subjects would prefer to talk to Jim. Moreover, large majority of the subjects prefer Blackwell more informative structures (i.e., earlier resolution of information), regardless of skew. We also explore relationships between different information preferences, and consistency across questions. Finally, we present an additional experiment that tests for robustness across questions, order of presentation and design features. We show that preferences are robust, individuals are willing to pay for their information structure choices, and their stated reasons for choosing an information structure map onto different desires to manage anticipatory emotions.

Many theoretical models of intrinsic preferences for information have similar motivations regarding demand for information. Moreover, most models can accommodate differences in the degree to which people want to be informed. Therefore, the vast majority of existing evidence, both empirical and experimental, cannot distinguish between predictions of these models. In Section 5, we derive a series of new theoretical results that identify the predictions of existing theories in our domain. We use these results to inform the design of the experiment. Therefore, we can assess the extent to which different models can accommodate the behavior we observe. Overall, the results provide the strongest support for the class of preferences introduced by Kreps and Porteus (1978) (which
in our setting is equivalent to the model of Caplin and Leahy, 2001) and extended by Grant, Kajii and Polak (1998). While in line with the psychological motives our subjects give, models proposed by Quiggin (1982), Gul (1991), Dillenberger and Segal (2015), Brunnermeier and Parker (2005), Kozsegi and Rabin (2009), and Ely, Frankel, Kamenica (2013) fail to capture certain features of the data. We discuss ways in which some of these models can be modified to capture the behavioral patterns we observe.

Our experiment and theoretical results also underscore the need for more theoretical work that directly characterizes preferences over information structures for a fixed prior (along the lines of Koszegi and Rabin 2009 and Ely, Frankel, Kamenica, 2013). The standard axiomatic approaches to informational preferences use a recursive methodology formalized by Segal (1990) which requires individuals to compare across both changing information structures and changing priors; something that hardly ever occurs in the real world. In contrast, directly eliciting preferences across information structures restricts us to focus on behavioral patterns that are observable in the real world. In addition, it also allows for a simple construction of indifference curves in a space that is very similar to standard consumption bundle space, thus making the tools and the intuition of standard microeconomic theory immediately available. We hope that our data provides new insights that are helpful in developing theoretical models that operate in this domain.

2 Framework

In this section, we outline the preliminaries of the setup and define the information structures we explore. We also specify important orderings on the set of information structures, which we use in deriving testable predictions regarding behavior from important classes of models in Section 5.

2.1 Preliminaries

We focus on individuals’ preferences for information where all probabilities are objectively known, rather than subjective. In order to capture preferences for information, our theory focuses on an idealized situation where there are three periods (0, 1 and 2). In Period 0, individuals have a prior probability distribution over states that will be realized and determine payoffs in Period 2. In Period 1 they receive a signal, which might cause them to update their prior to a posterior. In Period 2 the states are revealed and individuals receive their payoff. Importantly, individuals cannot take any actions, thus all preferences for information must come from intrinsic, rather than instrumental, motivations.

In order to derive predictions applicable to our particular experimental setting, we will focus on
situations where there are two outcomes, high and low, with utility values \( u(H) \), \( u(L) \), and so only two states. In this subsection, we normalize \( u(L) \) and \( u(H) \) to 0 and 1 respectively. Given the two outcomes, we denote the prior probability on the high outcome as \( f \). The decision-maker has access to a set of binary signal structures: the realizations are G (good) or B (bad). A good (bad) signal is a signal that increases (decreases) the beliefs about the outcome being high compared to the prior. The information structures in this context are fully characterized as points in \([0, 1]^2\): \((p, q)\), where probability of good signal conditional on high outcome is \( p = p(G|H) \) and probability of bad signal conditional on low outcome is \( q = p(B|L) \). Observing a good signal occurs with probability \( fp + (1 - q)(1 - f) \), and observing a bad signal occurs with probability \( f(1 - p) + q(1 - f) \). The posterior for a high outcome after observing a good signal is

\[
\psi_G = \frac{fp}{fp + (1 - f)(1 - q)}. \tag{5.5}
\]

After observing a bad signal the posterior is

\[
\psi_B = \frac{f(1 - p)}{f(1 - p) + (1 - f)q}. \tag{5.6}
\]

Formally, within the economics literature, intrinsic information preferences are typically modeled as preferences over two-stage compound lotteries — lotteries over lotteries. There is a natural bijection between prior-information structure pairs and two-stage compound lotteries. Each signal induces a lottery in period 1 regarding the outcomes in period 2. In period 0, the individual faces a lottery over these possible lotteries. Because our focus is on information, we will write preferences, and utility functionals, over the space of prior-information structure pairs. However, formal results will use the induced preferences in the space of two-stage compound lotteries in order to provide an immediate link with prior theoretical work.\(^4\)

We suppose that individuals have preferences over information structures given the prior \( f \), denoted by \( \succcurlyeq_f \). Among the domain of all possible signal structures represented as points in the \((p, q)\) space (with the horizontal axis being the \(p\)-value), we only consider preferences over those that lie above the line \( p + q = 1 \) along with the point \((.5, .5)\). We denote this set by \( \mathcal{S} := \{(p, q) | p + q > 1\} \cup (.5, .5) \). This focus is driven by two reasons. First, all points in \( \mathcal{S} \) have a natural interpretation: a good signal is good news (a bad signal is bad news). Lemma 1 formalizes this\(^5\).

**Lemma 1** For any \((p, q) \in \mathcal{S}\), observing a good signal increases the posterior on high outcome relative to the prior, and observing a bad signal decreases the posterior on high outcome relative to

\(^{4}\)For an extended discussion of these issues, please see Appendix A.

\(^{5}\)All proofs are included in Appendix B.
Moreover, this set of signals is a minimal set that still allows us to capture all possible posterior distributions, as shown by Lemma 2.

**Lemma 2** For any signal structure \((p', q') \in [0, 1] \times [0, 1]\), there exists a \((p, q) \in \mathcal{S}\) that generates the same posterior distribution. However, for any \(T \subset \mathcal{S}\) there exists a \((p', q') \in \mathcal{S}\) such that there is no element of \(T\) that generates the same posterior distribution as \((p', q')\).

Given this restriction, let us consider some examples of information structures depicted in Figure 1. The information structure denoted by \(A\) resolves all information as early as possible, because a good signal implies that the outcome is high for sure, and a bad signal indicates the outcome is low for sure \((p = q = 1)\). On the other hand, \(B\) is an information structure which conveys no information at all \((p = q = .5)\), since the posterior after either signal is equal to the prior. Information structure \(C\) \((p = q = .76)\) is another symmetric structure, i.e., on the diagonal, that resolves some interim uncertainty. As we move from \(B\) to \(A\), information structures on the diagonal resolve more uncertainty, always in equal degrees about the high and the low outcomes. We will refer to signals along the diagonal \(p = q\) as **symmetric**.

![Figure 1: Examples of Information Structures on (p,q) space](image)

Information structures off the diagonal, on the other hand, have the potential to resolve more uncertainty about one outcome over another. The information structures that are west of the diagonal, such as those denoted by \(D\) and \(F\) are positively skewed. For example, a good signal from information structure \(F\) resolves more uncertainty about the high outcome than a bad signal does about the uncertainty of the low outcome. Relatedly, a good signal from information structure \(D\) means that the outcome is high for sure, but a bad signal does not rule out a high outcome.
Suppose we fix $f = .5$. Then, the information structure $D$ provides a 25% chance to resolve all uncertainty in favor of the better outcome (giving a posterior of 1), while delivering worse-than-before news 75% of the time (delivering a posterior of $\frac{1}{3}$).

Conversely, the information structures that are east of the diagonal, such as those denoted by $E$ and $G$, are negatively skewed. For example, a bad signal from information structure $G$ resolves more uncertainty about the low outcome than a good signal does about the uncertainty of the high outcome. Similarly, a bad signal from information structure $E$ means that the outcome is low for sure, but a good signal does not rule out a low outcome. For example, when the prior is $.5$, $E$ provides a 25% chance to resolve all uncertainty in favor of the worse outcome (giving a posterior 0), while delivering better-than-before news 75% of the time (and giving a posterior of $\frac{2}{3}$).

Note that information structures $D$ and $E$, and $F$ and $G$ are symmetric across the diagonal, and thus are pairs of information structures of the form $(a, b)$ and $(b, a)$. For all such information structure pairs, the expectation of the posterior distribution is the same (by the Law of Iterated Expectations). Given a fixed prior, the variance of the posterior distributions are the same. But, they can be ranked in terms of skew. If $a \geq b$, the information structure $(b, a)$ has a posterior distribution with a positive third moment (positively skewed) while $(a, b)$ has a posterior distribution with a negative third moment (negatively skewed). In order to derive our theoretical predictions, we will compare positively and negatively skewed structures which are mean and variance preserving probability transformations of one another, as in Menezes et al. (1980), and use comparisons of pairs that are reflections of one another across the diagonal.6

2.2 Types of Informational Preferences

With these examples in mind, we now turn to some interesting preferences over information structures for a fixed prior. We use these preferences as motivation for our experimental design; for each of the following three types of preferences we have at least one (and often multiple) questions designed to elicit a choice that will shed light on the direction of that preference for each subject. Moreover, the direction of and relationships between these preferences, will allow us to test, non-parametrically, the predictions of widely used models of non-instrumental preferences for information. We detail this investigation in Section 5.

Preference for earlier versus later: Most of the theoretical models for non-instrumental information focus on accommodating preferences for early versus late resolution of information in

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6In the theoretical literature, there are other other several notions related to preferences for skewness, including third-order stochastic dominance, third-degree risk order, mean variance preserving probability transformations, the central third moment and the Dillenberger and Segal (2015) notion of skewness. Given a fixed prior and signal structures that are reflections of one another across the diagonal, all these different notions of skewness coincide.
both the decision theory literature (e.g., Kreps and Porteus, 1978; Epstein and Zin, 1989; Grant, Kajii, and Polak, 1998) and the behavioral literature (e.g., Koszegi and Rabin, 2009 and Koszegi, 2010).

We provide graphical examples of indifference curves where individuals display a strict preference for earlier or later resolution in the top row (Panels A-D) of Figure 2. Panel A provides an example of preferences for later resolution, while Panels B-D demonstrate preferences for earlier resolution. One can see that these preferences are similar in many ways, except that utility is either increasing or decreasing as we move northeast in the \((p,q)\) space.

A preference for early or late resolution of uncertainty is tightly linked to the most well-known ordering of information structures in economics, Blackwell’s ordering. In particular, an information structure resolves more uncertainty earlier than another if it is Blackwell more informative.\(^7\)

Intuitively, the posteriors under the more Blackwell informative information structure are a mean preserving spread of the posteriors under the less Blackwell informative one. Clearly, this will be true if \(p' > p\) and \(q' > q\), thus moving northeast on the diagonal line in Figure 1, we have symmetric information structures that are increasingly Blackwell more informative. However, Lemma 3 shows a signal can be Blackwell more informative under less stringent conditions. As a result, lotteries may be ranked in their informativeness even if all uncertainty is not resolved early (Period 1) or late (Period 2). Figure 3 illustrates the set of all signals that are Blackwell more and less informative than the signals \((p,q) = (.66,.66)\) and \((p,q) = (.3,.9)\) respectively, and gives some specific examples in these sets. We will rely on these observations in our experimental design.

**Lemma 3** \((p',q')\) Blackwell dominates (is Blackwell more informative than) \((p,q)\) if and only if
\[
p' \geq \max\{\frac{p}{1-q}(1-q'), 1-q'1-p\}.
\]

**Preference for one-shot versus gradual:** Another ordering over information structures that is discussed in the literature is a preference for one-shot resolution of uncertainty. Building on Palacios-Huertas (1999), Dillenberger (2010) provides a characterization of a preference for one-shot resolution of uncertainty. Dillenberger describes an individual who prefers full early resolution \((p = q = 1)\) or full late resolution \((p = q = .5)\) over any other information structure, fixing a prior \(f\). This phenomena is closely linked to the notion of a preference for clumping, introduced by Koszegi and Rabin (2009). Relatedly, Ely, Frankel and Kamenica (2013) model preferences for

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\(^7\)Blackwell’s ordering was originally designed to be used in situations where the individual’s payoff in Period 2 depends on both the state and an action taken by individuals in Period 1. However, as Kreps and Porteus (1978) and Grant, Kajii and Polak (1998) demonstrate, there is a meaningful mapping between Blackwell’s ordering and information preferences even when information is non-instrumental (i.e., individuals cannot take any action based on it).

\(^8\)For the exact parameterization of preferences in each panel, please see Appendix A.
gradual resolution of information, where full early resolution \((p = q = 1)\) or full late resolution \((p = q = .5)\) are the worst structures.

The lower row (Panels E-H) of Figure 2 demonstrates preferences for one-shot and gradual resolution of uncertainty. Panel E provides an example of preferences for gradual resolution of uncertainty, while Panels F-H demonstrate preferences for one-shot resolution of uncertainty. Thus, in Panel E, the optimal point is in the interior of the panel, while in Panels F-H the utility-minimizing point is in the interior panel. Preferences for one-shot resolution of uncertainty means that utility initially declines when moving to the northeast of (.5, .5).

**Preference for positive versus negative skewness:** The last ordering we want to discuss, and a novel contribution of this paper, is preferences for skewed information — whether in Period 1, individuals prefer to resolve more uncertainty about the high outcome or the low outcome. A preference for positive skewed information occurs if the decision maker prefers \((b, a)\) to \((a, b)\), when \(a \geq b\).

Figure 2 also demonstrates preferences for skewness. The left two columns (Panels A, B, E, F) demonstrate preferences that are indifferent to skewness: \((a, b) \sim (b, a)\). The right two columns demonstrate preferences for skewness. The third column (Panels C and G) show preferences for positive skew over negative skew. The fourth column (Panels D and H) show preferences for negative skew over positive skew. One can see that the primary difference between preferences for positive or negative skew is the slope of the indifference curves. As we further discuss in Section 5,
the existing theoretical models we consider predict both a preference over these “extreme” skewed information structures as well as same preference for interior cases where information is always resolved gradually.

3 Experimental Procedures and Design

The experimental design is mainly motivated by testing whether people prefer information structures that, given equal priors, are more accurate at predicting the worse outcome than those that are more accurate in predicting the better outcome when information is entirely non-instrumental (i.e., preferences for skewed information). Another motivation of the design is to test the relationship between preferences over skewness and preferences over the timing of information. Although existing theories were primarily motivated to explain preferences over the timing of information, they also make specific predictions regarding preferences over skewness. We derive these predictions in Section 5 and discuss them in the light of the data. Clearly, the design was motivated by testing these predictions; however, we delay the particulars of this discussion to Section 5. This section highlights the important design features. For a more complete description please see Appendix D.

3.1 Protocol

A total of 250 subjects were recruited for a 60 minute study using an online subject management system designed by the [blinded for review] lab. Subjects received a raffle ticket upon entering the lab, which gave them a 50% chance of winning $10 in addition to their $7 show-up compensation.
and a 50% chance of winning no additional money. They were told that the winning ticket numbers would be announced at the end of the study, and that they could choose whether and what kind of information they received in the middle of the study by making choices among information options. Subjects were aware that the information would not change whether they actually won the lottery or not, nor would it help them elsewhere in the experiment. The subjects were also informed that they would sit with this information until the outcome of the lottery was announced at end of the experiment. Finally, they learned that in the second half of the experiment they would be answering hypothetical questions that had no impact on their earnings. After reading these instructions, they answered comprehension questions that checked their understanding.

Subjects faced a series of five pairwise choices between information structures, knowing that one of the questions would be chosen at random after they had made all pairwise choices. Each information structure was represented with a pair of boxes from which the computer would draw a ball according to whether the subject won or lost the lottery. For example, Figure 4 depicts information structures (1, .5) and (.5, 1) as Option 1 and Option 2, respectively. The subjects could not see which box the computer was drawing a ball from, but could observe the color of the ball. The box that the computer would draw from if the subject won the lottery had weakly more red balls (and so fewer black balls) than the box that the computer would draw from if the subject lost the lottery, but the composition greatly varied across information structures. Each box had 100 balls. Our theoretical construct $p$ is equivalent to the number of red balls in the box if the subject won the lottery; $q$ is equivalent to the number of black balls in the box if the subject did not win the lottery.

Subjects watched an instructional video before each question that presented two such information structures, explained the percentage of the instances a red or a black ball would be drawn from each option, and displayed the posterior probability of winning or losing associated with observing a red or a black ball from each information structure. In order to minimize information processing cost of subjects to ensure that preferences reflect utility and not cognitive processing constraints we chose to display the posteriors after a given signal (and the probability of each signal) prominently. After this instructional video, subjects completed comprehension questions that checked

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9Implementation using a random-lottery incentive system is quite common in the literature. However, it has been criticized (Holt, 1986) as possibly inducing different choices than would be observed if each question was answered in isolation. Experimental evidence, although mixed, has been generally supportive; Starmer and Sugden (1991) and Cubitt et al. (1998) are supportive, while Harrison et al. (2013) finds distortions. Such concerns could be magnified given that we are explicitly modeling individuals who do not reduce compound lotteries. We alleviate such concerns in two ways. First, we ran a robustness check which involved a single pairwise choice which we discuss in Section 4.2. Our results are qualitatively similar. Second, if preferences satisfy recursivity (an assumption satisfied by most of the models we consider) random implementation should generate the same pattern of choice as choices made in isolation.
their understanding before proceeding to making their choices. The information presented by the video was also repeated on the page that described each information structure and asked for their choice.

After the subjects made choices in all five questions, the computer randomly picked one question among the five to be carried out for each subject. The program displayed the chosen question, the subject’s choice of information structure, the color of the ball drawn from it, and repeated the posterior probability of the subject having won the lottery based on the color of the ball. Subjects were asked to answer a comprehension question regarding the posterior probability of having won and several qualitative questions regarding their choice before moving onto the filler task which asked hypothetical questions that each presented two options to elicit their risk preferences, ambiguity aversion, ability to reduce compound lotteries and attitude differences towards common ratios.

Our experimental setup addresses three important challenges in identifying preferences for non-instrumental information. First, it ensures that information is entirely non-instrumental. We introduced a considerable delay between the time of information acquisition to the time of uncertainty resolution, while keeping the subjects in a controlled environment to rule out any potential instrumental use of the information acquired. In other words, subjects could not engage in any actions in the experiment or elsewhere based on the information about their future earnings. Second, it ensures that the observed preferences are for information that impact subjects’ beliefs about future outcomes and their belief-utility, and not for information that shapes their self-perceptions, confidence or ego-utility, etc. Third, it reduces information processing cost of subjects to ensure that preferences reflect utility and not cognitive processing constraints. As a part of the experiment we explained to subjects the probability they will observe any given signal, and what posteriors they
should have after observing said signal. Thus, choices we observe are not the result of individuals incorrectly updating, or being confused by what the information is telling them. By construction, preferences are elicited in a situation where information must be resolved at some point.\textsuperscript{10} Thus, although subjects cannot avoid having their beliefs change, they can control the timing between shifts in beliefs, and related emotional reactions, due to information revelations.

3.2 Design

There were two between-subject conditions, each presenting five questions. Table 1 details the order of questions and options presented in Condition 1 and Condition 2. Conditions 1 and 2 varied the order of the options presented in Q1, Q2, Q5b, and counterbalanced the order in which Q3 and Q5a were presented, and also asked different Q4a and Q4b.\textsuperscript{11}

<table>
<thead>
<tr>
<th></th>
<th>Condition 1</th>
<th>Condition 2</th>
<th>Assignment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Q1</td>
<td>(1, 1)</td>
<td>(.5, .5)</td>
<td>all subjects</td>
</tr>
<tr>
<td>Q2</td>
<td>(1, .5)</td>
<td>(.5, 1)</td>
<td>all subjects</td>
</tr>
<tr>
<td>Q3</td>
<td>(.9, .3)</td>
<td>(.3, .9)</td>
<td>all subjects</td>
</tr>
<tr>
<td>Q4</td>
<td>(.76, .76)</td>
<td>(.3, .9)</td>
<td>if (1, 1) ≥ (.5, .5)</td>
</tr>
<tr>
<td></td>
<td>(.55, .55)</td>
<td>(.66, .66)</td>
<td>if (1, 1) ≤ (.5, .5)</td>
</tr>
<tr>
<td>Q5</td>
<td>(.9, .6)</td>
<td>(.9, .3)</td>
<td>random</td>
</tr>
<tr>
<td></td>
<td>(.55, .55)</td>
<td>(.55, .55)</td>
<td>random</td>
</tr>
</tbody>
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Q1 elicited preferences regarding full early resolution of uncertainty (indicated by (1,1)) versus full late resolution of uncertainty (indicated by (.5, .5)). Q2 elicited preferences between (.5, 1) and (1, .5), a positively skewed structure and a negatively skewed structure. Note that Q2 asked subjects to compare skewed information structures that may lead to full resolution of uncertainty given some signal realizations. Q3 and Q5 presented additional comparisons of positively skewed structures to negatively skewed structures, (.3, .9) versus (.9, .3), or (.6, .9) versus (.9, .6), where information is always resolved gradually. Half the time, Q5 presented another signal structure that tested preferences for full late resolution (.5, .5) and another symmetric signal structure that is slightly more informative (.55, .55). This comparison tested preferences for one-shot versus gradual

\textsuperscript{10}This distinguishes us from environments where it is possible for individuals to avoid learning at all, such as in Alaoui (2009).

\textsuperscript{11}We did not test richer question order randomization for two reasons. First, the video instructions explaining each question built on one another. Second, starting with Q1-Q2 made most sense because they were the simplest to explain. We ran an additional experiment, detailed in the next section, that presented only one question per subject, partly to address potential concerns regarding order or framing effects.
resolution of uncertainty.

Across both conditions, different versions of Q4 tested whether the preferences of subjects who exhibit a preference for Blackwell informativeness over symmetric signal structures also respect that same Blackwell ordering when comparing positively skewed structures to symmetric structures. If subjects preferred late resolution, they were asked to choose between a positively skewed signal to a symmetric signal that was Blackwell less informative than that skewed signal, e.g. (.5, 1) to (.66, .66). Similarly, if they preferred early resolution, they were asked to choose between a skewed signal to a symmetric signal that was Blackwell more informative, e.g. (.3, .9) to (.76, .76). We varied the skewed and symmetric structures across conditions for robustness. The data generated by Q4 i) helps us better distinguish between models that capture non-instrumental preferences for information, and ii) allows us to assess to what extent preferences for skewness may interact with preferences for Blackwell dominance.

Note that we specifically chose to test preferences between pairs of information structures.\footnote{Because our domain appears similar to a standard consumption domain, it would be possible to give consumers a “budget” constraint and have them choose their favorite signal within the budget constraint. We do not do so because we believe this would make it harder for the subjects to understand the posterior distribution induced by any given signal and the probabilities with which a given signal is realized. Pairwise choices are less cognitively demanding.} While a theoretical parallel exists between preferences over compound lotteries and over information structures, we want to directly test for preferences over information structures, because such choices more closely mirror real-life scenarios of information acquisition. We also focus on a particular prior, where $f = .5$, which produces sharper predictions of some of the existing theories in our domain.\footnote{Many of the commonly used functional forms in the theoretical literature rely on the recursive assumption formalized by Segal (1990). Recursivity requires individuals to compare across both changing information structures and changing priors; something that hardly ever occurs in the real world.}

4 Data and Results

Table 2 summarizes choices across the information structures tested by Q1-Q5 and reports p-values from two-sided binomial tests against the null hypothesis of random choice. For each option, Table 2 also summarizes the preference strength subjects reported, and reports the p-values from two-sided t-tests that compare the means among subjects with different choices in a given question. The results patterns are the same across the two conditions, therefore we collapse the data. Tables 7 and 8 in Appendix C report results per condition.

The first set of results presented in Table 2 describes preferences over information structures that are symmetric, but vary in terms of Blackwell informativeness. These results indicate that individuals generally prefer full early resolution relative to full late resolution. Moreover, individuals prefer learning a little bit earlier rather than full late resolution in just as large a proportion.
Therefore, the results do not support a general preference for one-shot resolution of uncertainty. Examining the preference strength data, we see that the relative preference for the option chosen by the majority of subjects is stronger. For example, subjects who prefer (1, 1) to (.5, .5) reported an average of 8.31 preference strength for option (1, 1) over the option (.5, .5) on a range from 0 to 10. This preference strength was on average 6.37 for option (.5, .5) over the option (1, 1) among those who choose (.5, .5).

The second set of results relates to preferences for negatively versus positively skewed information structures. We observe that most individuals prefer the positively skewed information structure relative to the negatively skewed information structure. In fact, the preference for positively skewed information is almost as prevalent in the population as the preference for early resolution. In addition, the preference strength for the chosen option is stronger among those who prefer the positively skewed information structure than among those who prefer the negatively skewed information structure. In the data, we also observe considerable consistency in the choice of positively skewed information. Among the subjects who prefer the positively skewed option (.5, 1) to the negatively skewed option (1, .5), 83% of those who faced only one additional question over positively and negatively structures also prefer the positively skewed option over the negatively skewed option presented in the future question. Analyzing the set of subjects who answered three questions that presented a choice between a positively skewed and a negatively skewed information structures, we see that 71% of subjects who prefer the positively skewed option (.5, 1) to the negatively skewed option (1, .5) also prefer the positively skewed option in both of the future questions. This consistency in choice was much higher among those who prefer positive skew. Among the subjects who faced two questions regarding skewness, of those who prefer (1, .5) to (.5, 1), only 40% prefer the negatively skewed option over the positively skewed option in the later question. Moreover, among the subjects who faced three questions regarding skewness, only 18% of the subjects who prefer (1, .5) to (.5, 1) indicated a persistent preference for the negatively skewed information structure in the other two questions.

The third set of results presented in Table 2 concerning choices between symmetric and skewed information options require more interpretation due to the conditional nature of the experimental design. Recall that individuals only compared (.76,.76) to (.3,.9) (or (.1,.95) to (.67,.67)) if they previously indicated they preferred full early resolution of information to full late resolution. Individuals compared (.3,.9) to (.55,.55) (or (.66,.66) to (.5,1)) if they made the opposite choice regarding the timing of full resolution of information. Thus, we can interpret these questions as asking, whether preferences consistently order Blackwell ranked information structures in two situations: first, when comparing symmetric structures; and second, when comparing positively-skewed
structures to symmetric structures. Because most individuals prefer positively-skewed structures, and because the comparisons are to symmetric structures that are just barely more or less Blackwell informative, these questions also test whether preferences for skewness can dominate preferences for Blackwell informativeness.

From the comparisons of (.76, .76) to (.3, .9) and (.1, .95) to (.67, .67), we see that most of the individuals who exhibit a preference for early resolution over symmetric structures also prefer Blackwell more informative signals to skewed signals. The test is underpowered for choices between (.3, .9) vs. (.55, .55) and (.66, .66) vs. (.5, 1) due to small sample size. However, the directional results suggest that the preferences of individuals who preferred full late to full early resolution of uncertainty when comparing symmetric information structures may not necessarily respect the same ordering induced by Blackwell dominance when comparing a positively skewed structure to a symmetric structure. Overall, we conclude that the choices of subjects who prefer early resolution are consistent with monotonic preferences over information, because they are willing to accept less

Interestingly, we find that such reversals of preference regarding Blackwell ordering among the individuals who prefer full late to full early resolution of uncertainty are more likely among those with a weak preference for late resolution ($p - value = .009$, logistic regression of conditional Q4 choice on preference strength in Q1). Those who always prefer less information have rated their preference for full late resolution to be on average 8.8 out of a 10 point scale, whereas those who prefer the more informative skewed signal have rated their preference for full late resolution to be 6.5 on average. Therefore, it seems that at least some of the individuals who do not seem to have a consistent preference regarding Blackwell informativeness of signals may have weaker preferences of late resolution of uncertainty to begin with. Differences in strength of preference do not predict whether individuals who exhibit a preference for early resolution over symmetric structures also prefer Blackwell more informative signals to skewed signals, most probably because only a minority of subjects fail to do so.
positive skew in exchange for greater Blackwell informativeness.

4.1 Relationship between different information preferences

Even previous theoretical work does not consider the relationship between preferences for early versus late resolution of uncertainty and preferences for skewness, the within-person nature of our experiment’s design allows us to investigate whether there exists correlation between preferences.

Table 3: Early or Late vs Skewed

<table>
<thead>
<tr>
<th></th>
<th>Extreme</th>
<th>Medium</th>
<th>Slight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Early</td>
<td>(.5,1) (1.5)</td>
<td>(.6,.9) (.9.6)</td>
<td>(.3,.9) (.9.3)</td>
</tr>
<tr>
<td>Late</td>
<td>(.5,.5)</td>
<td>44 10</td>
<td>54</td>
</tr>
<tr>
<td></td>
<td>167 83</td>
<td>250</td>
<td>144 52</td>
</tr>
</tbody>
</table>

Table 3 cross-tabulates within-person choice patterns regarding skewness and choice for early resolution. We see that subjects who have a preference for early resolution of uncertainty are relatively less likely to choose the extremely positively skewed signal, compared to those who prefer late resolution ($p$-value=.012, logistic regression of Q1 choice onto Q3 choice). However, such a relationship does not exist between medium or slight positive skewness and late resolution preferences. Therefore, the evidence is intriguing, but inconclusive.

Table 4 relates within-person choices of late vs. early and gradual vs. one-shot resolution of uncertainty. As expected, a preference for (.5, .5) over (.55, .55) is significantly correlated with a preference for (.5, .5) over (1, 1) (logistic regression, $p$-value=.001).

We can use our results to try and understand to what extent preferences are “monotone” in the Blackwell ordering of information. We consider two notions of monotonicity. One is strong monotonicity. We say a subject obeys strong monotonicity whenever the decision-maker always chooses the information structure which is Blackwell more informative or Blackwell less informative (when they are ranked). In contrast, we say a subject obeys weak monotonicity if the decision-maker chooses the Blackwell more informative signal in both Q1 and in Q4 or the Blackwell less informative signal in both Q1 and Q4.

Among the 121 subjects who made choices that allow us to test both our strong and weak monotonicity conditions, 4 only violate weak monotonicity, 28 only violate strong monotonicity, 2 violate both, and 87 do not violate either.

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15 A cross tabulation of choices across different questions comparing two skewed information structures is presented in Appendix C.

16 Thus, weak monotonicity is violated if a subject chooses Option 2 in Q4A, or Option 1 in Q4B in condition 1 or Option 2 in Q4B in condition 2.
Table 4 provides details of subjects consistency with these conditions. Of the 196 subjects who prefer \((1, 1)\) to \((.5, .5)\), none violate weak monotonicity. Of the 93 subjects who prefer \((1, 1)\) to \((.5, .5)\) and had a test of strong monotonicity, 77 satisfy the condition. Subjects who have a preference for late resolution are more likely to violate both strong and weak monotonicity conditions. Of the 54 subjects who prefer \((.5, .5)\) to \((1, 1)\), 12 violate weak monotonicity, and of the 28 subjects who prefer \((.5, .5)\) to \((1, 1)\) and had a test of strong monotonicity, half fail. Since subjects are less likely to have strong preferences for their choice of \((.5, .5)\) over \((1, 1)\), the higher degree of violating our monotonicity conditions may be driven by the fact that they are close to indifferent regarding the timing of uncertainty resolution.\(^{17}\)

<table>
<thead>
<tr>
<th>Gradual ((.55, .55))</th>
<th>One-shot ((.5, .5))</th>
<th>Weakly Monotone</th>
</tr>
</thead>
<tbody>
<tr>
<td>Early ((1, 1))</td>
<td>77</td>
<td>16</td>
</tr>
<tr>
<td>Late ((.5, .5))</td>
<td>14</td>
<td>14</td>
</tr>
<tr>
<td></td>
<td>91</td>
<td>30</td>
</tr>
</tbody>
</table>

4.2 Robustness: Between Subjects Design and WTA Measurement

One plausible concern regarding the design of the experiment is that we did not directly elicit a willingness to pay for the preferred information structure. We did this to avoid further complicating an already complex elicitation procedure. A second plausible concern is that in having individuals make several pairwise choices, we elicited preferences different from what they would express if they were making a single pairwise choice (despite the fact that only one of the pairwise choices would be implemented).

In order to ensure our results are robust to these concerns, we ran an additional experiment. The experiment mirrored the setup of the main study. It featured a lottery that would either pay $10 or nothing, with a 50% prior on the high outcome. However, it differed from the main experiment in three main regards. First, each subject made only a single pairwise choice between two information structures. Second, we elicited the amount of monetary compensation subjects required in order to switch their choice from the more to the less preferred information structure, in order to provide a monetary measure for the strength of their preference. To this end, the experiment also included a practice round to familiarize the subjects with the willingness to accept elicitation mechanism. Third, in a post-decision questionnaire, subjects explained the reasons for their choice among the

\(^{17}\) Also, subjects who prefer \((.5, .5)\) over \((.55, .55)\) were more likely to violate strong and weak monotonicity conditions (logistic regressions, \(p - value = .000\) and \(p - value = .031\) respectively).
two information structures. All experimental details are presented in Appendix E.

The binary comparison of interest presented to each subject was determined by five between-subject treatments. Treatments A-D repeated the questions presented as Q1, Q2, Q3 and Q5 in the main experiment. We also included a pairwise comparison not tested by the main experiment: subjects in treatment E chose between an information structure that provided no additional information (i.e., (.5, .5)), and a positively skewed information structure (i.e., (.5, 1)) to test if subjects preferred skewed information over no information at all. The choice options and their order in each treatment are listed in Table 5, along with the experimental results.18

<table>
<thead>
<tr>
<th>Treatments</th>
<th>N</th>
<th>Choice Percentage</th>
<th>Intensity</th>
<th>Average MCTS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>First</td>
<td></td>
</tr>
<tr>
<td>A (1, 1) vs (.5, .5)</td>
<td>38</td>
<td>69% .017</td>
<td>8.19 6.84 .036</td>
<td>26.4 28.8 .350</td>
</tr>
<tr>
<td>B (1, .5) vs (.5, 1)</td>
<td>38</td>
<td>19% .000</td>
<td>6.42 7.29 .229</td>
<td>16.5 33.5 .010</td>
</tr>
<tr>
<td>C (.3, .9) vs (.9, .3)</td>
<td>38</td>
<td>74% .003</td>
<td>5.50 6.10 .270</td>
<td>18.4 25.1 .118</td>
</tr>
<tr>
<td>D (.9, .6) vs (.6, .9)</td>
<td>40</td>
<td>30% .008</td>
<td>5.75 6.86 .072</td>
<td>31.3 25.2 .157</td>
</tr>
<tr>
<td>E (.5, .5) vs (.5, .1)</td>
<td>36</td>
<td>14% .000</td>
<td>6.40 8.26 .026</td>
<td>35.3 33.5 .433</td>
</tr>
</tbody>
</table>

In parentheses we report the p-values from one-sided binomial tests to evaluate the null hypothesis that choice percentages are either larger or smaller than 50%, and p-values from one-sided t-tests to evaluate the ordering of preference intensity and average MCTS across option 1 and option 2.

The results from the robustness study corroborate our earlier findings. People have a strong preference for earlier resolution of uncertainty (treatment A) and for positive skew over negative skew (treatments B, C, and D). Moreover, subjects strongly prefer the positively skewed information structure over an uninformative one (treatment E). Interestingly, the average preference intensity reported for each option is very similar to those reported in the main study. We again see that the option preferred by more of the subjects to be associated with a higher preference intensity in general. However, the differences are not always significant, possibly due to the smaller sample size in this study. We find preference strength assessments to be positively associated with the amount of payment subjects are willing to accept to let go of their choices. In particular, one point increase in the preference strength on a scale of 0-10 is associated with a 3 cents increase in the minimum compensation to switch (MCTS) one’s choice from her preferred option to the other option ($\beta = 2.96$, p-value = .000).

We find that subjects are willing to forgo monetary compensation in order to observe a signal from their preferred information structure, rather than from the alternative. Overall, 90% of the subjects have non-zero willingness to pay to keep their preferred information structure. In addition, more than half the subjects reject a payment of 25 cents and a quarter of them reject a payment...
of 50 cents in exchange for seeing a ball from the information structure they did not prefer. The average MCTS ranges from 18.4 cents to 35.3 cents across different options of choice.\textsuperscript{19} All of these average MCTS measures are significantly larger than zero (one-sided t-tests, p-values $\leq .001$). As we can see from Table 5, except in treatment B, there are no significant differences between the MCTS reported by subjects based on which option they chose.

Some insights into what made subjects prefer certain information structures over others may be obtained by examining their answers to the post-decision questionnaire. The general message is that while subjects understand that the information offered to them was non-instrumental, the subjects who prefer positively skewed information structures have an intrinsic preference to preserve hope about winning the lottery. For instance, a representative sample of responses includes the following:

- “While info is essentially the same to me, slightly prefer to keep hope alive, i.e., prefer less certainty about losing.”
- “I would rather be sure of the good news if/when I receive it.”
- “I would rather have my good news be very good and my bad news be not so bad as opposed to probably getting good news in option 1 that’s only kind of good.”

On the other hand, subjects who prefer negatively skewed information structures generally discuss avoiding potential disappointment:

- “I wouldn’t want to be led on by the hope that I won ten dollars. I would rather have a very strong indication that I didn’t win by getting a black ball so that I wouldn’t have uncertainty or false excitement.”
- “I’d rather know more surely that I lost if I got a black ball, then deceive myself into keeping false hope that my black ball actually will yield a positive result.”
- “I would rather be more sure that I lost than be confident that I won because I don’t want to get my hopes up.”

\textsuperscript{19}Subjects in the experiment indicated whether they would switch their choice for a compensation of 1 cent, 5 cents, 10 cents, 15 cents, 20 cents, 25 cents, 30 cents, 35 cents, 40 cents and 50 cents. We employ the most conservative measure of MCTS. For example, if the subject rejects a compensation of 10 cents, but accepts a compensation of 15 cents, we set his MCTS to be 10.1 cents. Similarly, if the subject rejects a compensation of 50 cents, we set his MCTS to be 50.1 cents. Therefore, our measure is a lower-bound on the actual MCTS.
Thus, it seems that differences across preferences for non-instrumental information indeed maps onto differential desires to manage anticipatory emotions.\footnote{When discussing whether they prefer full early or full late resolution, subjects give motivations such as “I would rather know now rather than dwell over it for the next 20 minutes,” or “I feel like Option 1 would cause unnecessary stress in the middle of the study.”}

Overall, the data from the robustness experiment suggest that 1) the choice patterns in the main experiment are robust to order effects and other biases that may result from a within-person experimental design, and 2) subjects are willing to pay for their preferred information structures, even though their choice will not change their expected monetary payoffs.

### 4.3 Interpretating the Data

There are two concerns that we want to address regarding the interpretation of the data from these experiments. First, we might be concerned that individuals are so used to having information be instrumentally valuable that they simply apply the instrumental heuristic in non-instrumental settings. This would be a good reason why individuals choose more informative over less informative signals. However, there are many simple instrumental settings where choosing the negatively skewed information structure gives a higher expected payoff than choosing the positively skewed structure, and so it is hard to conceive that this preference is purely heuristic in nature.

Second, positively skewed structures, compared to negatively skewed structures, always generate a higher posterior probability of winning conditional on observing either signal. Thus, one might be concerned that people are mainly focusing on these posterior probabilities. The real concern is that this is not a true preference but simply a boundedly rational way of evaluating the signals. However, our data shows that individuals do not simply want to maximize the posterior probability of winning, conditional on observing a signal. We find that individuals prefer Blackwell more informative symmetric signals to positively skewed signals. The former have the same posterior probability of winning conditional on a red ball, but a lower posterior probability of winning conditional on a black ball. In addition, the answers in the post-experiment questionnaire also support the idea that the data reflect preferences, rather than a misguided focus on the posterior probability of winning conditional on observing either signal.

### 5 Discussion

Our data indicates three main patterns:

- Individuals consistently prefer Blackwell more informative structures. For a given (uncondi-
individual) pairwise choice over symmetric structures, between 69% and 78% percent of subjects prefer the Blackwell more informative structure.

- Individuals consistently prefer positively skewed structures. For any single pairwise comparison, we find that between 67% and 81% of subjects prefer the positively skewed to the negatively skewed information structure.

- Individuals prefer symmetric Blackwell more informative structures over those that are Blackwell less informative, but more positively skewed. Between 64% and 71% of subjects are willing to accept less positive skew in exchange for greater Blackwell informativeness.

Moreover, individuals also consistently exhibit these preferences across questions. Recall that of subjects who face three (two) questions regarding skewness, 71% (83%) of those who choose the extreme positively skewed structure over the extreme negatively skewed structure always choose the positively skewed option in the future. Similarly, of the 196 individuals who face two questions that tested for preferences over Blackwell ranked signals and initially choose (1, 1) over (.5, .5), all of them also choose the Blackwell more informative signal in the second question. Of the 93 subjects who face three questions that tested for preferences over Blackwell ranked signals and initially choose (1, 1) over (.5, .5), 77 of them choose the Blackwell more informative signal in both subsequent questions.

5.1 Relating Theory to Data

The anticipatory motivations provided by our subjects reflect the intuitions provided in much of the theoretical literature. Such a parallel naturally raises the following question: To what extent do existing theoretical models that rely on these same motivations capture the stylized patterns we observe in choice?

There are a variety of theoretical models that predict preferences over information structures. In this section we link functional forms used to capture non-instrumental preferences for information to observable patterns of choice, which we then compare to our data. This allows us to use our data to test a variety of assumptions and functions used in the literature. Our data, and the linkage we provide to theory, also allows us to reflect on the intuitive psychological motivations for why we observe the patterns we do.

We first discuss the general conditions that preferences should satisfy in order to be consistent with the three main patterns previously mentioned at the beginning of the Section. We then relate these patterns to particular functional forms used in the literature.
In testing existing theory, we primarily work with the functional forms used to try to capture intrinsic preferences for information. We do so because some of the models we consider have no formal axiomatic basis, and so the axioms themselves cannot be directly tested in our framework. By way of analogy, most of these models have no known “Independence”-like axiom we can test regarding skewness. Moreover, verifying the properties of the local utility functions for a given preference can be quite difficult. We will not describe the models themselves in detail in this section. The interested reader can see Appendix A for a more detailed description of the formal set-up and models we utilize and Appendix B for the proofs of the predictions.

**Theoretical Predictions**

Traditional economic theory assumes that individuals do not have non-instrumental preferences over information; Segal (1990) describes these individuals as satisfying an axiom called Reduction of Compound Lotteries. When re-framed in our domain, information structures with a fixed prior, this axiom simply says that an individual should not care about what information structure they face, i.e., \((p, q) \sim_f (p', q')\).

**Prediction 1** Fixing \(f\), if a decision maker satisfies Reduction of Compound Lotteries then they should be indifferent between all information structures.

Of course, it is easy to imagine that individuals are not indifferent between all information structures even when information has no instrumental value. Thus, the literature has considered various weakenings of the Reduction of Compound Lotteries assumption. One assumption, introduced by Segal (1990), is that rather than being indifferent between all lotteries that have the same reduced form probabilities over final outcomes, individuals are only indifferent between full early resolving lotteries (i.e., \(p = q = 1\)) and full late resolving lotteries (i.e., \(p = q = .5\)) that have same reduced form probabilities over final outcomes (i.e., the same \(f\)). Segal describes these individuals as satisfying the Time Neutrality axiom.

**Prediction 2** Fixing \(f\), if a decision-maker satisfies Time Neutrality they should be indifferent between \((1, 1)\) and \((.5, .5)\).

Because Time Neutrality imposes a type of stationarity on preferences, they have been widely used in the literature, such as Dillenberger (2010). In contrast, a large number of papers, beginning with Kreps and Porteus (1978), have discussed the importance of a preferences that do not satisfy Time Neutrality. In particular, they focus on individuals who have a preference for earlier (later) resolution of uncertainty. This means that given two lotteries which generate the same reduced
form probability distribution, individuals always prefer a compound lottery which is more (less) Blackwell informative in the first stage. Grant, Kajii and Polak (1998) show that given mild differentiability assumptions on the utility function $V$ that represents the preferences, a preference for more (less) Blackwell informative signals is equivalent to the local utility function of $V$ being convex (concave).\footnote{Recall that convexity and concavity, as well as the local utility functions, used in both this and the following proposition, are defined in the space of two-stage compound lotteries induced by the prior-information structure pair.}

**Prediction 3** Let $\succsim_f$ be represented by $V$, where $V$ is Gateaux differentiable. Then the local utility function of $V$ is everywhere convex (concave) if and only if the decision-maker prefers Blackwell more (less) information structures.

Intuitively, more information earlier means that the two-stage compound lottery undergoes a mean-preserving spread in the second-stage (posterior) lotteries. Convexity of $V$ implies that a decision-maker likes this increase in spread.\footnote{Machina (1982) shows that under mild smoothness conditions one can use local utility functions whenever $V$ is not expected utility to do the same type of analysis that is possible for expected utility preference.}

Regardless of the individual’s preference for information, what determines an individual’s preference obtaining signals from positively or negatively skewed information structures? We know that an individual prefers positively skewed lotteries if the derivative of the local utility function is convex. As Prediction 4 demonstrates, this intuition naturally maps into compound lotteries, and thus information structures.\footnote{Our requirement on the differentiability of the utility functional and the local utility functions is stronger than it actually needs to be in Prediction 3 and Prediction 4. Using the techniques of Cerreia-Vioglio, Maccheroni and Marinacci (2014) we can relax the differentiability assumptions.}

**Prediction 4** Let $\succsim_5$ be represented by $V$, where $V$ is Gateaux differentiable. If the local utility function of $V$ is thrice differentiable and has a convex (concave) derivative everywhere, then $(x,y) \succsim_5 (\succsim_5)(y,x)$ whenever $x \leq y$.

The predictions discussed up until now rely on very general conditions. We can extend these insights and use the data to directly test specific functional forms that have been used in the literature.

We first turn to a class of preferences, “recursive preferences,” first formalized by Segal (1990). In this class, decision-makers evaluate situations with information revelation using a folding-back procedure by using two functionals $V_1$ and $V_2$, which represent the utility at Period 1 and 2, respectively. Although recursivity provides a useful structure on utility, it cannot be directly tested in a setting where individuals make choices over information structures. Recursivity is only testable
by changing the prior belief of individuals. Thus, we must test recursivity in conjunction with other assumptions about the structure of the preferences.

We consider the predictions of models that specifically assume recursivity and can address preferences for skewness.\textsuperscript{24} The first model to implicitly use recursive preferences to address non-instrumental preference for information was introduced by Kreps and Porteus (1978). Another influential model, Caplin and Leahy (2001), nests Kreps and Porteus’ specification in our framework. They assume both $V_1$ and $V_2$ have expected utility representations. Given their specification, we now provide a stronger version of Predictions 3 and 4.

**Prediction 5** Suppose preferences have a recursive representation $(V_1, V_2)$ such that $V_1$ and $V_2$ have expected utility representations with Bernoulli utilities $u_1$ and $u_2$. Then $u_1 \circ u^{-1}_2$ is convex (concave) if and only if the decision-maker prefers Blackwell more (less) information structures. Moreover, if the derivative of $u_1 \circ u^{-1}_2$ is convex (concave), then $(x, y) \succeq_{.5} (y, x)$ whenever $x \leq y$.

In Figure 2, Panels A-D exhibit preferences that are within the Kreps-Porteus class. Panel A demonstrates preferences that prefer later resolution and are indifferent to skewness. Panel B-D demonstrates preferences that prefer earlier resolution. Panel B has preferences that are indifferent to skewness. Panels C and D show preferences for positive and negative skew respectively.

There are also other models assuming recursivity, used in a variety of applications, which make other particular functional form assumptions. Two well-known classes of models used in dynamic applications are the recursive extensions of Gul’s (1991) model of disappointment aversion and rank dependent utility. Both of these models can accommodate a preference for positively skewed information or for negatively skewed information. However, they also generate additional predictions regarding behavior that can separate them from the basic Kreps-Porteus model. Our next prediction is one such behavior; it states that if an individual’s preferences fall within either of these classes and are consistent with the empirical evidence on the Allais paradox and first-order risk aversion, then they must exhibit local preference for late resolution.

**Prediction 6** Suppose preferences have a recursive representation $(V_1, V_2)$ such that $V_1$ and $V_2$ are both in Gul’s class of disappointment aversion functionals (or rank-dependent utility) and the decision-maker is disappointment averse (has a strictly convex weighting function). Then there exists an $0 < \epsilon'$ such that for all $\epsilon < \epsilon'$, $(.5, .5) \succ_{.5} (.5 + \epsilon, .5 + \epsilon)$.

\textsuperscript{24}Eliaz and Spiegler (2006) discuss an impossibility result related to preferences for skewness. However, their exact results rely on existential quantifiers that are impossible to violate and calibrate.
Panels G and H of Figure 2 demonstrate graphically dynamic Disappointment Aversion and Rank-Dependent preferences respectively. In the graphic example, the Dynamic Disappointment Aversion preferences exhibit a preference for positive skew, while the dynamic Rank-Dependent preferences exhibit a preference for negative skew.

One paper directly addressing preferences for skewed information is Dillenberger and Segal (2015). They provide sufficient conditions such that, fixing a prior, if an individual prefers full late resolution \((.5,.5)\) over all more informative structures, \((p,q)\) where \(p \geq .5\) and \(q \geq .5\), then they must also prefer \((.5,.5)\) over all negatively skewed structures. However, these individuals prefer some positively skewed structures over \((.5,.5)\). We refer the interested reader to their paper for a full description of the conditions.\(^{25}\)

**Prediction 7** Suppose preferences belong to the class defined by Dillenberger and Segal (2015). Then, \((.5,.5) \succeq_{.5} (x,x)\) for all \(x \geq .5\), implies that for all \(x \leq y\), \((.5,.5) \succeq_{.5} (y,x)\). However, it is possible that \((.5,.5) \preceq_{.5} (x,y)\).

We also want to consider three important models of preferences which do not satisfy recursivity, but which are used in many applications to generate preferences over information. Brunnermeier and Parker (2005) introduce a well-known model of optimal expectations. In their model, individuals trade off having (distorted) optimistic beliefs today with possibly taking incorrect actions in the future based on those incorrect beliefs. Of course, in our environment there are no actions to take, so individuals should be indifferent between all structures. We refer to their functional form as BP.

**Prediction 8** Suppose preferences represented by a BP functional form. Then the decision-maker should be indifferent between all information structures.

A second, important class of non-recursive preferences are those of K˝ oszegi and Rabin (2009). We refer to their functional form as KR. These preferences, although flexible enough to capture preferences for early versus late resolution of information and a preference for clumping, have strong predictions regarding preferences for skewness. This is because their functional form imbeds strong symmetry assumptions regarding the payoffs over beliefs.

The non-recursive preferences using in Ely, Frankel, and Kamenica (2013), referred to here as EFK, also imbed similar intuitions. Although EFK originally designed their model to explain preferences for gradual resolution of information in contexts such as sporting events, their functional

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\(^{25}\)Note that Dillenberger and Segal (2015) provide a different definition of skewness. In our particular domain, their definition, as well as all other notions of skewness, coincide because of the binary nature of the outcome and priors being equal to 50%.
form is flexible enough to be applied to other settings and can generate other patterns of behavior (including behavior very similar to KR). They have two functional forms. One they describe a capturing surprise, the other suspense; both have strong symmetry assumptions regarding how beliefs effect payoffs. Thus, we obtain the same prediction as in Köszegi and Rabin (2009) regarding preferences for positive versus negative skew.

Moreover, we also demonstrate that under the standard assumption of loss aversion KR preferences generate a similar preference for local one-shot resolution of uncertainty in the neighborhood of ($.5, .5)$ to that seen in Prediction 6. Moreover, we also provide conditions for when EFK’s models generate a preference for local one-shot resolution of uncertainty in the neighborhood of ($.5, .5)$.

**Prediction 9** Suppose preferences represented by a KR or EFK functional form. Then $(x, y) \sim_.5 (y, x)$. Moreover, if preferences are represented by a KR functional form that is loss averse, or an EFK suspense functional form with a sufficiently convex surprise function, or an EFK surprise functional form with a decreasing surprise function, then there exists an $0 < \epsilon'$ such that for all $\epsilon < \epsilon'$, $(.5, .5) \succ_.5 (.5 + \epsilon, .5 + \epsilon)$.

Panels E and F of Figure 2 graphically demonstrate preferences within the KR and EFK classes respectively.

**Evaluation of Theoretical Predictions**

Our design allows us to directly relate the theoretical predictions to the questions. Prediction 1 can be tested by all questions, as it says that the decision-maker should always be indifferent. Prediction 2 is specifically tested in Q1. The data is clearly inconsistent with Predictions 1 and 2 since individuals exhibit strong preferences over information structures in general and between ($.5, .5)$ and (1, 1) in particular.

However, Predictions 3 and 4 suggest that there exist utility functions that could accommodate our data. In particular, Prediction 3 demonstrates that if the utility function $V$ has convex local utility functions, then it will possess a preference for Blackwell more informative signals. Our experiment elicits preferences for symmetric information structures that vary in their informativeness in Q1, Q4 and the second possible Q5 question. From Prediction 3, we know our data regarding preference for early resolution are consistent with a convex $V$. Moreover, if $V$ has convex derivatives of the local utility functions, Prediction 4 demonstrates that it will possess a preference for positively skewed signals. Prediction 4 is tested by looking at preferences for skewness, i.e., Q2, Q3 and the first possible Q5 question. Using Prediction 4, we know that our observed choices regarding
skewness are consistent with a positive third derivative of $V$.\textsuperscript{26}

We can now turn directly to evaluating the predictions of specific functional forms proposed by previous literature. Prediction 5 is tested by looking at both preferences for skewness, i.e., Q2, Q3 and the first possible Q5 question, as well as preferences for earlier or later resolution, which is tested in Q1, Q4 and the second possible Q5 question. Prediction 6 is tested by the second possible Q5 question. Prediction 7 is tested by Q1 and the second part of Q5. Like Prediction 1, Prediction 8 is tested by all questions. The first part of Prediction 9 is tested by Q2, Q3, and the first part of Q5, and the second part of Prediction 9 by the second part of Q5.

Because individuals exhibit preferences over different information structures with the same prior, they violate the predictions of Prediction 8. According to the model of Brunnermeier and Parker, our subjects should simply distort their beliefs to believe the best possible thing about the future. In essence, individuals need to experience a cost of holding certain beliefs that is intrinsic, rather than arising from distorted actions.

In line with this, in the models of KR and EFK, individuals experience gains and losses from changing beliefs. Prediction 9 tells us that if preferences are in either class, then for $f = .5$ individuals should be indifferent between $(p, q)$ and $(q, p)$. In fact, at both aggregate and individual levels we do not find such an indifference — people prefer the positively skewed structure.\textsuperscript{27} The issue is that these models do not feature a consistently convex derivative of the local utility functions. More intuitively, these models build in a great deal of symmetry regarding the effect of changes in beliefs; a change in a very high belief causes the same utility effect as an equivalent sized change in a very low belief. Given a prior of .5, this implies that individuals will be indifferent between our positively and negatively skewed signal structures. If this symmetry assumption is relaxed so that changes in high beliefs matter differently than changes in low beliefs, these models may be able to capture the behavioral patterns presented by our data.

A variety of models have the possibility of predicting preferences for skewed information, even when $f = .5$. These include Gul’s model of Disappointment Aversion and Rank Dependent Utility. However, Prediction 6 indicates that those preferences should also prefer $(.5, .5)$ to $(p + \epsilon, q + \epsilon)$ for a $\epsilon$ close enough to .5. We find no evidence for this type of preference for clumping.\textsuperscript{28} Our

\textsuperscript{26}Recall that we find that individuals tend to have strongly monotone preferences; they always choose the Blackwell more informative signals. However, this does not mean that preferences are lexicographic. As an example, imagine preferences are increasing in the second moment and the third moment of the posterior distribution. For example, if we compare $(.3, .9)$ to $(.76, .76)$, it is the case the $(.76, .76)$ is “just barely” more Blackwell informative than $(.3, .9)$. However, $(.76, .76)$ has a much larger second moment than $(.3, .9)$, as well as a smaller third moment. Thus, preferences can be continuous in the tradeoff between the second and third moment.

\textsuperscript{27}We also find that the part of Proposition 9 which predicts a local preference for one-shot resolution of uncertainty is not consistent with our data.

\textsuperscript{28}One potential objection is that perhaps we did not set $\epsilon$ close enough to 0. In fact, simple calibrations show
data also fails to be consistent with the approach of Dillenberger and Segal (2015) for the same reason. Prediction 7 requires that individuals prefer (.5, .5) to any other more informative symmetric signal. We find that this is not the case, as most individuals prefer (.55, .55) to (.5, .5). Thus, these models, although able to accommodate a preference for skewness, fail at predicting the ranking of “late resolution”, i.e., (.5, .5) to earlier resolution structures, such as (.55, .55) and (1, 1).

In contrast, our data is generally consistent with the traditional model of Kreps and Porteus (1978). This model allows for preferences to have a convex local utility function and a convex derivative of the local utility function. In order to provide more context for these results, consider the Epstein and Zin (1989) parameterization of the Kreps-Porteus model. Then

\[ V_1(l) = \sum_{x \in l} u_1(x) l(x) = \sum_{x \in l} x^\rho l(x) \]  
\[ V_2(l) = \sum_{x \in l} u_2(x) l(x) = \sum_{x \in l} x^\alpha l(x). \]

In this case, the local utility function is convex if and only if \( u_1(u_1^{-1}(x)) \) is convex — or \( x^\alpha \) is convex, which is the same as \( \rho \geq \alpha \). Similarly, the derivative of the local utility function is convex if and only if the derivative of \( u_1(u_2^{-1}(x)) \) is convex. Given \( \rho \geq \alpha \), this condition is equivalent to \( \rho \geq 2\alpha \). Thus, individuals must have a strong preference for early resolution. Figure 2 Panel C demonstrates indifference curves of preferences that satisfy such conditions, given the Epstein-Zin parameterization of the Kreps-Porteus model.

We can relate our restrictions to the larger literature estimating Kreps-Porteus and Epstein-Zin preferences. Epstein-Zin preferences are used widely in macroeconomics and have been estimated from a variety of data. Thus, we can compare the restrictions implied by our data to the estimates obtained from an entirely different domain. In fact, recent estimates are consistent with the restrictions our observed preferences for skewness place on the data (i.e., the convexity of the first derivative of \( u_1(u_2^{-1}) \)). For example, Brown and Kim (2013) and Binsbergen et al. (2012) find that \( \rho \geq 2\alpha \) (much greater in fact).

### 5.2 Related Experimental Literature

In addition to the theoretical literature reviewed in the previous subsection, we also want to carefully relate our results to the existing experimental literature examining preferences over information structures as well as preferences over compound lotteries. We discuss the literature for compound lotteries separately; although preferences over compound lotteries and information structures are theoretically linked, the framing is quite different across the two domains. Therefore, we want to be careful to discuss the results separately.

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### Footnotes

- the power of our test, where \( \epsilon = .05 \). Suppose preferences in \( V_1 \) and \( V_2 \) both have a disappointment aversion representations \((u_i, \beta_i)\). Moreover, suppose, as is plausible for small stakes, the \( u_i \) is linear. In this case, if an individual prefers (.55, .55) over (.5, .5), then for any plausible value of \( \beta_2 \) (i.e., \( 0 \geq \beta_2 \leq 100 \)), \( \beta_1 \) must be less than .01, or in other words, people must be ‘almost’ expected utility over gambles that resolve now.
Preferences for skewed information: There has been very little empirical investigation of preferences for skewness in non-instrumental information. Boiney (1993) finds a preference for positively skewed compound lotteries. Although he describes these compound lotteries as “ambiguous,” they could also be interpreted as “objective.” Importantly, the experiment differs from ours in two crucial ways: 1) the subjects are not incentivized, and 2) the information could be interpreted to have instrumental value. More recently, Eliaz and Schotter (2010) (ES) investigate preferences for skewness within a broader investigation of demand for non-instrumental information for confidence utility. They investigate a very different driver of information demand. While we focus on the demand for non-instrumental information to manage belief utility induced by anticipatory emotions in the absence of any choice or agency regarding the future outcome, they focus on the intrinsic demand for information to manage confidence utility induced by facing a choice in the absence of any anticipatory emotions.

In particular, Eliaz and Schotter (2010) employ a two-stage compound lottery context with two actions, but where one action dominates the other in all states of the world. They provide subjects with the opportunity to obtain information about the degree to which the dominating action is superior before they make a choice. Even though information should not affect the subjects' ultimate choice, many of the subjects demonstrate a positive willingness to pay for this information before they make the (obvious) choice. The authors argue that this demand is driven by a desire to feel more confident about choosing the dominating option. The Treatment 4 of this experiment tests preferences over skew and shows that individuals prefer a negatively skewed signal over one that is positively skewed.

Compared to our protocol, the ES experiment introduces the need to make a choice between two uncertain options, thereby evoking the need to bolster confidence. Our experiment purposefully eliminates any self-relevant utility, such as ego-utility or confidence-utility, by providing a context that is free of choice, agency or other perceptions of control regarding the outcome. Moreover, the ES experiment does not feature a delay between the receipt of information and the full resolution of information, reducing the role of anticipatory emotions and belief utility.

Preferences for early versus late resolution: The theoretical literature on early and late resolution (beginning with Kreps and Porteus, 1978) has spawned a great deal of empirical tests. Although the literature has found general support for early resolution of uncertainty, there is also substantial heterogeneity within the subject population of a given study, and across studies, which may be due to different framing effects.

Using the Epstein-Zin parameterization of the Kreps-Porteus model, macroeconomists infer
attitudes towards the timing of information using estimates of risk preferences and inter-temporal
elasticity. The data in the early investigations provided by Epstein and Zin (1991) indicate a
preference for late resolution of uncertainty. However, more recent papers, such as Binsbergen et
al. (2012) have found a strong preference for early resolution of uncertainty.

Direct tests of preferences over information structures, such as Chew and Ho (1994), Arai
generally find a preference for early rather than late resolution of information. Other studies have
emphasized the heterogeneity among subjects; Kocher, Krawczyk and Van Winden (2014) find a
substantial fraction of subjects prefer delayed resolution. Moreover, Von Gaudecker et al. (2011),
find that their median subject is essentially indifferent between early and late resolution.

Studies have also found various factors can influence preferences for early versus late resolution.
Lovallo and Kahneman (2000) find that moving from gains to losses strengthens the preference
for early resolution of uncertainty; and, at least in the domain of gains, a negatively skewed prior
(which is quite distinct from a skewed information structure) induces a greater interest in speeding
up resolution for gains compared to positively skewed gambles. Ganguly and Tasoff (2014) find
that individuals' demand for earlier information increases in the size of the gain they are facing.
Similarly, larger losses lead to a preference for delaying information.

Delaying (or speeding up) the resolution of uncertainty can also affect the risk preferences of
players, and may be related to their informational preferences. In a real-stakes investment task,
von Winden, Krawczyk, Hopfensitz (2011) find that subjects invest more in a risky investment if
resolution is sooner. Erev and Haruvy (2010) find that subjects value a delayed chance at winning
a prize more than an immediate chance.

PREFERENCES FOR ONE-SHOT VERSUS GRADUAL RESOLUTION: Similar to the results on skewness,
there is only a small, and somewhat contradictory, set of results regarding preferences for gradual
versus one-shot resolution.

Using incentivized choices, although allowing for the possibility of instrumental value of in-
formation, Zimmerman (2014) finds no evidence that subjects are averse to gradual resolution of
information in the gain domain. Our results corroborate this finding. On the other hand, when
outcomes are in the loss domain (in their case losses are due to electric shocks), Falk and Zimmer-
man (2014) do find a preference for one-shot resolution. Moreover, Bellemare, Krause, Kroger, and
Zhang (2005) demonstrate that if individuals receive information more often about their risky in-
vestment, they tend to invest less in that option and favor a safe investment where such information

29 One caveat is that many of these studies either ask hypothetical questions or examine demand for information
in contexts where information may be instrumentally valuable.
is essentially eliminated.

Preferences over compound lotteries: Some experiments consider choice over compound lotteries, rather than information structures. Halevy (2007), Abdellaoui, Klibanoff and Placido (2013), and Abdellaoui, l’Haridon, and Nebout (2015) all find that the subjects tend to prefer one-shot lotteries to compound lotteries (i.e., those that feature gradual resolution of uncertainty), although Abdellaoui, l’Haridon, and Nebout (2015) find that subjects (on average) prefer a positively skewed lottery to one that features one-shot resolution.

However, it isn’t clear whether subjects view a one-stage lottery as an early resolving lottery or a late resolving lottery, therefore making it difficult to fit these results into the information framework. Miao and Zhong (2012) explicitly address this concern, and find, in contrast to the literature on information, that individuals prefer compound lottery structures that feature full late resolution to most other compound lottery structures — even to those that induce full early resolution.

6 Conclusion

We present results from an experiment that provides a broad investigation of intrinsic preferences for information. Our results provide some new insights. Individuals overwhelmingly prefer information structures that are positively skewed information structures. Such information structures have the potential to resolve more uncertainty regarding the desired outcome than the undesired outcome, in exchange for generating bad signals more frequently. Interestingly, individuals exhibit these preferences alongside a strong desire to obtain non-instrumental information overall. In fact, their preferences seem to be monotonic regarding the ordering induced by Blackwell informativeness, even ruling out preferences for clumped information.

We believe that these results are relevant for the design of information provision in domains where intrinsic preference for information lead to large welfare effects, such as in medical testing and financial markets. Our results both provide novel insights into information preferences in the real-world and also point to new avenues for exploration. Events that induce strong anticipatory emotions, such as the possibility of a serious disease, often involve either rare outcomes or losses relative to the status quo. Future research that examines whether preferences for non-instrumental information vary with initial expectations, and/or with different valuations of potential outcomes would also be helpful in designing context-sensitive policies.

Our experimental investigations allow us to demonstrate how observed preferences for skewed information (as well as other types of information) can shed light on existing models. We provide
some conclusions showing what types of theories are consistent or inconsistent with our data. In particular, we hope our results can help researchers modify existing theory and guide the development of new models.
References


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Appendix A: Formal Definitions

We will provide formal definitions for the theoretical discussion in the paper. We first discuss the environment, then axiomatic characterizations of preferences, then particular functional forms of preferences. In order to link our discussion more closely to the existing literature, this Appendix will work with a domain of two-stage compound lotteries, the set of which are equivalent to the set of prior, information structure pairs, the domain used in the body of the paper.

Formally, consider an interval \([w, b] = X \subset \mathbb{R}\) of money. Let \(\Delta_X\) be the set of all simple lotteries on \(X\). A lottery \(F \in \Delta_X\) is a function from \(X\) to \([0, 1]\) such that \(\sum_{x \in X} F(x) = 1\) and the number of prizes with non-zero support is finite. \(F(x)\) represents the probability assigned to the outcome \(x\) in lottery \(F\). For any lotteries \(F, G\) we let \(\alpha F + (1 - \alpha)G\) be the lottery that yields \(x\) with probability \(\alpha F(x) + (1 - \alpha)G(x)\). Denote by \(\delta_x\) the degenerate lottery that yields \(x\) with probability 1. Next, denote \(\Delta(\Delta_X)\) as the set of simple lotteries over \(\Delta_X\). For \(P, Q \in \Delta(\Delta_X)\) denote \(R = \alpha P + (1 - \alpha)Q\) as the lottery that yields simple (one-stage) lottery \(F\) with probability \(\alpha P(F) + (1 - \alpha)Q(F)\). Denote by \(D_P\) the degenerate, in the first stage, compound lottery that yields \(F\) with certainty. \(\succeq\) is a weak order over \(\Delta(\Delta_X)\) which represents the decision-maker’s preferences over lotteries and is continuous (in the weak topology). Moreover, we will define a reduction function that maps compound lotteries to reduced one-stage lotteries: \(\phi(P) = \sum_{F \in \Delta_X} P(F)F\).

Given a function \(V\) on the set of probability measures \(\Delta_X\), then for each \(P \in \Delta(\Delta_X)\) we say that \(V\) is Gateaux differentiable at \(P\) in \(\Delta(\Delta_X)\) if there is a measurable function \(v(\cdot; P)\) on \(\Delta_X\) such that for any \(Q \in \Delta(\Delta_X)\) and any \(\alpha \in (0, 1)\):

\[
V(\alpha Q + (1 - \alpha)P) - V(P) = \alpha \int v(z; P)(Q(dz) - P(dz)) + o(\alpha)
\]

where \(o(\alpha)\) is a function with the property that \(o(\alpha) \to 0\) as \(\alpha \to 0\). \(v(\cdot; P)\) is the Gateaux derivative of \(V\) at \(P\). \(V\) is Gateaux differentiable if \(V\) is Gateaux differentiable at all \(P\). We call \(v(\cdot; P)\) the local utility function at \(P\).

Now consider the set of prior-information structure pairs, such that the prior \(f\) has support on \([w, b]\). Formally, we imagine there are a finite number \(N\) of indexed states \(\omega_i\). Each state corresponds to a different payoff for the individual. Moreover, there are \(M\) signals indexed by \(s_j\). An information structure \(I\) is an \(N \times M\) matrix, such that the entries in each row sum to 1. The \(i, j\)-th entry of the matrix, denoted \(I_{ij}\), gives the probability that signal \(s_j\) is realized if the state is \(\omega_i\). Given a prior distribution \(f\) over states, if the individual utilizes Bayes’ rule then a posterior probability of state \(\omega_i\) conditional on observing signal \(s_j\) is given by:

\[
\psi_j(\omega_i) = \frac{f(\omega_i) I_{ij}}{\sum_k f(\omega_k) I_{kj}}
\]

As mentioned in the body, we suppose that individuals have preferences over information structures given the prior \(f\), denoted by \(\succeq_f\). Also, as mentioned, formally, within the economics literature, these are typically modeled as preferences over two-stage compound lotteries; lotteries over lotteries. Each signal \(s_i\) induces a lottery over outcomes — the posterior distribution \(\psi_j\). This is the lottery that individuals face in period 1 after receiving information. In period 0, the individual faces a lottery over these possible lotteries — signal \(s_j\) is received with probability \(\sum_i f(\omega_i) I_{ij} = p(s_j)\). There is a natural bijection between prior-information structure pairs and two-stage compound lotteries. Not only can we map a prior-information structure pair into a (unique) two stage compound lottery, we can also show that any given two-stage compound lottery maps into a unique prior-information structure pair. Given a two-stage lottery \(P\) with support \(p_1, \ldots, p_n\) we first
can find \( f \), the prior: \( \phi(P)(\omega_i) = f(\omega_i) \). To identify \( I \), observe that we have a set of equations \( p_j(\omega_i) = \psi_j(\omega_i) = \frac{f(\omega_i)I_{ij}}{\sum_k f(\omega_k)I_{kj}} \), along with restrictions on the elements of \( I \) discussed in the main text (and with a known \( f \)). These form a set of equations that generates a unique solution \( I \). Given this we can naturally map preferences and utility functionals, from the space of prior-information structure pairs to the space of compound lotteries and vice versa.

We can now turn to discussing the formal properties and models related to our predictions, using the framework of compound lotteries. First, Reduction of Compound Lotteries implies that individuals only care about the reduced one-stage lotteries that they face:

**Reduction of Compound Lotteries:** For all \( P, Q \in \Delta(\Delta_X) \) if \( \phi(P) = \phi(Q) \) then \( P \sim Q \).

In deriving additional predictions, it will be useful to formally define early and late resolving lotteries. Let \( \Gamma = \{ D_F | F \in \Delta_X \} \) be the set of degenerate lotteries in \( \Delta(\Delta_X) \). These are the set of late resolving lotteries. Let \( \Lambda = \{ Q \in \Delta(\Delta_X) | Q(F) > 0 \implies F = \delta_x \) for some \( x \in X \} \) be the set of compound lotteries whose outcomes are degenerate in \( \Delta_X \). These are the set of early resolving lotteries.

Early resolving lotteries have all uncertainty resolved in the first stage and so the second stage lotteries are degenerate. These are equivalent to situations where the information structure reveals all information in Period 1; thus, posteriors after observing the signal are degenerate. In contrast, late resolving lotteries have all uncertainty resolved in the second stage and so their first stage is degenerate. These are equivalent to situations where the information structure reveals no information in Period 1. Thus, posteriors after receiving information are exactly the same as the priors before receiving information. We define the restriction of \( \succsim \) to the subsets \( \Gamma \) and \( \Lambda \) as \( \succsim_\Gamma \) and \( \succsim_\Lambda \). Independence within \( \Gamma \) and \( \Lambda \) is defined as per standard for any one-stage lottery.

Given these definitions, we can now state Time Neutrality.

**Time Neutrality:** If \( P \in \Gamma \) and \( Q \in \Lambda \) and \( \phi(P) = \phi(Q) \) then \( P \sim Q \).

Grant, Kajii and Polak (1998) formally define a preference for early resolution of information in the setting of compound lotteries as:

**Definition:** \( \succsim \) displays a preference for early resolution of uncertainty if for all \( Q, P \in \Delta(\Delta_X) \) where \( P(F') = Q(F') \) for all \( F' \notin \{ F, G_1, G_2 \} \), \( P(G_1) = \beta Q(F) \), \( P(G_2) = (1 - \beta)Q(F) \), and \( P(F) = 0 \) and \( \beta \in [0, 1] \); if \( F = \beta G_1 + (1 - \beta)G_2 \) then \( P \succsim Q \).

Grant, Kajii and Polak (1998) define a notion of “elementary linear bifurcations” which is equivalent to a binary relation over compound lotteries. They show that one compound lottery is an elementary linear bifurcation of another if and only if the former Blackwell dominates the latter.

We next turn to discussing recursivity.

**Recursivity:** For all \( F, G \in \Delta_X \), all \( Q \in \Delta(\Delta_X) \) and \( \alpha \in (0, 1) \), \( D_F \succsim D_G \) if and only if \( \alpha D_F + (1 - \alpha)Q \succsim \alpha D_G + (1 - \alpha)Q \).

As discussed in the text recursivity is useful because decision-makers with recursive preferences evaluate compound lotteries using a folding-back procedure — preferences over two stage lotteries can be evaluated using preferences over one stage lotteries. Decision-makers replace the second stage of any given compound lottery by the certainty equivalent generated by \( \succsim_\Gamma \). The resulting lottery is evaluated using \( \succsim_\Lambda \).
We say that a preference over two stage lotteries has a recursive representation \((V_1, V_2)\) if the preference can be represented with a functional \(V\) such that (i) \(V\) is derived using \(V_1\) and \(V_2\) in the folding-back procedure described above, and (ii) \(V_2\) represents \(\succsim_2\) and \(V_1\) represents \(\succsim_1\). Let \(\text{CE}_2(F)\) denote the certainty equivalent of \(F\) using \(\succsim_2\). More formally,

**Definition 1** Suppose preferences over two-stage lotteries can be represented by \(V\). We say preferences have a recursive representation \((V_1, V_2)\), where \(V_1\) and \(V_2\) are utility functions over one-stage lotteries, if and only if for all \(P = (F_1, P(F_1); \ldots; F_n, P(F_n))\), it is the case that \(V(P) = V_1(\text{CE}_2(F_1), P(F_1); \ldots; \text{CE}_2(F_n), P(F_n))\).

We now sketch out some of the functional forms that are relevant for our predictions. If preferences satisfy recursivity, we can represent them using \(V_1\) and \(V_2\). Because \(V_i\) for \(i \in \{1, 2\}\) is defined over two-stage lotteries that are isomorphic to one stage lotteries, we can simply define \(V_i\) using one stage lotteries. We say \(V^{KP}\) represents the Kreps-Porteus class of preferences if \(V^{KP}_i = \sum u_i(x)F(x)\) for some \(u_i\) for \(i \in \{1, 2\}\).

We say \(V^D\) represents the recursive disappointment aversion preferences if \(V^D_i\) represents Gul’s class of disappointment aversion for \(i \in \{1, 2\}\). Formally

\[
V^D_i(F) = \sum_x u_i(x)F(x) + \beta \sum_{x \leq u_i^{-1}(V_i(F))} (u_i(x) - V^D_i(F))F(x)
\]

where \(u\) is a function mapping from wealth to the reals, and \(\beta\) is a scalar which is greater or equal to 0.

We say \(V^{RDU}\) represents the recursive rank-dependent preferences if \(V^{RDU}_i\) represents the rank-dependent class. Formally,

\[
V^{RDU}_i(F) = \sum_u u_i(x) \left[ w_i \left( \sum_{y \geq x} F(y) \right) - w_i \left( \sum_{y > x} F(y) \right) \right]
\]

where \(u\) is a function mapping from wealth to the reals, and \(w\) is a function mapping from \([0, 1]\) to \([0, 1]\), such that \(w(0) = 0, w(1) = 1\) and \(w\) is strictly increasing. Individuals are pessimistic if and only if \(w\) is convex.

Because Dillenberger and Segal’s (2015) conditions on preferences are quite specific to their aims (beyond the assumption of recursivity) we refer interested readers to their discussion. Moreover, since Brunnermeier and Parker’s (2005) model predicts that all information structures should be indifferent to one another, we direct the interested reader to their paper for the details of their functional form.

We next summarize Köszegi and Rabin’s functional form. Given a gain-loss functional \(\eta\), a scalar weight on expected utility \(\kappa\), a scalar weight on first period gain-loss utility of \(\nu\), and denoting, given a distribution \(h\) over the payoff across states, any \(\zeta \in (0, 1)\). Let \(u(\omega_h(\zeta))\) denote the utility of the payoff level at percentile \(\xi\). Then the functional form is:

\[
V^{KR}(f, I) = \kappa E_f(u(\omega_i)) + \nu \sum_j p(s_j) \int_0^1 \eta(u(\omega_{\psi_j}(\xi)) - u(\omega_{\psi_j}(\zeta)))d\xi + \sum_i \sum_j p(s_j)\psi_j(\omega_i) \int_0^1 \eta(u(\omega_i(\xi)) - u(\omega_{\psi_j}(\xi)))d\xi
\]

\(30\) Denoting beliefs in Period 0 as \(f\) (our prior) and the beliefs in Period 1 (after receiving signal \(s_j\)) as \(\psi_j\)
Because this is a complicated functional form, we will define the function for our simple binary-binary setup. The probability of good signal is 
\[ p(G) = fp + (1-f)(1-q), \]
and the probability of bad signal is 
\[ p(B) = f(1-p) + (1-f)q. \]
\( p_j(\omega_i) \) denotes the posterior probability of state \( i \) after observing signal \( j \). Normalizing the Bernoulli utility of the high and low outcomes to 0 and 1 the total utility of an information structure is:

\[
V_{KR}(f,I) = \kappa f + \nu \left[ p(G)\eta(1-0)(p_G(H) - f) + p(B)\eta(0-1)(f - p_B(H)) \right] \\
+ p(G) \left[ p_G(H)\eta(1-0)p_G(L) + p_G(L)\eta(0-1)p_G(H) \right] \\
+ p(B) \left[ p_B(H)\eta(1-0)p_B(L) + p_B(L)\eta(0-1)p_B(H) \right]
\]

The last functional forms we consider are those introduced in Ely, Frankel and Kamenica (2013). They have two models, both of which deliver the same predictions regarding skewness. We provide more general forms of their models and allow for individuals overall utility to: depend both on the expected utility of the two stage lottery as well as suspense or surprise; and weight suspense and surprise differently across periods. We denote \( \vartheta \) as a function that turns suspense and surprise into utils. As before we have a scalar weight on the expected utility term of \( \kappa \) and a scalar weight on first period suspense or surprise utility of \( \nu \).

We first consider a generalized version of Ely, Frankel and Kamenica’s model of suspense, where overall utility is given by:

\[
V_{sus}^{EFK}(f,I) = \kappa E_f(u(\omega_i)) + \nu \sum_j p(s_j) \sum_i \left( p(j(\omega_i) - f(\omega_i))^2 \right) \\
+ \sum_j p(s_j) \vartheta \left( \sum_i p_j(\omega_i) \sum_i (1 - p_j(\omega_i))^2 \right)
\]

Simplifying to our binary-binary environment, we obtain:

\[
V_{sus}^{EFK}(f,I) = \kappa f + \nu \vartheta \left( p(G)2(p_G(H) - f)^2 + p(B)2(f - p_B(H))^2 \right) \\
+ p(G)\vartheta \left( p_G(H)2p_G(L)^2 + p_G(L)2p_G(H)^2 \right) \\
+ p(B)\vartheta \left( p_B(H)2p_B(L)^2 + p_B(L)2p_B(H)^2 \right)
\]

Ely, Frankel and Kamenica also provide a model of surprise, which we generalize, so that utility is:

\[
V_{surp}^{EFK}(f,I) = \kappa E_f(u(\omega_i)) + \nu \sum_j p(s_j) \vartheta \left( \sum_i (p(j(\omega_i) - f(\omega_i))^2 \right) \\
+ \sum_j p(s_j) \sum_i p_j(\omega_i) \vartheta \left( \sum_i (1 - p_j(\omega_i))^2 \right)
\]
In our binary-binary setting, this becomes:

\[
V_{\text{surp}}^{\text{EFK}}(f, I) = \kappa f + \nu \left[ p(G)\vartheta\left(2(p_G(H) - f)^2\right) + p(B)\vartheta\left(2(f - p_B(H))^2\right) \right]
+ p(G)\left[p_G(H)\vartheta\left(2p_G(L)^2\right) + p_G(L)\vartheta\left(2p_G(H)^2\right) \right]
+ p(B)\left[p_B(H)\vartheta\left(2p_B(L)^2\right) + p_B(L)\vartheta\left(2p_B(H)^2\right) \right]
\]

We last turn to providing the exact parameterization of the preferences used in Figure 2. Panel A depicts Kreps-Porteus preferences where \( u_1(x) = -(x - 1)^2 + 1 \) and \( u_2(x) = x^2 \). Panel B depicts Kreps-Porteus preferences where \( u_1(x) = x^2 \) and \( u_2(x) = x \). Panel C depicts Kreps-Porteus preferences where \( u_1(x) = x^4 \) and \( u_2(x) = x \). Panel D depicts Kreps-Porteus preferences where \( u_1(x) = x^{1.1} \) and \( u_2(x) = x \). Panel E depicts EFK’s suspense preferences where \( \kappa = \nu = 1 \), and \( \vartheta(x) = \sqrt{x} \) (in line with EFK’s preferred specification in their paper). Panel F depicts KR preferences where \( \kappa = \nu = 1 \),

\[
\eta(z) = \begin{cases} 
z & \text{if } z \geq 0 \\
\lambda z & \text{if } z < 0 \end{cases}
\]

and \( \lambda = 2 \). Panel G depicts recursive preferences that have Gul’s (1991) functional form in both periods, where \( u_1(x) = u_2(x) = x, \beta_1 = 2 \) and \( \beta_2 = 2 \). Panel H depicts recursive preferences that have a rank-dependent functional form in both periods, where \( u_1(x) = u_2(x) = x, w_1(p) = p^{1.3} \) and \( w_2(p) = p^2 \).

Appendix B: Proofs

Before we prove the statements in the text, we will prove a useful lemma. As mentioned in the text, there are many ways of conceptualizing skewness. We are taking a particular notion, which ends up being formally related to the notion of downside risk aversion over lotteries (i.e., one stage lotteries) by Menezes, Geiss and Tressler. This notion allows us to relate preferences for skewness to the third derivative of the local utility functions that represent preferences over two stage compound lotteries. Formally, we can think of a signal realization as generating a posterior, which in our case is simply a number between 0 and 1. A signal structure \((p, q)\) then generates a distribution over possible posterior beliefs (and in fact a distribution that has support at two points). Lemma A demonstrates that, interpreting the posterior distribution as a ‘value’, the information structures we denoted as positively skewed will possess less downside risk than the corresponding structures we denoted as negatively skewed.

**Lemma A** Suppose \( f = .5 \) and \( x < y \). Then the posterior distribution induced by \((x, y)\) has more downside risk, in the sense of Menezes, Geiss and Tressler (1980), than that induced by \((y, x)\).

**Proof** We prove that, given \( x < y \) and a prior of .5, the posterior distribution induced by \((x, y)\) is a mean-variance preserving transformation of that induced by \((y, x)\). In other words, the posterior distribution induced by the latter has more downside risk than the former. In order to show this, we first construct the CDF of the posterior distributions induced by the two information structures. We denote the CDF of the posterior distribution induced by \((x, y)\) as \( F \) and of the \((y, x)\) as \( G \). Recall that both of these are distributions over posterior beliefs; or distributions over numbers between 0 and 1.

In order to prove Lemma A, we will use the conditions provided by Menezes, Tressler and Geiss in their Theorem 1. They have three conditions, which we will verify.
Condition (i) is that the two distributions induce the same mean posterior. This is true by the law of iterated expectations, and the mean is simply the prior. Condition (ii) is that \( \int_0^1 \int_0^y (G(b) - F(b))dbda = 0 \). Condition (iii) is that \( \int_0^y (G(b) - F(b))dbda > 0 \) for \( c < 1 \). We will prove these conditions together.

First we will describe the two CDFs.

\[
G(b) = \begin{cases} 
0 & \text{if } b \in [0, \frac{1-y}{1+y+x}) \\
.5(1+x-y) & \text{if } b \in [\frac{1-y}{1+y+x}, \frac{1}{1+y-x}) \\
1 & \text{if } b \in [\frac{1}{1+y-x}, 1] 
\end{cases}
\]

and

\[
F(b) = \begin{cases} 
0 & \text{if } b \in [0, \frac{1-x}{1+y-x}) \\
.5(1-x+y) & \text{if } b \in [\frac{1-x}{1+y-x}, \frac{x}{x+y}) \\
1 & \text{if } b \in [\frac{x}{x+y}, 1] 
\end{cases}
\]

In order to simply our discussion, we will subdivide the set of possible posteriors \([0,1]\) into regions. We denote region \( A \) as \([0, \frac{1-y}{1+y+x})\); \( B \) as \([\frac{1-y}{1+y+x}, \frac{1}{1+y-x})\); \( C \) as \([\frac{1-x}{1+y-x}, \frac{y}{y+1-x})\); \( D \) as \([\frac{y}{y+1-x}, \frac{x}{x+y})\); and \( E \) as \([\frac{x}{x+y}, 1]\).

We can then compute the difference between the CDFs in each region:

\[
G(b) - F(b) = \begin{cases} 
0 & \text{if } b \in A \\
.5(1+x-y) & \text{if } b \in B \\
x-y & \text{if } b \in C \\
.5(1+x-y) & \text{if } b \in D \\
0 & \text{if } b \in E 
\end{cases}
\]

This implies that

\[
\int_0^a (G(b) - F(b))db = \begin{cases} 
0 & \text{if } a \in A \\
.5a(1+x-y) - .5(1-y) & \text{if } a \in B \\
(a-.5)(x-y) & \text{if } a \in C \\
.5[1+x+y]a -.5x & \text{if } a \in D \\
0 & \text{if } a \in E 
\end{cases}
\]

We will now divide \( C \) into two separate intervals: \( C_1 = [\frac{1-x}{1+y-x}, \frac{5}{8}) \) and \( C_2 = [\frac{5}{8}, \frac{y}{y+1-x}) \). Observe that \( \int_0^a (G(b) - F(b))db \) is strictly greater than 0 when \( a \) is in \( B \) and \( C_1 \). Similarly, \( \int_0^a (G(b) - F(b))db \) is strictly less than 0 when \( a \) is in \( C_2 \) and \( D \).

Thus, to prove Conditions (ii) and (iii) we simply need show that \( \int_0^5 \int_0^y (G(b) - F(b))dbda = -\int_5^1 \int_0^y (G(b) - F(b))dbda \). Observe that \( \int_0^5 \int_0^y (G(b) - F(b))dbda = \frac{1}{8}([1-\frac{2y}{1+x-y}][\frac{(1+x-y)(1-x)}{1-x+y} - (1-y)]). Moreover \( \int_5^1 \int_0^y (G(b) - F(b))dbda = \frac{1}{8}([\frac{2x}{1+x-y} - 1][x-y][\frac{2y}{1+x-y} - 1]). Routine algebra shows that the first is then equal to \( \frac{1}{8} ([\frac{x+y-1}{1+x-y}]xy - \frac{y^2+y^2-x^2}{1-x+y}) \) and the second is equal to \( \frac{1}{8} ([\frac{x+y-1}{1+x-y}] - \frac{y^2+y^2-x^2}{1-x+y}) \).

Thus, Conditions (i), (ii) and (iii) of Theorem 1 of Menezes, Geiss and Tressler (1980) hold and so the posterior distribution \( G \) has more downside risk than the prior distribution \( F \).

**Lemma 1** For any \((p,q) \in S\), observing a good signal increases the posterior on high outcome relative to the prior, and observing a bad signal decreases the posterior on high outcome relative to the prior.

**Proof** We will prove each part of the Lemma in turn. First we prove the first part. Recall that for a given prior \( 0 < f < 1 \) on a high payoff and information structure \((p,q)\), the posterior for the
high payoff given the good signal is
\[ \psi_G = \frac{fp}{fp + (1 - f)(1 - q)}. \]
Now \( \psi_G > f \) if and only if
\[ \psi_G = \frac{fp}{fp + (1 - f)(1 - q)} > f, \]
which holds if and only if
\[ (1 - f)p > (1 - f) - (1 - f)q, \]
which is the same as
\[ p + q > 1. \]
An analogous series of steps establishes the result for the posterior after observing a bad signal. □

**Lemma 2** For any signal structure \((p', q')\) \(\in [0, 1] \times [0, 1]\), there exists a \((p, q)\) \(\in S\) that generates the same posterior distribution. However, for any \(T \subset S\) there exists a \((p', q')\) \(\in S\) such that there is no element of \(T\) that generates the same posterior distribution as \((p', q')\).

Assume that \(p + q < 1\) (observe that all signal structures on \(p + q = 1\) give the same posterior distribution). In this case, denote \(p' = 1 - p\) and \(q' = 1 - q\). We will work with likelihood ratios rather than posterior beliefs. Under \((p, q)\), likelihood ratio \(\frac{p}{1 - q}\) occurs with probability \(fp + (1 - f)(1 - q)\) and likelihood ratio \(\frac{1 - p}{q}\) occurs with probability \(f(1 - p) + (1 - f)q\).

Under \((p', q')\) likelihood ratio \(\frac{1 - p'}{q'} = \frac{p}{1 - q}\) occurs with probability \(f(1 - p') + (1 - f)q' = fp + (1 - f)(1 - q')\). Likelihood ratio \(\frac{p'}{1 - q} = \frac{1 - p}{q}\) occurs with probability \(f(p' + (1 - f)(1 - q')) = f(1 - p) + (1 - f)q\). Therefore \((p', q')\) generates the same posterior distribution as \((p, q)\). Moreover, \(p' + q' = (1 - p) + (1 - q) = 2 - p - q \geq 1\) since \(p + q \leq 1\). So therefore, instead of considering some \((p, q)\) we can always instead consider the corresponding \(p' = 1 - p, q' = 1 - q\).

To prove the second part observe that in order for two signal structures \((p, q)\) and \((p', q')\), both in \(S\), to generate the same posteriors it must be the case that \(\frac{p'}{1 - q'} = \frac{p}{1 - q}\) and \(\frac{1 - p'}{q'} = \frac{1 - p}{q}\).

Therefore \(p' - p'q = p - pq'\) and \(q - p'q = q' - pq\), which is equivalent to \(q = \frac{-p + pq' + p'}{p'}\) and \(q = q' - pq'\). Simplifying, we have \(-p + pq' + p' = q' - pq'\), or \(p'q' - pq'p' = -p + pq' + p' + pp' - pq'q' - p'q'\). This holds if and only if \(p'q' = -p + pq' + pq' - p'q'\), or \(p(1 - q' - p') = -p'q' + p'p = p'(1 - q' - p')\). This equality holds if and only if \(p = p'\) or \(q + p' = 1\). The latter case implies that \(p' = q' = .5\) which implies \(p = q = .5\). The former immediately implies \(q = q'\). □

**Lemma 3** \((p', q')\) Blackwell dominates (is Blackwell more informative than) \((p, q)\) if and only if \(p' \geq \max\{\frac{1 - p}{1 - q}, 1 - q'\frac{1 - p}{1 - q}\}\).

**Proof** Recall that one signal structure \((p', q')\) is Blackwell more informative than another \((p, q)\) if and only if the distribution of posteriors induced by \((p', q')\) is a mean preserving spread of the distribution induced by \((p, q)\). By the law of iterated expectations, the expected posterior under \((p', q')\) and \((p, q)\) must be the same — the prior. Because there are only 2 signals (and so 2 posteriors) as well as only 2 states, the problem reduces to showing that the posteriors under \((p', q')\) are more extreme (in the sense that they are farther from the prior) than the posteriors under \((p, q)\). In order to simplify the proofs, we will show an equivalent result — that the likelihood ratios under \((p', q')\) are more extreme (farther from 1) than the likelihood ratios under \((p, q)\).
The likelihood ratios after observing a good signal under \((p', q')\) and \((p, q)\) are (respectively) 
\[
\frac{p'}{1-q'} \quad \text{and} \quad \frac{p}{1-q}
\]
while the likelihood ratios after observing a bad signal are \(\frac{1-p'}{q'}\) and \(\frac{1-p}{1-q}\).

In order for the ratios under \((p', q')\) to be farther from 1 than \((p, q)\), then \(\frac{p'}{1-q'} \geq \frac{p}{1-q} \quad \text{and} \quad \frac{1-p'}{q'} \leq \frac{1-p}{1-q}\). This is equivalent to \(p' \geq \frac{p}{1-q} - \frac{p}{1-q}q'\) and \(p' \geq 1 - q'\frac{1-p}{q}\).

**Prediction 1** Fixing \(f\), if a decision maker satisfies Reduction of Compound Lotteries then they should be indifferent between all information structures.

**Proof** Under Reduction of Compound Lotteries this is true by definition.

**Prediction 2** Fixing \(f\), if a decision-maker satisfies Time Neutrality they should be indifferent between \((1, 1)\) and \((.5, .5)\).

**Proof** Under time Neutrality this is true by definition.

**Prediction 3** Let \(\succsim_f\) be represented by \(V\), where \(V\) is Gateaux differentiable. Then the local utility function of \(V\) is everywhere convex (concave) if and only if the decision-maker prefers Blackwell more (less) information structures.

**Proof** This is proved by Grant, Kajii and Polak (1998).

**Prediction 4** Let \(\succsim_{.5}\) be represented by \(V\), where \(V\) is Gateaux differentiable. If the local utility function of \(V\) is thrice differentiable and has a convex (concave) derivative everywhere, then \((x, y) \succsim_{.5} (y, x)\) whenever \(x \leq y\).

**Proof** Assume that all local utility functions are thrice differentiable and have a positive third derivative. Denote the local utility function \(v(\cdot, P)\). Given \(f = .5\), suppose information structure \((x, y)\) generates a posterior distribution \(Z_1\) and \((y, x)\) generates posterior distribution \(Z_0\). By Lemma A, \(Z_0\) has more downside risk aversion than \(Z_1\). We simply need to show that \(V(Z_1) - V(Z_0) \geq 0\).

Let \(Z(\alpha) = \alpha Z_1 + (1 - \alpha)Z_0\). By Grant, Kajii and Polak (pg 255) because \(V\) is Gateaux differentiable \(\frac{d}{d\alpha} V(Z(\alpha))|_{\alpha=\beta}\) exists for any \(\beta\) in \((0, 1)\) and is equal to \(\int v(z; \beta)|Z_1(dz) - Z_0(dz)\). Observe that this is simply the expected value of \(v\) under \(Z_1\) less the expected value of \(v\) under \(Z_0\). By Theorem 2 of Menezes, Geiss and Tressler (1980) this is positive for any \(\beta \in (0, 1)\). Integrating with respect to \(\beta\) yields \(V(Z(1)) - V(Z(0)) \geq 0\) which gives the required result since \(V(Z(1)) = V(Z_1)\) and \(V(Z_0) = V(Z(0))\).

**Prediction 5** Suppose preferences have a recursive representation \((V_1, V_2)\) such that \(V_1\) and \(V_2\) have expected utility representations with Bernoulli utilities \(u_1\) and \(u_2\). Then \(u_1 \circ u_2^{-1}\) is convex (concave) if and only if the decision-maker prefers Blackwell more (less) information structures. Moreover, if the derivative of \(u_1 \circ u_2^{-1}\) is convex (concave), then \((x, y) \succsim_{.5} (y, x)\) whenever \(x \leq y\).

**Proof** The first relationship between Blackwell informativeness and convexity/concavity is proved in Grant, Kajii and Polak (1998). For the next part, denoting \(\tau = u_1(u_2^{-1})\) the utility of \((p, q)\) is simply: 
\[
\tau\left((f(p + (1 - f)(1 - q))) + \tau\left(\frac{(1-p)f}{(1-p) + q(1-f)}((1-p)f + q(1-f))\right)\right)
\]
Observe that this implies the individual is an EU maximizer over a utility function defined over their posteriors. By Lemma A we know that given \(f = .5\) and \(x < y\) the posterior distribution induced by \((y, x)\) has more downside risk than \((x, y)\). Thus by Theorem 2 of Menezes, Geiss and Tressler (1980) if the third derivative of \(\tau\) is positive then \((x, y)\) must by preferred to \((y, x)\).
Prediction 6 Suppose preferences have a recursive representation \((V_1, V_2)\) such that \(V_1\) and \(V_2\) are both in Gul’s class of disappointment aversion functionals (or rank-dependent utility) and the decision-maker is disappointment averse (has a strictly convex weighting function). Then there exists an \(0 < \epsilon'\) such that for all \(\epsilon < \epsilon', (.5, .5) \succ (.5 + \epsilon, .5 + \epsilon)\).

Proof Recall that we have representations in period 1 and period 2 which are \((u_1, \beta_1)\) and \((u_2, \beta_2)\). If a good signal is realized, utility is \(\frac{p_G(H)}{1 + \beta_2 p_G(L)}\). If a bad signal is realized, utility is \(\frac{p_B(H)}{1 + \beta_2 p_B(L)}\). Iterating the process to period 1, and denoting \(\tau = u_1(u_2^{-1})\) ex-ante utility is:

\[
\frac{p(G)\tau \left( \frac{p_G(H)}{1 + \beta_2 p_G(L)} \right) + p(B)\tau \left( \frac{p_B(H)}{1 + \beta_2 p_B(L)} \right)}{1 + \beta_1 p(B)}
\]

Setting \(f = .5\) and \(p = q\) gives \(p(G) = p(B) = .5\). Then we have

\[
\tau \left( \frac{p}{1 + \beta_2 (1-p)} \right) + \tau \left( \frac{1 - p}{1 + \beta_2 p} \right) (1 + \beta_1) \left( \frac{1 + \beta_2}{1 + \beta_2 p} \right)
\]

Observe that utility is continuous and differentiable in the region around \(p = .5\). Clearly the term, \(\frac{1}{2 + \beta_2}\) is irrelevant for the derivative with respect to \(p\), so we will take the derivative of the numerator with respect to \(p\). This is:

\[
\frac{\tau'}{1 + \beta_2 (1-p)} \left( \frac{p}{1 + \beta_2 (1-p)} \right) - \frac{\tau'}{1 + \beta_2 p} \left( \frac{1 - p}{1 + \beta_2 p} \right) (1 + \beta_1) \left( \frac{1 + \beta_2}{1 + \beta_2 p} \right)
\]

Taking limit of the derivative as \(p \to .5\) gives:

\[
\frac{\tau'}{2 + \beta_2} \left( \frac{1 + \beta_2}{1 + 2 \beta_2} \right) - \frac{\tau'}{1 + \beta_2 p} \left( \frac{1 + \beta_1}{1 + \beta_2 p} \right) (1 + \beta_2) \left( \frac{1 + \beta_2}{1 + \beta_2 p} \right)
\]

Next we prove the result for RDU. If a good signal is realized, utility is: \(w_2(p_G(H))\). If a bad signal is realized, utility is \(w_2(p_B(H))\). Ex-ante, before any signal is realized, utility is:

\[
w_1(p(G))\tau(w_2(p_G(H))) + (1 - w_1(p(B)))\tau(w_2(p_B(H)))
\]

Observe that this function is continuous and differentiable in the neighborhood of \(p = q = .5\). Setting \(f = .5\) and \(p = q\) gives \(p(G) = p(B) = .5\). Then we have

\[
w_1(.5)\tau(w_2(p)) + (1 - w_1(.5))\tau(w_2(1-p))
\]

The derivative of this with respect to \(p\) is

\[
w_1(.5)w_2'(p)\tau'(w_2(p)) - (1 - w_1(.5))\tau'(w_2(1-p))w_2'(1-p)
\]

Taking the limit of this as \(p\) goes to \(.5\) gives

\[
\tau'(w_2(.5))w_2'(5)[2w_1(.5) - 1]
\]

When \(w\) is strictly convex, this must be negative, since \(w_1(.5) < .5\).

\[
\square
\]

Prediction 7 Suppose preferences belong to the class defined by Dillenberger and Segal (2015). Then if \((.5, .5) \succ (.5, .5)\) for all \(x \geq .5\), then for all \(x \leq y, (.5, .5) \succ (.5, .5)\). However, it is possible
that \((.5, .5) \succeq_5 (x, y)\).

**Proof** See Dillenberger and Segal (2015) for the proof.

**Prediction 8** Suppose preferences represented by a BP functional form. Then the decision-maker should be indifferent between all information structures.

**Proof** This is by construction. In BP the only reason individuals would not hold the most optimistic beliefs would be because such beliefs would cause them to take an incorrect action. Here there are no actions to be taken, so individuals always hold the highest beliefs, and so are indifferent across information structures.

**Prediction 9** Suppose preferences represented by a KR or EFK functional form. Then \((x, y) \sim_5 (y, x)\). Moreover, if preferences are represented by a KR functional form (an EFK suspense functional form with a sufficiently convex surprise function/an EFK surprise functional form with a decreasing surprise function), and they are loss averse then there exists an 0 < \(\epsilon'\) such that for all \(\epsilon < \epsilon'\), \((.5, .5) >_5 (.5 + \epsilon, .5 + \epsilon)\).

**Proof** We discussed KR’s functional form previously. In our environment utility is:

\[
V^{KR}(f, I) = \kappa f + \nu \left[ p(G)\eta(1)(p_G(H) - f) + p(B)\eta(-1)(f - p_B(H)) \right] \\
+ p(G) [p_G(H)\eta(1)p_G(L) + p_G(L)\eta(-1)p_G(H)] \\
+ p(B) [p_B(H)\eta(1)p_B(L) + p_B(L)\eta(-1)p_B(H)] \\
= \kappa f + \nu \left[ \eta(1)p(G)\left(\frac{fp}{p(G)} - f\right) + \eta(-1)p(B)f - \frac{f(1-p)}{p(B)} \right] \\
+ \left[ \eta(-1) + \eta(-1) \right] \left[ p(G)p_G(H)(1 - p_G(H)) + p(B)p_B(L)(1 - p_B(L)) \right] \\
= \kappa f + \nu \left[ \eta(1) + \eta(-1) \right] f(1-f)(p + q - 1) \\
+ \left[ \eta(-1) + \eta(-1) \right] \left[ p(G)p_G(H)(1 - p_G(H)) + p(B)p_B(L)(1 - p_B(L)) \right]
\]

Setting \(f = .5\), then we must have \(p(G)|_{(p,q)} = p(B)|_{(q,p)}\) and \(p_G(H)|_{(p,q)} = p_B(L)|_{(q,p)}\). Therefore,

\[
V^{KR}(.5, (p, q)) = V^{KR}(.5, (q, p))
\]

In addition, if we assume \(p = q\), then we have \(p(G) = .5 = p(B)\) and \(p_G(H) = p = p_B(L)\). Then

\[
V^{KR}(.5, (p, p)) = .5\kappa + (.25\nu(2p - 1) + (1 - p)p)\left[ \eta(1) + \eta(-1) \right]
\]

The derivative of this with respect to \(p\) is

\[
(.5\nu + 1 - 2p)\left[ \eta(1) + \eta(-1) \right]
\]

At \(p = .5\) this is less than or equal to 0 as long as \(\eta(1) + \eta(-1) < 0\).
We next turn to the EFK functional forms. Using their model of suspense, we have

\[ V_{\text{sus}}^{\text{EFK}}(f, (p, q)) = \kappa f + \nu \vartheta \left( p(G)2(p_G(H) - f)^2 + p(B)2(f - p_B(H))^2 \right) \]
\[ + p(G)\vartheta \left( p_G(H)2p_G(L)^2 + p_G(L)2p_G(H)^2 \right) \]
\[ + p(B)\vartheta \left( p_B(H)2p_B(L)^2 + p_B(L)2p_B(H)^2 \right) \]
\[ = \kappa f + \nu \vartheta \left( p(G)2\left( \frac{fp}{p(G)} - f \right)^2 + p(B)2\left( f - \frac{f(1-p)}{p(B)} \right)^2 \right) \]
\[ + p(G)\vartheta \left( 2p_G(H)(1 - p_G(H))^2 + 2(1 - p_G(H))p_G(H)^2 \right) \]
\[ + p(B)\vartheta \left( 2(1 - p_B(L))p_B(L)^2 + 2p_B(L)(1 - p_B(H))^2 \right) \]
\[ = \kappa f + \nu \vartheta \left( 2f^2(1 - f)^2(p + q - 1)^2 \left( \frac{1}{p(G)} + \frac{1}{p(B)} \right) \right) \]
\[ + p(G)\vartheta \left( 2p_G(H)(1 - p_G(H)) \right) + p(B)\vartheta \left( 2p_B(L)(1 - p_B(L)) \right) \]

Setting \( f = .5 \), then we must have \( p(G)|_{(p, q)} = p(B)|_{(q, p)} \) and \( p_G(H)|_{(p, q)} = p_B(L)|_{(q, p)} \). Hence, \( V_{\text{sus}}^{\text{EFK}}(.5, (p, q)) = V_{\text{sus}}^{\text{EFK}}(.5, (q, p)) \).

In addition, if we assume \( p = q \), then we have \( p(G) = .5 = p(B) \) and \( p_G(H) = p = p_B(L) \). Then

\[ V_{\text{sus}}^{\text{EFK}}(.5, (p, p)) = .5\kappa + \nu \vartheta \left( \frac{(2p - 1)^2}{2} \right) + \vartheta \left( 2p(1 - p) \right) \]

The derivative of this with respect to \( p \) is

\[ 2(2p - 1)\nu \vartheta' \left( \frac{(2p - 1)^2}{2} \right) + 2(1 - 2p)\vartheta' \left( 2p(1 - p) \right) \]

As \( p \) approaches .5, we have

\[ \frac{dV_{\text{sus}}^{\text{EFK}}(.5, (p, p))}{dp} \bigg|_{p \to .5^+} < 0 \text{ if } \nu \vartheta'(0) < \vartheta'(5) \]

We next derive the result for EFK’s model of surprise.

\[ V_{\text{surp}}^{\text{EFK}}(f, (p, q)) = \kappa f + \nu \left[ p(G)\vartheta \left( 2(p_G(H) - f)^2 \right) + p(B)\vartheta \left( 2(f - p_B(H))^2 \right) \right] \]
\[ + p(G)\vartheta \left( 2p_G(L)^2 + p_G(L)\vartheta \left( 2p_G(H)^2 \right) \right) \]
\[ + p(B)\left[ p_B(H)\vartheta \left( 2p_B(L)^2 \right) + p_B(L)\vartheta \left( 2p_B(H)^2 \right) \right] \]
\[ = \kappa f + \nu \left[ p(G)\vartheta \left( 2\left( \frac{fp}{p(G)} - f \right)^2 \right) + p(B)\vartheta \left( 2f - \frac{f(1-p)}{p(B)} \right)^2 \right] \]
\[ + p(G)\vartheta \left( 2(1 - p_G(H))^2 \right) + (1 - p_G(H))\vartheta \left( 2p_G(H)^2 \right) \]
\[ + p(B)\left[ (1 - p_B(L))\vartheta \left( 2p_B(L)^2 \right) + p_B(L)\vartheta \left( 2(1 - p_B(L))^2 \right) \right] \]
Then

\[ V_{EFK}^{surf}(f, (p,q)) = \kappa f + \nu \left[ p(G)\vartheta \left( \frac{2f^2(1-f)^2(p+q-1)^2}{p(G)^2} \right) + p(B)\vartheta \left( \frac{2f^2(1-f)^2(p+q-1)^2}{p(B)^2} \right) \right] \]

\[ + p(G) \left[ p_C(H)\vartheta \left( 2(1-p_C(H))^2 \right) + (1-p_C(H))\vartheta \left( 2p_C(H)^2 \right) \right] \]

\[ + p(B) \left[ (1-p_B(L))\vartheta \left( 2p_B(L)^2 \right) + p_B(L)\vartheta \left( 2(1-p_B(L))^2 \right) \right] \]

Setting \( f = .5 \), then we must have \( p(G)|_{(p,q)} = p(B)|_{(q,p)} \) and \( p_C(H)|_{(p,q)} = p_B(L)|_{(q,p)} \). Hence, we have

\[ V_{EFK}^{surf}(.5, (p,q)) = V_{EFK}^{surf}(.5, (q,p)) \]

In addition, if we assume \( p = q \), then we have \( p(G) = .5 = p(B) \) and \( p_C(H) = p = p_B(L) \). Then

\[ V_{EFK}^{surf}(.5, (p,p)) = \kappa .5 + \nu \vartheta \left( \frac{2p-1)^2}{2} \right) + p\vartheta \left( 2(1-p)^2 \right) + (1-p)\vartheta \left( 2p^2 \right) \]

The derivative of this with respect to \( p \) is

\[ 2(2p-1)\nu\vartheta' \left( \frac{(2p-1)^2}{2} \right) + 4p(1-p)\left[ \vartheta' \left( 2p^2 \right) - \vartheta' \left( 2(1-p)^2 \right) \right] \]

As \( p \) approaches .5, we have \( p^2 > (1-p)^2 \) and

\[ \frac{dV_{EFK}^{surf}(.5, (p,p))}{dp} \bigg|_{p=.5^+} < 0 \text{ if } \vartheta \text{ is decreasing} \]

Appendix C: Additional Investigations

<table>
<thead>
<tr>
<th>Extreme</th>
<th>Medium</th>
<th>Medium</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pos. (.5,1)</td>
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<td>149</td>
</tr>
<tr>
<td>Neg. (.5,1)</td>
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<td>Neg. (.5,1)</td>
<td>149</td>
<td>127</td>
</tr>
<tr>
<td>Pos. (.6,.9)</td>
<td>149</td>
<td>127</td>
</tr>
<tr>
<td>Neg. (.6,.9)</td>
<td>127</td>
<td>69</td>
</tr>
</tbody>
</table>

Table 6: Relationships: Skewness Preferences

Table 6 cross-tabulates within-person choice patterns in the questions that present positively and negatively skewed information structures. As we discussed above, we see that those who prefer one positively skewed signal are very likely to prefer another positively skewed signal.

Tables 7 and 8 report results of the main experiment, broken down by condition. It is easy to see that the choices and preference intensities are similar across the two conditions, with the exception of Q2. In Condition 1, 75% of the subjects prefer positive skew in Q2, whereas in condition 2 this fraction is 60%. The two fractions are statistically different at a p-value of 0.01.
Table 7: Main Experiment, Condition 1

<table>
<thead>
<tr>
<th></th>
<th>Option 1</th>
<th>Option 2</th>
<th>N</th>
<th>choice percentage</th>
<th>choice intensity for chosen option</th>
</tr>
</thead>
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<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>option 1 p-value</td>
<td>option 1 option 2 p-value</td>
</tr>
<tr>
<td>Q1</td>
<td>(1, 1)</td>
<td>(.5, .5)</td>
<td>119</td>
<td>0.77 .000</td>
<td>8.49 6.23 .000</td>
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<tr>
<td>Q2</td>
<td>(1, .5)</td>
<td>(.5, 1)</td>
<td>119</td>
<td>0.25 .000</td>
<td>5.4 7.32 .000</td>
</tr>
<tr>
<td>Q3</td>
<td>(.9, .3)</td>
<td>(.3, .9)</td>
<td>119</td>
<td>0.16 .000</td>
<td>5.05 6.54 0.015</td>
</tr>
<tr>
<td>Q5a</td>
<td>(.9, .6)</td>
<td>(.6, .9)</td>
<td>65</td>
<td>0.28 .000</td>
<td>5.39 5.96 0.421</td>
</tr>
<tr>
<td>Q5b</td>
<td>(.55, .55)</td>
<td>(.5, .5)</td>
<td>54</td>
<td>0.77 .000</td>
<td>6.45 5.67 0.406</td>
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</table>

Table 8: Main Experiment, Condition 2

<table>
<thead>
<tr>
<th></th>
<th>Option 1</th>
<th>Option 2</th>
<th>N</th>
<th>choice percentage</th>
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<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>option 1 p-value</td>
<td>option 1 option 2 p-value</td>
</tr>
<tr>
<td>Q1</td>
<td>(.5, .5)</td>
<td>(1, 1)</td>
<td>131</td>
<td>0.21 .000</td>
<td>6.48 8.15 .000</td>
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<tr>
<td>Q2</td>
<td>(.5, 1)</td>
<td>(1, .5)</td>
<td>131</td>
<td>0.6 .035</td>
<td>7.14 6.64 0.192</td>
</tr>
<tr>
<td>Q3</td>
<td>(.6, .9)</td>
<td>(.9, .6)</td>
<td>131</td>
<td>0.74 .000</td>
<td>6.22 5.53 .155</td>
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<tr>
<td>Q5a</td>
<td>(.9, .3)</td>
<td>(.3, .9)</td>
<td>64</td>
<td>0.23 .000</td>
<td>6.77 6.53 0.755</td>
</tr>
<tr>
<td>Q5b</td>
<td>(.5, .5)</td>
<td>(.55, .55)</td>
<td>67</td>
<td>0.27 .000</td>
<td>4 5.75 0.04</td>
</tr>
</tbody>
</table>

Appendix D: Experimental Protocol

The experimenters gave participants a ticket from a raffle ticket roll in the sequence with which they entered the lab. The ticket assignment was simple and public, making it transparent to all participants that each participant had equal chances in the lottery coming up. The participants read the instructions displayed on their screens and waited for the experimenter to begin the study. The instructions on the screen, included in D.1 below, informed participants that the study was 75 minutes long and had two parts and that they would receive $7 for participating in the study. These instructions also informed the participants that they would be participating in a lottery with the ticket they received as they entered the room. With 50% chance, they would earn an additional $10, and with 50% chance they would not earn any additional money.

The experimenter told the participants to put on their headphones in order to listen to the instructions that will be given on the next page. The participants were asked if they had any difficulties with the video or audio components of the program. Only 1 person did, and his/her microphone was adjusted immediately. The instructional video, transcribed in D.2, explained that whether a particular ticket wins or loses the lottery is determined by the last digit of the ticket number and the outcome of a 10-sided die throw. They learned that the experimenter would roll the die and cover it with a cup after seeing the die outcome. They were told that if the die outcome is an odd (even) number and the last digit of the ticket the participant is holding is also odd (even), the participant would win $10. And, if the last digit of the ticket and the die outcome fail to match in this way, the participant does not win any money. Importantly, the instructions emphasized that none of the participants would learn the outcome of the die and thus whether they won or lost, before the experiment was over. They were told that one of the participants would be invited to lift the cup and read the number on the die out loud at the end of the experiment for everyone to learn the outcome. The participants were also told that they would enter their ticket number and the experimenter would supply a code to be entered so that the computer program would know
whether they won or lost, right from the beginning of the experiment. Then, participants were given hypothetical examples of this process and understood how the computer would be able to know more than they did and would be able to generate clues if needed. The instructions also explained that in the first part of the study was expected to take around half the allotted time for the experiment and the participants would be answering five questions, each with two clue-generating options, about their preferences about what kind of clues they would like to get about whether their ticket won or lost. The instructions explained that 1) one of these five questions would be chosen at random to be carried out at the end of the first part, 2) that they would observe the clue generated by the option they chose in that question at that time, and 3) they would sit with that clue for the rest of the experiment until they were able to learn whether they won or lost the lottery at the end of the 75 minutes. The participants also learned that they would be answering questions unrelated to the lottery in the second part and that these questions did not have any informational or monetary value associated with them.

Throughout the study, we rely on video technology to deliver instructions that are either very long or very important, or both. We find that visual delivery aids comprehension and increases attention compared to text. In addition, the same amount of information can be conveyed faster. The links for the videos and the transcriptions for a representative sample are included in D.5.

When the initial instructional video was over, participants were asked to enter the last digit of their ticket number and the experimenter rolled a 10-sided die on the table publicly and covered it with a cup so that the outcome was not visible to the participants. The experimenter informed the participants “I rolled the die. At this point, the outcome of the lottery for everyone is determined. I will now look at the outcome and give you a code to enter, so that the computer knows what the outcome was.” and gave one of the following codes: sugar, milk, cake, candy, coffee, butter; where sugar, cake or coffee informed the computer that the die outcome was an odd number. We used more than one code and changed it around across sessions to prevent participants from learning the codes across sessions.

After entering the code and the last digit of their ticket numbers, the participants answered several comprehension questions regarding the instructions they received. The program instructed them if they answered any question incorrectly.

On the next page, they were asked to rate their happiness in order to elicit an initial baseline happiness measure. The question asked “Please indicate how happy/unhappy you are feeling in the current moment by sliding the scale. -100 means you are feeling ‘very unhappy’, 100 means you are feeling ‘very happy’, 0 means you are feeling ‘neutral’.” After this question, instructions (included in D.3) informed the participants that they were proceeding to part 1 of the study where they would be making choices about the kind and amount of information they would like to get about whether their ticket won or lost the lottery.

Before each question in part 1, they listened to video instructions that presented the options in the question. The transcription of the instructions for Q2 is included as an example in D.4. All videos can be accessed from links provided in D.5. The videos for each question were all structured in the following manner: 1) The two options in the question were presented, and the text indicating the contents of each box in the options were read. 2) For each option, the box from which the ball would be drawn if the participant won the lottery was highlighted, followed by the box from which the ball would be drawn if the participant lost the lottery. 3) The percentage of the instances a red or a black ball would be drawn from Option 1 was indicated and explained, 4) The meaning (posterior probability of winning or losing) associated with observing a red or a black ball from Option 1 was defined and explained, 5) steps 3 and 4 were repeated for Option 2, 6) Option 1 and Option 2 were displayed next to one another and a summary of the information regarding the likelihood of
observing each ball color and the posterior probability of winning associated with each color was included below each option. This final comparison visual is the same graphic as the one that the participants saw when they were making a choice between the two options. The video instructions did not provide any additional information than the information already included on their screens right at the time of making a choice, however we believe that watching the video instructions before making a choice forced participants to pay more close attention to this information and provided them with more of an understanding of how the posterior probabilities were calculated.

After watching the video and completing the comprehension questions, the participants arrived at a page that displayed the two options graphically and explained each verbally. Figure 5 displays a screen shot of Q1, Figure 4 displays a screen shot of Q2, and Figure 8 displays a screen shot of Q4 to give a sense of the information subjects could see on the page at the time they were making their decisions. After each choice, subjects also indicated how strongly they preferred the option they chose over the option they did not. The scale ranged from 0 (indicating indifference), to 10 (indicating a very strong preference). Figure 6 displays this question.

After participants answered all five questions, one question was randomly chosen for each participant to be carried out and the program randomly drew a ball from the option the participant chose in that question. The program displayed the two options in the chosen question along with the participant’s choice in that question on the screen. It also indicated whether the ball drawn from the option the participant chose was red or black. Given the color of the ball drawn from the option, and the information about the posteriors included in the graphics of the option, the participant was asked to enter the probability that s/he won the lottery (which s/he could simply read from the graphic if s/he paid attention). A screen shot of this page is displayed in Figure 9.

On the next page, the participants were asked to rate their happiness in that moment using the same scale as before. On the following pages, they were also asked to rate how optimistic/pessimistic they feel about winning the lottery, to note whether they had any questions or confusions about part 1 and to provide a short explanation for the reason behind their choices in the first three information-preference questions in part 1.

In the remaining time before the outcome of the lottery was to be revealed, subjects were also asked a series of hypothetical questions across 5 blocks in Part 2 of the study. Each block featured 10 questions, asking whether individuals preferred to take Option A or Option B. In blocks 1-3, Option B was receiving some amount of money for sure, beginning with $2 and increasing in $2 increments to $20 dollars. In block 1, Option A was a gamble that was structured as follows: “a ball will be drawn from a box with 50 white and 50 blue balls. If a blue ball is drawn you receive $30, otherwise nothing.” In block 2, Option A was a gamble that was structured as follows: “a ball will be drawn from a box with white and blue balls (the respective number were not specified). If a blue ball is drawn you receive $30, otherwise nothing.” Option B was receiving some amount of money for sure, beginning with $2 and increasing in $2 increments to $20 dollars. In block 3, Option A was a gamble that was structured as follows: “a ticket will be drawn from an urn that features 101 tickets labeled from 0 to 100. The number on the ticket determines how many blue balls will be in a box of 100 blue and white balls. Next, a ball will be drawn from the box. If a blue ball is drawn you receive $30, otherwise nothing.” In block 4, Option A allowed the individual to receive $30 for sure. Option B was a gamble that paid an 80% of x and a 20% of 0. x varied from $34 to $74 in $4 increments. In block 5, Option A was a gamble which allowed the individual to receive a 25% chance of $30 and 75 % chance of $0. Option B was a gamble that paid an 20% of x and a 80% of 0. x varied from $34 to $74 in $4 increments.

31 These questions were hypothetical in order to ensure that subjects could not use the information to adjust their responses to questions that would result in actual monetary rewards.
At the end, when all participants were done (or when time was running out), one participant was invited to lift the cup and announce the die outcome. All participants were asked to indicate this outcome and whether they won or lost the lottery as a result on their screens. On the next page, right after learning the outcome of the lottery, the participants were asked once again to rate their happiness in that moment.

The experimenters went to each participant’s stall to pay him or her in private. The experimenter checked the ticket number, paid the participant in cash and asked him or her to fill out the receipt form and answer one more question on the last page of the study and advanced the participant’s program to that last page. On the last page, after receiving the cash, the participants were asked once again to rate their happiness in that moment.

Experimental Materials

D.1. General Instructions

Welcome to our informational decision making study! Please read the instructions carefully. We will ask comprehension questions in a little bit.

You may have participated in different kinds of studies across campus. The instructions we give in this study are accurate and reflect exactly how the study will unfold. We will explain how the study is programmed, how the computer will determine the questions and information you will see and how you will get paid in accordance with what actually will happen. In other words, there is no deception of any kind.

This study will take 75 minutes and has two parts. You will receive $7 for your participation. If you fail to follow the instructions or disturb the flow of the study in any way, you will be asked to leave the study. In addition to the $7 for participation, you may also win an additional $10 in the lottery we will conduct. The chances of winning are 50% and whether you win $10 will be determined by the ticket number you have.

Please silence your phones and put your belongings under the table, and leave them alone during the entire study. We need your full engagement; even when you are not actively participating in the study, please wait patiently and refrain from using your cell phone, checking email, surfing the internet, etc. This is a silent study. Please do not make any noise, you will be asked to leave the study without any compensation if you do. If you are having technical difficulties at any time, raise your hand quietly and the experimenter will come to help. You are not allowed to ask questions about the content of the study to the experimenter, please read and listen to the instructions very carefully to avoid confusion.

Please stay on this page and do not proceed before instructed to do so. During the study, we will need you to listen to instructional videos before you make decisions. Therefore, please put on your headphones now and listen to the following instructions.

D.2. Lottery and Information: Transcription of video instructions

You will participate in a lottery with the ticket you got when you arrived. The chances of winning are 50%. If you win the lottery, you will get an additional $10. If you lose the lottery you will not get any additional payment. We will determine whether you won or lost at the beginning of the study. The experimenter will roll a 10-sided die and cover it with a cup. The die outcome can be 0, 1, 2, 3, 4, 5, 6, 7, 8, 9, each with equal chance. If the die outcome is even, and your ticket’s last digit is even, it means that you won the lottery. If the die outcome is odd, and your ticket’s last digit is odd, it also means that you won the lottery. Otherwise, it means that you lost the lottery. So,
you have a 50% chance of winning and 50% chance of losing. Note that the chance of winning and 
losing is equal for everyone and does not depend on how many people are in the session. Multiple 
people in the same session will win the lottery. Whether you win or lose is entirely determined by 
your ticket number and the die roll. There is an important detail about how we will reveal the 
outcome of the die roll. When the experimenter rolls the die, she or he will hide the outcome with 
a cup placed over the die until the end of the study. The experimenter will know the outcome at 
that time, but the cup will only be removed at the end of the study. So you will not learn about 
the outcome of the die roll until the very end of the study. So even though you know your ticket 
number, since you don’t know the die roll, you will not know whether you won or lost the lottery, 
even though it is determined already. At the end of the study, the experimenter will remove the cup 
and everyone will be able to see the die roll. Even though you will not learn about the outcome of 
the die roll right away, the experimenter will give you a code to enter, in order to let your computers 
know whether the die roll was even or odd. For example, say that we programmed the survey such 
that the computer knows that the die roll was even if you typed in the code word ‘home’, and that 
the die roll was odd if you typed in the code word ‘house’. If the die roll is even, the experimenter 
will instruct you to enter the code word ‘home’. Of course, we will be using different code words in 
the study. You will not know whether a given code corresponds to even or odd outcome, but the 
computer will. You will also be asked to enter the last digit of your ticket number. Having both 
pieces of information, the computer will be able to know immediately whether you won or lost the 
lottery. Now, let’s talk about the study itself. During the first half of the study, we will ask your 
preferences about what kind of clues you would like to get about whether your ticket won or lost. 
Remember, the outcome of the lottery is determined at the beginning of the study, but stays hidden 
from you until the experimenter removes the cup. However, the computer whether you won or lost, 
and as a result, it is able to give you signals about the outcome. These signals will come from 
your choice of clue generating options. You will make five decisions across five different questions, 
each presenting two clue generating options. Each of the clue generating options has the potential 
to provide signals about whether you won or lost. The amount and the type of information will 
differ across these options. We are interested in learning about your preferences regarding different 
types of clue generating options. Before each decision, you will watch an instructional video that 
explains each of the clue generating options. It is very important that you pay attention to these 
videos. At the moment you started the study, the computer picked one question at random among 
the 5 questions you will answer. Each question has equal chance of being picked. Your decision 
in the question that is picked at random will be carried out at the end of Part 1. In other words, 
at the end of Part 1, you will observe a signal generated by the option you chose in that question. 
This is done in order to make sure that you answer each of the 5 questions as if it were the only 
question being asked. So please pay attention to each question. One will be carried out to give you 
the type of clue you prefer about whether you won or lost. Once you observe a clue according to 
your choice in the chosen question, you will sit with that clue until the end of the study. Please 
take this into account when making your choices. While everyone will eventually learn the winning 
lottery numbers at the end of the study, people may differ in their preferences regarding the type of 
clue they want to sit with until they learn the winning ticket numbers. As you are waiting to learn 
the winning ticket numbers, we will ask you other questions that are unrelated to the lottery in 
the Second Part of the Study. Please take your time in answering all questions carefully. Finishing 
early does not mean you get to leave. Please wait patiently and do not engage in any other activity 
such as using your phone, web browsing, etc. Please also make sure not to make any distracting 
optices At the very end of the study, the experimenter will invite a participant to lift the cup hiding 
the die roll outcome and announce the winning ticket numbers. At that time you will fill out the
D.3. Introduction to Information Structure Choices

In the first half of the study, there will be 5 questions, each asking you to choose 1 out of 2 options that generate different clues about your chances of having won the lottery. Some options can give you further information about the likelihood that you won or lost the lottery. Some options do not give any additional information at this time. Some options give more information than others. And importantly, all these options differ in the kind of information you can get. Please pay close attention to the instructional videos and the options descriptions to make sure you understand these differences before you make a choice. At the end of Part 1, we will ask you to provide a brief description of why you made each choice, so please consider the options carefully, remembering that each option can provide different amounts and types of information. The computer randomly picked a question among these 5 questions at the time you started the survey. Your choice in that question will be honored and you will get the clue you expressed a preference for. You will sit with the information you gained (if you gained any) for the rest of the experiment. Until you are done answering all questions, you will not know which question is picked. The chances of each question being picked are the same. Therefore, please treat each question as if that is the only question being asked. These questions are independent of one another. Only one is selected randomly, and you will receive information based on your preferred option. Now, please make sure that you have your headphones on. You will be asked to keep them on until you are done with the first half of the study.

D.4. Introducing Q2: Transcription of video instructions

We want to overview some of the general points at this time. Remember that regardless of which Option you pick, the computer draws a ball from the left box in that option if you won the lottery, and it draws a ball from the right box if you lost the lottery. Before you see the color of the ball drawn from an option, you know that the overall chances of winning are 50%. If your ticket number is an odd number and die roll is also an odd number: you win Also, If your ticket number is an even number and die roll is also an even number: you win Otherwise: you lose. So there is an equal chance of that you won or lost the lottery. Remember that the computer knows whether you won or lost, and, the color of the ball the computer draws from an option may give you more information. Also, another common feature you may have already realized in the first Question, is that across all the questions, seeing a red ball means that your chances of having won are either equal to or higher than 50%, and seeing a black ball means that your chances are either equal to or lower than 50%. How much your expectations of having won changes after you see a red or a black ball depends on the contents of the boxes. Now, let’s move onto Question 2 and examine the options it presents. Now, we will review Question 2. Question 2 asks you to choose between these two options. These options are quite different than the simpler options you saw in Question 1. So, take a moment to inspect them carefully. If you pick Option 1 and you won the lottery, the computer draws a ball from the box with 50 red and 50 black balls, and if you lost the lottery, it draws a ball from the box with 100 black balls. If you pick Option 2 and you won the lottery, the computer draws a ball from the box with 100 red balls; and if you lost, it draws a ball from the box with 50 red and 50 black balls. How do these two options differ in the type of information they can provide about whether you won or lost the lottery? Let’s look into Option 1 first. You can expect to see a red ball from Option 1 25% of the time and a black ball 75% of the time. Because for half the participants who won, the computer will draw a ball from the left box, getting a red ball
in half of those instances and a black ball in the other half of those instances. And for the other half of participants who lost, the computer will draw from the right box, always getting a black ball. So overall, you can expect to see a red ball 25% of the time and a black ball 75% of the time. Now, let’s think about what it means if you see a red ball and what it means if you see a black ball. If you see a red ball from Option 1, you learn right away that you won the lottery. Why? Because red balls can only come from the left box. The computer draws from the left box only if it determines that you won the lottery. How about if you see a black ball? Note that the black ball could have come from (either) the left box or the right box. So, you cannot conclude you won or lost for sure. However, note that there are twice as many black balls in the right box than in the left box. So it is more likely to observe a black ball if you lost than it is to observe it if you won. Therefore, seeing a black ball is basically getting news that your chances of losing are less than the general 50% chance, albeit still uncertain. In fact, seeing a black ball from option 1 means that the chances that your ticket won are 33%. We reviewed Option 1. Now, let’s look at Option 2. You can expect to see a red ball from Option 2 75% of the time and a black ball 25% of the time, because for half the participants who won, the computer draws a ball from the left box and all of those instances, the color of the ball will be red. If you see a black ball from Option 2, it means that you lost the lottery. You know this for sure, because the only way you can see a black ball is if it comes from the right box and the computer only draws from that box if you lost. How about if you see a red ball? Note that the red ball could have come from (either) the left box or the right box. But there are twice as many red balls in the left box than in the right. So seeing a red ball is a signal that your chances of winning are better than 50%, albeit still uncertain. In fact, seeing a red ball from option 2 means that the chances that your ticket won are 67%. Question 2 asks you to choose between these two options. These options are quite different than the simpler options you saw in Question 1. So, take a moment to inspect them carefully. In Option 1 you are more likely to see a black ball and in Option 2 you are more likely to see a red ball. In Option 1, Seeing a black ball means that your chances of winning are 33%. Seeing a red ball means that you won for sure. In comparison, in Option 2, seeing a black ball means that you lost for sure and seeing a red ball means that your chances of winning are 67%. Please take a moment to think about the kind of information these options offer and what kind of information you would like to get about your chances of winning. Remember you will get this information at the end of Part 1, sit with it and learn the outcome of die roll at the end of the study. Now, please move on to the comprehension and choice questions by clicking the next button when it appears.

D.5. Video Links
Lottery and Information: http://tinyurl.com/infopref-general
Q1: http://tinyurl.com/infopref-q1
Q2: http://preview.tinyurl.com/infopref-q2
Q3: http://tinyurl.com/infopref-q3
Q4: http://tinyurl.com/infopref-q4
Q5: http://tinyurl.com/infopref-q5

Appendix E: Experimental Protocol, Robustness Study
In July 2015, 223 subjects participated in a real-choice study conducted at the [blinded for review] Lab. This study presented only one pairwise comparison of information structure to each subject.
It also elicited a monetary evaluation of utility differences between information structures. Each participant is paid $7 for participating the hour-long experiment and could win $10 in the lottery, receive a pen or a postcard, and earn up to $1 as a result of their choices and luck in the preference elicitation mechanisms. The average earnings were $12.38.

When the subjects arrived at the lab, they received raffle tickets. The study had three parts. Part 1 involved a choice between a pen and a postcard. Its main objective was to introduce the subjects to the preference elicitation mechanism to be used in Part 2. In Part 2, subjects participated in a lottery with the raffle ticket, and indicated preferences between two information structures that could reveal certain amounts and types of information regarding the lottery outcome. Questions in this part elicited the preference ranking among the two information structure options, as well as the compensation the subject required in order to receive the option s/he did not prefer instead of the option s/he preferred. Part 3 included hypothetical questions regarding risky choices. Each part has its own detailed instructions, but subjects were given an overview of what they involved in the initial instructions, as detailed below in E.1.

In Part 1, subjects completed a seemingly unrelated training session that approximately lasted 10 minutes and gave them experience with the willingness to accept protocol. They were given two collegiate memorabilia to choose from: a pen and a postcard from the university they were currently attending. They were told that they could keep the item of their choice. After they indicated their choice, they were asked to indicate the strength of their preference for the item they chose. Figures 10 and 11 display screen shots of these questions.

Next, they were presented with the option of receiving money for switching their choice. First, they watched an instructional video explaining this option, as transcribed in E.2. We presented 10 consecutive statements of the following form: “For a compensation of \(x\) cents I would change my choice,” where \(x\) varied from 1 to 50. They indicated ‘Yes’ or ‘No’ for each of these statements. We informed them 1) that on the next page, they would see a random number between 1 and 10 generated by an independent web service (http://reporting.qualtrics.com/projects/randomNum-Gen.php), 2) that this number would determine the statement we carry out, and 3) about the consequences of their choices. In particular, we explained that if they marked ‘No’ for a statement that got chosen, they would get the option they preferred, but if they marked ‘Yes’, they would be given the other option and the amount of money indicated in the statement. The statements were ordered in an ascending order of \(x\). All subjects only switched once from ‘No’ to ‘Yes’, if they switched at all. Figure 12 displays the screen shot of the willingness to switch elicitation page. After a random statement was chosen, subjects were asked 1) what item they would be receiving as a result, and 2) whether they regretted their decision. Subjects had to wait for everyone else to be done with Part 1 before they proceeded to Part 2.

In the beginning of Part 2, subjects were asked to watch an instructional video that explained the setup of Part 2. This instructional video outlined the details of the lottery, information revelation time line and the task they face in Part 2 (transcription presented in E.3). The participants were then asked to enter the last digit of the raffle ticket they received. The experimenter rolled a 10-sided die, and covered the outcome with a cup. S/he then provided a code for the subjects to enter in the program, as in the main study, to indicate the die outcome to the program, without letting the subject know.

The subjects saw one of the following five binary comparisons across five between-subject treatments as described in Table ?? of the main text. They watched an instructional video outlining the information structures. The transcription of the video introducing the binary choice in Treatment A is included in E.4 as an example. After watching the video and answering questions that checked their comprehension of the material presented, subjects made a choice between Option 1
and Option 2, and indicated their preference strength. The information displayed on the screen and the question style was identical to the main experiment, as depicted by Figure 5 and 6.

We then offered them the option to change their choice in exchange for some money. Similar to the willingness to accept task they completed in Part 1, they indicated whether they would give up their original choice and instead see a ball drawn from their unpreferred information structure in exchange for \( x \) cents where \( x \) ranged from 1 to 50. Figure 13 displays the preamble to this elicitation and Figure 14 shows the set of 10 questions. We then picked one statement randomly and carried it out. Figure 15 displays the page informing the subject of the chosen question. If they said ‘No,’ they saw a ball from the information structure of their choice. If they said ‘Yes,’ they saw a ball from the other structure, and received \( x \) additional cents at the end of the experiment. After seeing a ball, subjects were reminded of the posterior likelihood of having won the lottery. Figure 16 displays the page where the subjects received a signal from their information structure of choice.

Part 2 also asked the subjects to explain the reason why they preferred one information structure over another, asked a comprehension question to check that they understood the implication of their choice in the statement drawn at random, and also asked for some demographics information.

In Part 3, they indicated their choices between a gamble that paid $50 or nothing versus a sure payment, when the risk was realized today versus in a week. They also wrote short essays regarding the difference between motives and intentions behind an action. Part 3 took approximately 30 minutes for subjects to complete. At the end of the study, the die outcome was announced and the holders of the winning tickets were paid an additional $10. All subjects were paid any additional compensation resulting from the willingness to accept elicitations in Part 1 and 2 at this time, and were given either the pen or the postcard to take home with them.

Only 190 passed the checks included in the study. We report the data from these subjects in Table 5 of the main text. For completeness, Table 9 below presents the same data from all 223 subjects. None of our conclusions are subject to the omission of data from subjects who were not paying attention or who were confused.

### Table 9: Robustness Study

<table>
<thead>
<tr>
<th>Treatments</th>
<th>((1, 1)) vs ((.5, .5))</th>
<th>((1, .5)) vs ((.5, 1))</th>
<th>((.3, .9)) vs ((.9, .3))</th>
<th>((.9, .6)) vs ((.6, .9))</th>
<th>((.5, .5)) vs ((.5, .1))</th>
</tr>
</thead>
<tbody>
<tr>
<td>N</td>
<td>43</td>
<td>45</td>
<td>47</td>
<td>46</td>
<td>42</td>
</tr>
<tr>
<td>Choice Percentage</td>
<td>65% (.033)</td>
<td>18% (.000)</td>
<td>68% (.009)</td>
<td>30% (.006)</td>
<td>12% (.000)</td>
</tr>
<tr>
<td>Intensity</td>
<td>First</td>
<td>Second</td>
<td>First</td>
<td>Second</td>
<td>First</td>
</tr>
<tr>
<td>MCTS</td>
<td>8.32</td>
<td>6.93</td>
<td>6.38</td>
<td>7.24</td>
<td>5.75</td>
</tr>
<tr>
<td>Average MCTS</td>
<td>27.0</td>
<td>32.4</td>
<td>20.7</td>
<td>32.9</td>
<td>20.2</td>
</tr>
</tbody>
</table>

In parentheses we report the p-values from one-sided binomial test to evaluate the null hypothesis that choice percentages are either larger or smaller than 50%, and p-values from one-sided t-tests to evaluate the ordering of preference intensity and average MCTS across option 1 and option 2.

### Experimental Materials

#### E.1. General Instructions

Welcome to our informational decision making session. Please read the instructions carefully. We will ask comprehension questions in a little bit. You may have participated in different kinds of studies across campus. The instructions we give in this study are accurate and reflect exactly how the study will unfold. We will explain how the study is programmed, how the computer will
determine the questions and information you will see and how you will get paid in accordance with what actually will happen. In other words, there is no deception of any kind and you will be fully informed of the workings of the study at all times.

The session will last 60 minutes. You will receive $7 for your participation. You will also get a pen or a postcard and may earn an additional $10 as a result of luck. If you fail to follow the instructions or disturb the flow of the study in any way, you will be asked to leave the study.

Please silence your phones and put your belongings under the table, and leave them alone during the entire study. We need your full engagement; even when you are not actively participating in the study, please wait patiently and refrain from using your cell phone, checking email, surfing the internet, etc.

This is a silent study. Please do not make any noise, you will be asked to leave the study without any compensation if you do. If you are having technical difficulties at any time, raise your hand quietly and the experimenter will come to help. You are not allowed to ask questions about the content of the study to the experimenter, please read and listen to the instructions very carefully to avoid confusion. All information pertinent to the study is contained in the instructions. Therefore it is of utmost importance that you follow the instructions carefully. At certain points in time, we may also ask you basic facts about the study to make sure you are following what is going on.

In this session, you will participate in two different studies. In Study 1, we will ask you to indicate your preference between the pen and the postcard and answer related questions. In Study 2, you will participate in a lottery with the raffle ticket you got when you arrived. If you win the lottery, you will earn an additional $10. If you lose the lottery, you will not get any additional money. Both studies will be explained in detail with video instructions. Your decisions and payments will depend on your understanding of these instructions.

In both studies, we will be using an independent web service (http://reporting.qualtrics.com/projects/randomNumGen.php) to randomly pick numbers between 1 and 10. These numbers will be helpful in determining outcomes in uncertain events. Each number has an equal chance of being picked for any given event. The numbers are drawn completely randomly and do not follow any particular sequence.

All payments will be made in cash at the end of the study.

E.2. Willingness to Switch Elicitation: Transcription of video instructions

Thank you for indicating your choice among the pen and the postcard. Whether you get what you chose, or the other item, will depend on your answers in the next task. The next task will help us put a monetary value on the strength of your preference between the two options. You’ve already indicated your strength of preference. Now, we will ask you a list of questions that will translate the difference in your liking to how much we would have to compensate you in order to give you the item you did not want to receive. You will see 10 questions, each of which will ask you whether you would change your choice if we compensated you for the amount specified in the question. You will answer by selecting yes or no. The stronger your preference for the item you chose over the item you rejected, the more money we would need to pay you to give you the item you did not want to receive rather than the item you chose. Let’s look at how these questions will look like. On your screen you will see the following list. Question 1 asks whether you would change your choice if we paid you 1 cent to do that. If you say no, you will get the item you preferred to take with you at the end of the study today. If you say yes, you will receive 1 cent and instead get the item you did not prefer. Question 2 increases the compensation to 5 cents and asks you if you would switch for that amount. In this manner, questions keep increasing the compensation
amount, until Question 10, which offers you 50 cents to change the item you will get at the end of the study. Clearly, you may say No to all the questions if you would need more than 50 cents to be OK with getting the item you rejected. Or you can say yes to all these questions if you don’t care much about which item you get. Everyone’s preferences are different, so everyone will require different amounts to change their choice. For example, if 15 cents is not enough compensation to give up your choice, but you would be OK with getting your unwanted item if we paid you 20 cents or more, your answers would look like this. Or instead, if 30 cents is not enough compensation to give up your choice, but you would be OK with getting your unwanted item if we paid you 35 cents or more, your answers would look like this. Clearly, if you switch from answering NO to answering YES on this list of questions, you should only switch once. That will tell us which compensation is too low for you, and which compensation is high enough. There are no right or wrong answers. Please think about how much you like the item you chose versus the item you rejected. This task is designed to elicit your true preferences. As such, we will randomly draw a number between 1 and 10 using the online random number generator. This will determine the question we will carry out. For example, if the number comes up 6, we will look at Question 6. If you said No to that question, you will keep the item you prefer. If you said Yes, you will let that item go and switch to the other item, and receive the monetary compensation specified in Question 6. You should consider each question independently and indicate your true preferences. If you say No when you would rather take the money, or if you say Yes when you’d rather keep the item you prefer, you may feel regret when we carry out your choice. So please think carefully and answer these questions according to your own preferences. We show you the task one more time before you proceed. Think about what compensation is too little for you to switch your choice, and what compensation would be enough. Accordingly, click Yes or No for each question. Please raise your hand now if you had any technical difficulties in hearing/reading these video instructions. Otherwise, click the next button.

E.3. Lottery and Information: Transcription of video instructions

You will participate in a lottery with the raffle ticket you were given. The chances of winning are 50%. If you win the lottery, you will get an additional $10. If you lose the lottery you will not get any additional payment. We will determine whether you won or lost right after these instructions. The experimenter will roll a 10-sided die and cover it with a cup. The die outcome can be 0, 1, 2, 3, 4, 5, 6, 7, 8, 9, each with equal chance. If the die outcome is even, and your ticket’s last digit is even, it means that you won the lottery. If the die outcome is odd, and your ticket’s last digit is odd, it also means that you won the lottery. Otherwise, it means that you lost the lottery. So, you have a 50% chance of winning and 50% chance of losing. Note that the chance of winning and losing is equal for everyone and does not depend on how many people are in the session. Multiple people in the same session will win the lottery. Whether you win or lose is entirely determined by your ticket number and the die roll. There is an important detail about how we will reveal the outcome of the die roll. When the experimenter rolls the die, she or he will hide the outcome with a cup placed over the die until the end of the study. The experimenter will know the outcome at that time, but the cup will only be removed at the end of the study. So you will not learn about the outcome of the die roll until the very end of the study. So even though you know your ticket number, since you don’t know the die roll, you will not know whether you won or lost the lottery, even though it is determined already. At the end of the study, the experimenter will remove the cup and everyone will be able to see the die roll. Even though you will not learn about the outcome of the die roll right away, the experimenter will give you a code to enter, in order to let your computers know whether the die roll was even or odd. For example, say that we programmed the survey such
that the computer knows that the die roll was even if you typed in the code word 'home', and that
the die roll was odd if you typed in the code word 'house'. If the die roll is even, the experimenter
will instruct you to enter the code word 'home'. Of course, we will be using different code words
in the study. You will not know whether a given code corresponds to even or odd outcome, but
the computer will. You will also be asked to enter the last digit of your ticket number. Having
both pieces of information, the computer will be able to know immediately whether you won or
lost the lottery. Now, let's talk about the study itself. During the first half of the study, we will
ask your preference regarding the type of clue you would like to get about whether your ticket
won or lost. Remember, the outcome of the lottery is determined at the beginning of the study,
but stays hidden from you until the experimenter removes the cup. However, the computer knows
whether you won or lost, and as a result, it is able to give you information about the outcome.
You will choose between two clue generating options, each of which can provide a different kind
of information. Please choose between the two options carefully. After you make your choice and
answer a few related questions, the computer will show you the information generated by the option
you chose. Once you observe this information, you will sit with it until the end of the study. Please
take this into account when making your choice. While everyone will eventually learn the winning
lottery numbers at the end of the study, people may differ in their preferences regarding the type
of clue they want to sit with until they learn the winning ticket numbers. As you are waiting to
learn the lottery outcome, you will be sitting with the information you learned. In the meantime,
we will ask you other questions that are unrelated to the lottery in the second part of the study.
Please take your time in working on this part. If you finish early, please wait patiently and do
not engage in any distracting activities. Even if you finish early, you cannot leave early. At the
very end of the study, the experimenter will invite a participant to lift the cup hiding the die roll
outcome and announce the winning ticket numbers. At that time you will fill out the receipt forms
and get paid. Please make sure that you understand the flow of this study. When you are ready,
please click next to proceed with the study.

E.4. Introducing Treatment A: Transcription of video instructions

We will now explain the question that will ask you to choose between two clue generating options.
Please pay close attention to this video. The question presents two options. Let's first overview
the general structure of these options. Both options have two boxes inside, as shown on this slide.
Each of the boxes will have colored balls inside. But first, let's explain what these boxes are for.
When you choose one of the two options, the computer will draw a ball from the left box if you
won the lottery, and it draws a ball from the right box if you lost the lottery. Remember that the
computer knows whether your ticket number is a winning number or not, because you entered its
last digit and the code that the experimenter supplied. You will not see which box the computer
is drawing a ball from. You will only see the ball that came out. The boxes will have red and/or
black balls inside. The number of red and black balls in each box will differ. As a result, the color
of the ball that the computer draws from the option you chose will be an informative signal about
your chances of winning the lottery. The composition of the balls in the boxes will vary across the
two options. Therefore, the options will differ in the kind of information they can provide. The two
options you will choose between look like this. Please pay attention to the contents of the boxes
in each option. We will now talk about them in detail. Let's first look at Option 1. In the left
box, all of the 100 balls are red. In the right box, all of the 100 balls are black. So if you won
the lottery, the computer draws a ball from the box with 100 red balls; and if you lost, it draws a
ball from the box with 100 black balls. Now, look at Option 2. In the left box, there is an equal

mix of 50 red balls and 50 black balls. In the right box, there is also an equal mix of 50 red balls and 50 black balls. So if you won the lottery computer draws a ball from the (left) box with 50 red and 50 black balls, and if you lost the lottery, it draws a ball from the (right) box with 50 red and 50 black balls. Now, let’s think about how these two options differ in the information they can provide. First, let’s look at Option 1. You can expect to see a red ball from this option 50% of the time and a black ball from this option 50% of the time. Why? Remember the computer is equally likely to draw a ball from either of the boxes, because the chances of winning overall are 50%. So, 50% of the time you will see a red ball and 50% of the time you will see a black ball. If you see a red ball from Option 1, You learn right away that you won the lottery for sure. Because red balls can only come from the left box and the computer draws from the left box only if it determines that you won the lottery. And, if you see a black ball from Option 1, You learn right away that you lost for sure, because black balls can only come from the right box. So, regardless of the color of the ball the computer draws from Option 1, you will learn the outcome of the lottery right away, at the end of Part 1. We reviewed Option 1. Now, let’s look at Option 2. In Option 2, you can expect to see a red ball 50% of the time and a black ball also 50% of the time. Remember that the chances that the computer draws from either box are equal, because the overall chances of winning are 50%. Moreover, regardless of which box the computer draws a ball from, the chances of drawing a red or a black ball are 50%, since there are 50 black and 50 red balls in each box. If you observe a red ball, it means that the chances that you won the lottery are 50%, because the red ball could have come from the left box or the right box with equal chance, and each box has 50 red and 50 black balls. Note that this is the same chance of winning as you expected before seeing a red ball. Therefore, observing a red ball from this option gives you no additional information about whether your ticket has already won. Similarly, if you see a black ball, you also learn that your chances of winning are 50%. So, in Option 2, regardless of the color of the ball drawn, you learn that your chances of winning are 50%. This means that Option 2 does not give you any additional information over and beyond what you already knew. So, if you pick Option 2, you will get no additional information about whether you won or lost at the end of Part 1. You will learn the outcome at the end of the study. Let’s review the two options in Question 1 side by side. In both options, the chances of seeing a red or a black ball are equal to 50%. When you see a ball drawn from Option 1, regardless of its color, you immediately learn whether you lost or won the lottery. Conversely, when you see a ball drawn from Option 2, regardless of its color, you do not learn anything new about whether you lost or won the lottery. Therefore, a choice between these two options is a choice about when you would like to learn the outcome of the lottery. Option 1 reveals whether you won or lost immediately. Option 2 doesn’t give you any new information at the end of the study. Please take a moment to think about whether you want to the outcome early in the study or at the end of the study. When the next button appears, please proceed to answering comprehension questions by clicking the next button.

E.5. Checks

[Attention check]: Please indicate the color of the ball you observed.
[Confusion prompt]: We want to know if there was any part of the study that was confusing. Please think about what instructions or procedures in this study that were confusing and list your confusions/questions below.
[Demographics questionnaire]: Please indicate your age. What is your gender? Please indicate how many experimental studies you participated in at the [blinded for review] Lab in the past. Please indicate how many experimental studies you participated in on the [blinded for review] campus
(any lab) in the past. Please choose all departments on campus where you have participated in experiments before.

E.6. Filler Task Instructions and Payment

Thank you for your answers. We will now ask you to work on an unrelated study while you sit with the information you received and wait for the outcome of the lottery to be revealed. There are only a few questions in this part. Please take your time answering them in detail. Please think carefully. You have plenty of time to answer these questions. Please do not rush. If you finish early, you will sit and wait for the end of the experiment.

[For about 20-30 minutes, the subjects worked on the filler tasks. They saw the following instructions upon completion of these tasks.]

Thank you. You’ve reached the end of the study. Please wait patiently for the announcement of the roll die which will determine whether you won or lost the lottery. It is likely that others have not yet finished answering all questions. Please wait silently in your seat. Do not distract others in any way. Do not engage with any electronic devices (e.g. cell phones, iPods,..). Do not browse the web or open any other tab. Do not proceed without further instructions. You will be given a code to proceed once the winning last digits are announced. While waiting, you may fill out the receipt form on your desk as much as you can. Please do not guess how much you earned, we will complete that part last, when you get paid in cash.

[The subjects were given a passcode to enter once all subjects arrived at this page. Therefore, all subjects proceeded to the next page at the same time.]

[Instructions on the payment page depended on the die outcome, last digit of the raffle ticket the subject was holding, and the subjects decisions in the experiment. An example is provided below.]

We rolled a 10-sided die to determine the winning last digits at the beginning of this study. The code you entered in the program told the computer that the die came up even. You indicated that the last digit of your lottery ticket number is 4. You won the lottery. You will get an additional $10.

As a result, your total payment will be the sum of $17 + 0 cents + 10 cents. Please enter the total amount on your receipt form and complete all fields of the form. You are also taking the pen with you.

Explanation: You are getting $7 for participation, $10 from the lottery. In the question concerning the choice between the postcard and the pen, you chose the pen. In Q4, “For a compensation of 15 cents I would change my choice,” you indicated No. In the question concerning the choice between clue-generating Option 1 and Option 2, you chose option 1. In Q3 “For a compensation of 10 cents I would change my choice.” you indicated Yes.

[After the subjects were paid in private, they returned back to their computers to fill in the receipt forms and to share final comments about the study if they had any. All sessions ended on time.]
Question 1.

Remember that the chances of winning this lottery are 50%.

When you choose one of the two options below, a ball will be drawn based on the specifications of that option if the computer chooses this question to be carried out. You will observe the color of the ball and sit with that clue until the end of the study.

Option 1: If you won the lottery, a ball will be drawn from a box that contains 100 red and 0 black balls. If you lost the lottery, a ball will be drawn from a box that contains 0 red and 100 black balls. You will observe the color of the ball only (not which box it comes from). Your chance of observing a red ball is 50%. Your chance of observing a black ball is 50%. If you observe a red ball, it means that you won the lottery. If you observe a black ball, it means that you lost the lottery. Therefore, observing a ball from this option gives you all the information about the outcome of the lottery right away.

Option 2: If you won the lottery, a ball will be drawn from a box that contains 50 red and 50 black balls. If you lost the lottery, a ball will be drawn from a box that contains 50 red and 50 black balls. You will observe the color of the ball only (not which box it comes from). Your chance of observing a red ball is 50%. Your chance of observing a black ball is 50%. If you observe a red ball, it means that your chances of having won the lottery are 50%, same as what you knew before. If you observe a black ball, it means that your chances of having won the lottery are 50%, same as what you knew before. Therefore, observing a ball from this option gives you no additional information at this time.

These options are also presented graphically below. People differ in their preferences in this choice. Consider what kind of information you may get from each option. Please pick according to your own preferences. There are no right or wrong answers.

![Diagram of Option 1 and Option 2 with colors and outcomes](Figure 5: Q1 screen shot)
You indicated that you would prefer to see a ball drawn from Option 2 rather than a ball drawn from Option 1. Please indicate the strength of your preference below.

(The higher the number, the more strongly you preferred Option 2 over Option 1.)

Figure 6: Preference strength elicitation
Question 2.

Remember that the chances of winning this lottery are 50%.

When you choose one of the two options below, a ball will be drawn based on the specifications of that option if the computer chooses this question to be carried out. You will observe the color of the ball and sit with that clue until the end of the study.

Option 1: If you won the lottery, a ball will be drawn from a box that contains 100 red and 0 black balls. If you lost the lottery, a ball will be drawn from a box that contains 50 red and 50 black balls. You will observe the color of the ball only (not which box it comes from). Your chance of observing a red ball is 75%. Your chance of observing a black ball is 25%. If you observe a red ball, it means that your chance of having won the lottery is 67%, which is higher than what you thought it was before. If you observe a black ball, it means that your chance of having won the lottery is 0%, since you can only observe a black ball if you lost the lottery.

Option 2: If you won the lottery, a ball will be drawn from a box that contains 50 red and 50 black balls. If you lost the lottery, a ball will be drawn from a box that contains 0 red and 100 black balls. You will observe the color of the ball only (not which box it comes from). Your chance of observing a red ball is 25%. Your chance of observing a black ball is 75%. If you observe a red ball, it means that your chance of having won the lottery is 100%, since you can only observe a red ball if you won the lottery. If you observe a black ball, it means that your chance of having won the lottery is 33%, which is lower than what you thought it was before.

These options are also presented graphically below. People differ in their preferences in this choice. Consider what kind of information you may get from each option. Please pick according to your own preferences. There are no right or wrong answers.

Which option do you prefer to see a ball from?

Option 1

Option 2

Figure 7: Q2 screen shot
Question 4.

Remember that the chances of winning this lottery are 50%.

When you choose one of the two options below, a ball will be drawn based on the specifications of that option if the computer chooses this question to be carried out. You will observe the color of the ball and sit with that clue until the end of the study.

Option 1: If you won the lottery, a ball will be drawn from a box that contains 55 red and 45 black balls. If you lost the lottery, a ball will be drawn from a box that contains 45 red and 55 black balls. You will observe the color of the ball only (not which box it comes from). Your chance of observing a red ball is 50%. Your chance of observing a black ball is 50%. If you observe a red ball, it means that your chances of having won are 55%. If you observe a black ball, it means that your chance of having won are 45%.

Option 2: If you won the lottery, a ball will be drawn from a box that contains 30 red and 70 black balls. If you lost the lottery, a ball will be drawn from a box that contains 10 red and 90 black balls. You will observe the color of the ball only (not which box it comes from). Your chance of observing a red ball is 20%. Your chance of observing a black ball is 80%. If you observe a red ball, it means that your chances of having won are 75%. If you observe a black ball, it means that your chances of having won are 44%.

These options are also presented graphically below. People differ in their preferences in this choice. Consider what kind of information you may get from each option. Please pick according to your own preferences. There are no right or wrong answers.

Which option do you prefer to see a ball from?

- Option 1
- Option 2

Figure 8: Q4 screen shot
Figure 9: Observing the signal from the randomly chosen question

Figure 10: Elicitation of preference in the practice round
Figure 11: Elicitation of preference strength in the practice round

Figure 12: Willingness to switch elicitation in the practice round
You chose Option 1 among the options below.

**Option 1**
- Ball drawn from this box if you won the lottery: 30 red, 70 black
- Ball drawn from this box if you did not win the lottery: 10 red, 90 black

- 20% red, 80% black
- Black: 44% win
- Red: 75% win

**Option 2**
- Ball drawn from this box if you won the lottery: 90 red, 10 black
- Ball drawn from this box if you did not win the lottery: 70 red, 30 black

- 80% red, 20% black
- Black: 25% win
- Red: 55% win

We now offer you the option to change your choice in exchange for some money. In particular, we will ask, if for a given amount, you would be willing to switch you choice to (Option 2), instead of the option you chose (Option 1). If you care about your choice, then you would require a higher payment in order to give it up and settle for the other alternative. If you don’t have a strong preference, then this payment does not have to be very high for you to change your choice.

When you are done with answering the 10 questions below, we pick a random number between 1 and 10 to select the question to be carried out. Therefore, please take each question seriously, as they all have the same chance to be selected.

Given this setup, your choices here should truthfully reflect your preferences, such that you have no regrets when we carry out your decision in any of these questions.

Figure 13: Preamble to willingness to switch elicitation
Please indicate your choices.

Think about how much compensation you would need in order to see a ball that is drawn from the option you did not prefer (Option 2) instead of a ball that is drawn from the option you preferred (Option 1).

<table>
<thead>
<tr>
<th>Question</th>
<th>No</th>
<th>Yes</th>
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</thead>
<tbody>
<tr>
<td>Q1. If you give me 1 cent I would change my choice</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td>Q2. If you give me 5 cents I would change my choice</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td>Q3. If you give me 10 cents I would change my choice</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td>Q4. If you give me 15 cents I would change my choice</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td>Q5. If you give me 20 cents I would change my choice</td>
<td>☐</td>
<td>☐</td>
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<tr>
<td>Q6. If you give me 25 cents I would change my choice</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td>Q7. If you give me 30 cents I would change my choice</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td>Q8. If you give me 35 cents I would change my choice</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td>Q9. If you give me 40 cents I would change my choice</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td>Q10. If you give me 50 cents I would change my choice</td>
<td>☐</td>
<td>☐</td>
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</tbody>
</table>

Figure 14: Willingness to switch elicitation

You chose Option 1 over Option 2.

The randomly chosen question was:
Q8. If you give me 35 cents I would change my choice.

Your answer was Yes.

Explanation:
If your answer was "No", you will see a ball drawn from Option 1.
If your answer was "Yes", you will instead see a ball drawn from Option 2 and receive an additional 35 cents at the end of the study as compensation for switching your choice.

As a confirmation that you understand the explanation above, which of the following is correct?

☐ I will see a ball drawn from Option 1
☐ I will see a ball drawn from Option 2

Figure 15: Randomly chosen willingness to switch question
According to your choices, on the next page, you will see a random ball drawn according to the specifications of Option 2.

The color of the ball randomly drawn from Option 2 according to whether you won or lost the lottery was:

RED

Given this clue, what are the chances that you won the lottery?

<table>
<thead>
<tr>
<th>Chance that I won</th>
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<table>
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<tr>
<th>Chance that I lost</th>
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Total

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Figure 16: Observing a signal