

Intrinsic Information Preferences and Skewness*

Yusufcan Masatlioglu[†]
University of Michigan

A. Yeşim Orhun[‡]
University of Michigan

Collin Raymond[§]
Amherst College

March 17, 2016

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 more or less informative information structures, and how individual preferences over the skewness and the degree of information relate to one another. The results not only reveal new insights regarding intrinsic preferences for information, but also distinguish between theoretical models in this domain. Models based on the framework of Kreps and Porteus (1978) and Caplin and Leahy (2001), are the most consistent with the data we observe.

*We thank the Michigan Institute for Teaching and Research in Economics, Ross School of Business Faculty Grant Fund, and the University of Oxford John Fell Fund for support. We thank seminar participants at Microsoft, University of Michigan, University of Pittsburgh, Risk, Uncertainty and Decision 2015, SICS, as well as David Dillenberger, Kfir Eliaz, Emel Filiz-Özbay, David Gill, Yoram Halevy, David Huffman, John Leahy, Tanya Rosenblat, Ryan Oprea, Erkut Özbay and Neslihan Üler for helpful comments. Jeffrey Kong, Hannah Lee and Michael Payne provided excellent research assistance. Remaining errors are ours alone.

[†]Email: yusufcan@umich.edu

[‡]Email: aorhun@umich.edu

[§]Email: collinbraymond@gmail.com

1 Introduction

Imagine having recently submitted a paper to a top journal. You are attending a conference where two of your previous mentors, Paul and Nell, are also present. You are considering asking them about their opinions 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. Paul likes to be quite certain of a good outcome before he gives you a thumbs-up, whereas Nell gives a thumbs down only if she is quite certain of a bad outcome. Would you talk to either of your mentors at the conference? If so, to whom would you prefer to talk?

Psychologists have long recognized the desire to regulate anticipatory emotions, such as hope, anxiety, and suspense, regarding an uncertain outcome in the future by managing expectations (Norem and Cantor, 1986; Showers, 1986, 1992). The desire to manage expectations leads to intrinsic preferences for information: a desire for or dislike of certain types of information over and above preferences for the information's instrumentality for the person's future actions. In some cases, intrinsic preferences for information may lead to a demand for information in the absence of an ability to act on that information. For example, hopeful voters park themselves in front of the TV on election night, even though it costs them a good night's sleep. In other cases, intrinsic preferences for information may lead to avoiding useful information. For example, anxious patients with potential symptoms of a disease may put off taking a diagnostic test, even if it means delaying possible treatments.

The impact of intrinsic information preferences on the process of information search, acquisition, consumption, and dissemination has implications for individual decision-making and policy. Economists have recently highlighted these implications for health (Kőszegi, 2003; Oster, Shoulson and Dorsey, 2013; Schweizer and Szech, 2013), media consumption (Mullainathan and Shleifer, 2005), finance (Andries and Haddad, 2014), collective beliefs (Benabou, 2013), and information design policy (Caplin and Eliaz, 2003; Caplin and Leahy, 2004). Given the importance of these implications, a significant amount of theoretical work has examined intrinsic preferences for information (see Brunnermeier and Parker, 2005; Caplin and Leahy, 2001; Dillenberger and Segal, 2015; Ely, Frankel and Kamenica, 2013; Grant, Kajii, and Polak, 1998; Kőszegi and Rabin, 2009; Kreps and Porteus, 1978). Surprisingly, evidence regarding the nature of these preferences is limited.

This paper provides experimental evidence of intrinsic information preferences by eliciting choices between a variety of different information sources that resolve varying degrees and forms of uncertainty regarding a desired outcome over which individuals have no control. Many real-world

comparisons of information structures, such as the information provided by Nell versus Paul which are neither more or less informative than each other, but provide very different types of information. Clearly, individuals may evaluate information sources not only by the degree to which they eliminate uncertainty overall (their informativeness) but also by how likely they are to eliminate uncertainty about each possible outcome (their skewness). Some 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 Nell). 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 Paul). Previous experimental research has mostly focused on preferences for the degree of informativeness among information sources that are equally precise in outcomes (i.e. without any skewness) — for example, whether people prefer full information to no information.¹ The focus on whether individuals prefer more or less information can limit our understanding of intrinsic preference for information. For example, an individual who prefers not to receive full information may be willing to acquire skewed information. Indeed, Caplin and Eliaz (2003) hypothesize that diagnostic tests that are precise in ruling out a disease but imprecise in ruling it in may be preferred by patients who would otherwise not get tested. In summary, to understand demand for information in the market, evaluation of preferences across a wide range of information structures is required.

The first contribution of this paper is to conduct a broad experimental investigation of intrinsic preferences for information. We explore (1) whether people prefer negatively or positively skewed information structures when they are equally informative, (2) whether they prefer more informative information structures, and (3) how individual preferences for skewness and the degree of information are related.² As a result of pursuing a more comprehensive understanding of these preferences, we are also able to offer an experimental design that can distinguish between existing models in this domain. Therefore, a second contribution of this paper is to offer a novel testing ground for theories of intrinsic preferences for information.

The experiment features one outcome of interest that has two potential payoffs: winning the lottery, which pays \$10, or losing it, which pays \$0. For each participant, the likelihood of winning is

¹For example, Abdellaoui, Klibanoff and Placido (2013), Ahlbrecht and Weber (1997), Arai (1997), Chew and Ho (1994), Chew, Miao and Zhong (2015), Falk and Zimmerman (2014), Halevy (2007), Kocher, Krawczyk and Van Winden (2014), Lovallo and Kahneman (2000), Von Gaudecker et al. (2011), and Zimmerman (2014) test preferences for the degree of informativeness. Abdellaoui, l’Haridon, and Nebout (2015), Boiney (1993), and Eliaz and Schotter (2010) explicitly test for preferences over skewness, but these studies differ from our investigation in important ways. We provide a detailed discussion in Section 5.

²We formalize our notion of informativeness using Blackwell’s (1951) ranking, and our notion of skewness using downside risk aversion introduced by Menezes et al. (1980). There are several other notions related to skewness, but these notions coincide with one another in our setting. Details are provided in Section 2.

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 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 an unrelated nature before the winning ticket numbers are finally revealed. Section 3 details the experimental design.

The experimental design has several important features that address the common challenges in identifying preferences for non-instrumental information. First, the experiment creates an environment in which the information cannot influence actions. Second, it ensures that the observed preferences are for information that influences participants' beliefs about future outcomes and their belief utility, and not for information that shapes their self-perceptions, confidence, or ego-utility.³ Third, it greatly reduces participants' information processing costs 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 regarding compound lotteries to make inferences about informational preferences. While there is a theoretical one-to-one mapping between compound lotteries and information structures, an empirical equivalence is not obvious.

We present the results in Section 4. They reveal a stronger preference for positive than negative skewness — that is, for ruling out more uncertainty about the desired outcome (and tolerating uncertainty about the undesired outcome) than for ruling out more uncertainty about the undesired outcome (and tolerating uncertainty about the desired outcome). In our running example, these preferences suggest that most of our participants would prefer talking to Paul. Importantly, our design allows us to identify preferences for skewness independent of whether or not an individual prefers more or less informative structures. We find that a large majority of participants prefer more informative structures (i.e., earlier resolution of information). Relatedly, individuals are not willing to forgo information for the sake of skewness. Most individuals prefer more informative structures over those that are less informative but more positively skewed. We also explore relationships

³Hoffman (2011), Eil and Rao (2011), and Mobius et al. (2011) provide examples in which information of interest is about the action or characteristics of the participant, and Eliaz and Schotter (2010) study a case where confidence matters due to agency.

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 and subjects' stated reasons for choosing an information structure map onto different desires to manage anticipatory emotions. Moreover, we demonstrate that individuals are willing to pay for their information structure choices; over half the subjects are willing to forgo 25 cents in order to keep their preferred information structure regarding a lottery with an expected payoff of \$5.

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. We derive a series of new theoretical results, tailored to our experimental design, that identify the predictions of existing theories. 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), Kőszegi 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.

As an important methodological contribution, our paper uses a novel and natural domain to test for information preferences by directly eliciting choices among information structures for a given prior. We believe this method not only reflects real-life decisions regarding information acquisition more closely but also underscores the need for more theoretical work that directly characterizes preferences for information structures for a fixed prior (along the lines of Kőszegi 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 enables us to focus on behavioral patterns that are observable in the real world. In addition, it allows for a simple construction of indifference curves in a space that is similar to a 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 $f(1-p) + q(1-f)$. Importantly, p and q do not represent the posterior beliefs that an individual should hold after observing a good or bad signal; rather the posterior belief can be derived from p , q and the prior f using Bayes' rule. In fact, the posterior for a high outcome after observing a good signal is

$$\psi_G = \frac{fp}{fp + (1-f)(1-q)}.$$

After observing a bad signal the posterior is

$$\psi_B = \frac{f(1-p)}{f(1-p) + (1-f)q}.$$

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

Within the context of our experiment, the two states are whether an individual has won the 10 dollars (the high state) or won 0 dollars (the low state). The signal is a colored ball. A good signal is a red ball, while a bad signal is a black ball. An information structure, or a (p, q) pair, can then be thought of as a pair of boxes. Each box contains 100 balls of either red or black color. The first box contains $100p$ red balls, and $100(1-p)$ black balls. The second box contains $100(1-q)$ red balls and $100q$ black balls. For example, Figure 1 depicts information structures $(1, .5)$ and $(.5, 1)$ as Option 1 and Option 2, respectively. If the state is high (i.e., the individual will win the 10 dollars) a ball is drawn from the first box and shown to an individual. If the state is low (i.e., the individual will win 0 dollars) a ball is drawn from the second box and shown to the individual. At no time does the individual observe the full contents of the box that the ball is drawn from. Thus, observing the color of a single drawn ball serves as a signal regarding the state of the world.

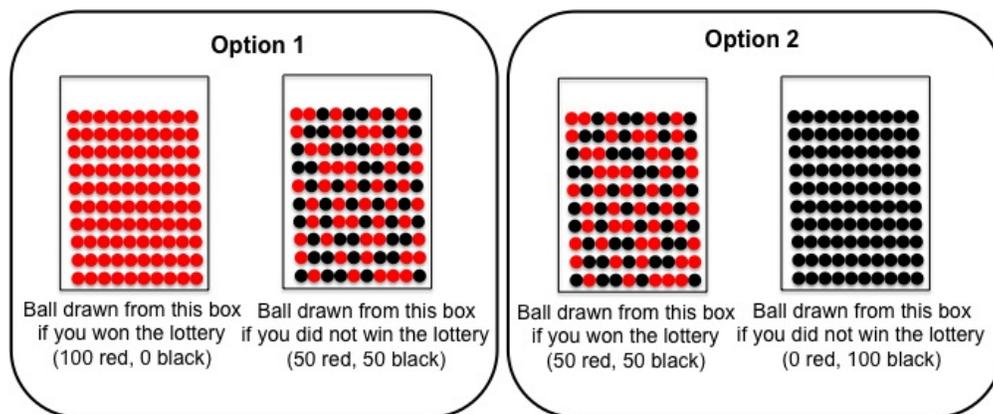


Figure 1: Representation of information structures $(1, .5)$ and $(.5, 1)$

⁴For an extended discussion of these issues, please see Appendix A.

We suppose that individuals have preferences over information structures given the prior f , denoted by \succsim_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 $\mathbb{S} := \{(p, q) \mid p + q > 1\} \cup (.5, .5)$. This focus is driven by two reasons. First, all points in \mathbb{S} have a natural interpretation: a good signal is good news (a bad signal is bad news). Lemma 1 formalizes this⁵.

Lemma 1 *For any $(p, q) \in \mathbb{S}$, 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.*

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 $(p, q) \in \mathbb{S}$ that generates the same posterior distribution. However, for any $T \subset \mathbb{S}$ there exists a $(p', q') \in \mathbb{S}$ 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 2. 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*.

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 $\frac{1}{3}$).

⁵All proofs are included in Appendix B.

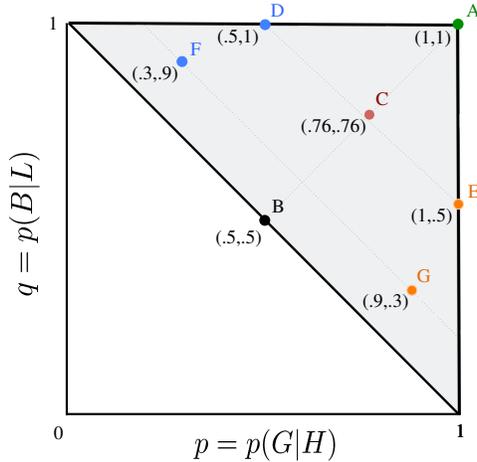


Figure 2: Examples of Information Structures on (p,q) space

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

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.

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. In order to provide better intuition, we relate the various types of preferences under discussion to indifference curves representing these preferences in (p, q) space. The illustration of indifference curves not only provide general intuition for the types of preferences we are considering, they are also parameterizations of the models that we formally test 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 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., Kőszegi and Rabin, 2009 and Kőszegi, 2010).

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 (1951) 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 2, we have symmetric information structures that are increasingly Blackwell more informative. More generally, moving to the northeast represents an increase in Blackwell informativeness. 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.

⁷Blackwell'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).

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

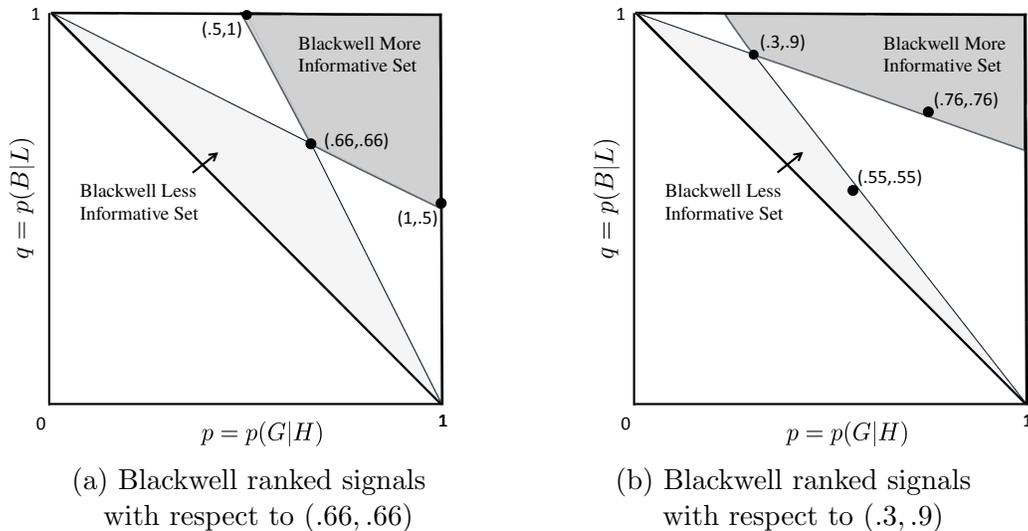


Figure 3: Examples of Blackwell more and less informative sets

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 4. 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. If the utility level of indifference curves is increasing as we move northeast (as in Panels B-D), then the individual exhibits a preference for earlier resolution of information. In contrast, if the utility level of indifference curves is decreasing as we move northeast (as in Panel A), then the individual exhibits a preference for later resolution of information.

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 Kőszegi and Rabin (2009). Relatedly, Ely, Frankel and Kamenica (2013) model preferences

⁸For the exact parameterization of preferences in each panel, please see Appendix A.

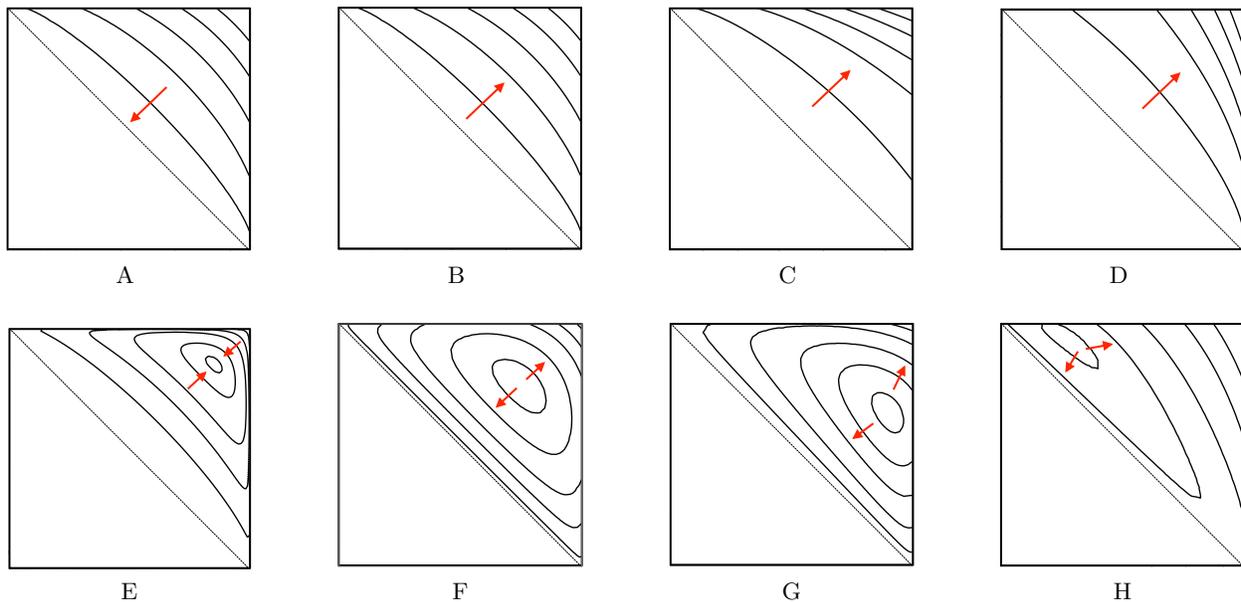


Figure 4: Indifference Curves in (p, q) space.⁸

for gradual resolution of information, where full early resolution ($p = q = 1$) or full late resolution ($p = q = .5$) are the worst structures. Thus, many important recent models in behavioral economics and decision-theory have focused on modeling preferences for one-shot versus gradual resolution of information. They try to capture the fact that individuals experience positive or negative emotions just from the fluctuation of beliefs. If, as in Dillenberger (2010) or Kőszegi and Rabin (2009), individuals dislike fluctuating beliefs, then they prefer to have beliefs change as infrequently as possible; and so prefer to receive information all at once, whether it be immediately or later. In contrast, if individuals enjoy fluctuating beliefs, as in Ely, Frankel and Kamenica (2013), then they prefer to receive some information now and some information later. In either case, individuals will not always prefer more or less informative signals. In order to illustrate, we can use the indifference curves in Figure 4.

The lower row (Panels E-H) of Figure 4 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. Observe that none of these preferences exhibits a universal preference for more or less information — in other words, the utility levels of indifference curves is not strictly monotone as we move to the northeast. Thus, depending on how much information an individual is currently going to receive, she may prefer to receive slightly more (or slightly less) information. In Panel E, the utility maximizing information structure is in the interior of the panel. Thus, an individual with preferences as

in Panel E would prefer partial revelation of information to either the prospect of learning nothing at all, or learning for sure what the state is. In contrast, in Panels F-H the utility-minimizing point is in the interior panel. An individual with preferences as in in Panels F-H would prefer to learn nothing at all to learning just a little information about the state; in other words utility initially declines when moving to the northeast of $(.5, .5)$. Moreover, they would prefer to know for sure what the state is to learning almost for sure what the state is; utility is increasing when moving to the northeast in the neighborhood of $(1, 1)$.

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 4 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. A relatively flat indifference curve means that if $a \geq b$, (b, a) must be located on a higher indifference curve than (a, b) ; thus, the individual will exhibit a preference for positively skewed information structures. In contrast, a relatively steep indifference curve means that (b, a) must be located on a lower indifference curve than (a, b) ; thus, the individual will exhibit a preference for negatively skewed information structures. Importantly, our set-up allows us to identify preferences for skewness independent of whether or not an individual prefers more or less Blackwell informative structures, or whether they exhibit a preference for one-shot or gradual resolution of information; this is a result of the fact that (a, b) and (b, a) are not Blackwell ranked relative to one another.

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 (which were drawn from Dean and Ortoleva, 2015). 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.⁹ 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 1 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

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; see Starmer and Sugden (1991) and Cubitt et al. (1998). Azrieli, Chambers and Healy (2014) provide a useful theoretical framework for considering such issues. 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.

lost the lottery, but the composition greatly varied across information structures. Each box had 100 balls. As discussed previously, 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 always had to make a choice between information structures, even if one of them was uninformative (i.e., (.5, .5)). This was done in order to rule out demand for information as driven by experimenter demand.

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 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.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.¹¹

Table 1: The order of questions and options in Condition 1 and 2

	Condition 1		Condition 2		Assignment
	Option 1	Option 2	Option 1	Option 2	
Q1	(1, 1)	(.5, .5)	(.5, .5)	(1, 1)	all subjects
Q2	(1, .5)	(.5, 1)	(.5, 1)	(1, .5)	all subjects
Q3	(.9, .3)	(.3, .9)	(.6, .9)	(.9, .6)	all subjects
Q4	(.76, .76)	(.3, .9)	(.67, .67)	(.1, .95)	if $(1, 1) \succeq (.5, .5)$
	(.55, .55)	(.3, .9)	(.66, .66)	(.5, 1)	if $(1, 1) \preceq (.5, .5)$
Q5	(.9, .6)	(.6, .9)	(.9, .3)	(.3, .9)	random
	(.55, .55)	(.5, .5)	(.5, .5)	(.55, .55)	random

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

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

¹¹We 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.

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 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.¹² 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.¹³

One contribution of our paper is using (p, q) space to evaluate preferences for information. Although we are not the first experiment to directly elicit preferences for information, we are, to our knowledge, the first to use this framework. Using this space, and its associated machinery, has several benefits. First, it forms a natural analogue to standard consumption space. Second, it allows us to depict preferences for models, which often have complicated functional forms using intuitively appealing indifference curves. Third, it allows us to precisely control the different types of information we provide to subjects.

We focus on understanding preferences over information structures, for a fixed prior, as opposed to preferences over compound lotteries. We do so because directly eliciting preferences across information structures enables us to focus on behavioral patterns that are observable in the real world.

¹²Because 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.

¹³Many 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.

Moreover, it neatly allows us to summarize preferences in (p, q) space using indifference curves. 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.

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.

Table 2: Percentage and Intensity of Choices

	N	Choice Percentage		Intensity		
		First	<i>p</i> -value	First Option	Second Option	<i>p</i> -value
Early vs. Late						
(1, 1) vs (.5, .5)	250	78%	.000	8.31	6.37	.000
(.55, .55) vs (.5, .5)	121	75%	.000	6.08	4.67	.027
Pos. Skewed vs. Neg. Skewed						
(.5, 1) vs (1, .5)	250	67%	.000	7.23	6.19	.001
(.3, .9) vs (.9, .3)	183	81%	.000	6.54	5.79	.099
(.6, .9) vs (.9, .6)	196	74%	.000	6.13	5.48	.101
Symmetric vs. Skewed						
(.76, .76) vs (.3, .9)	92	71%	.000	6.42	6.93	.403
(.3, .9) vs (.55, .55)	27	67%	.122	6.11	7.44	.203
(.67, .67) vs (.1, .95)	104	64%	.004	6.67	6.24	.453
(.66, .66) vs (.5, 1)	27	56%	.701	6.87	5.58	.123

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

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.¹⁴ 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 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

		Extreme					Medium					Slight		
		Pos. (.5,1)	Neg. (1,.5)				Pos. (.6,.9)	Neg. (.9,.6)				Pos. (.3,.9)	Neg. (.9,.3)	
Early	(1,1)	123	73	196			113	41	154			117	28	145
Late	(.5,.5)	44	10	54			31	11	42			32	6	38
		167	83	250			144	52	196			149	34	183

Table 3 cross-tabulates within-person choice patterns regarding skewness and choice for early resolution.¹⁵ We see that subjects who have a preference for early resolution of uncertainty are

¹⁴Interestingly, 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.

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

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 Q4.¹⁶ 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.

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

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

in Appendix C.

¹⁶Thus, 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.

¹⁷Also, 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).

Table 4: Early or Late vs One-shot or Gradual and Monotonicity

		Gradual (.55,.55)	One-shot (.5,.5)	Weakly Monotone			
				Yes	No		
Early	(1,1)	77	16	93	196	0	196
Late	(.5,.5)	14	14	28	42	12	54
		91	30	121	238	12	250

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.¹⁸ Third, in a post-decision questionnaire, subjects explained the reasons for their choice among the 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.¹⁹

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

¹⁸Before the main elicitation task, the experiment also included an opportunity to experience the operation of the willingness to accept elicitation mechanism, as in Halevy (2007). The practice task involved making a choice between a pen and a postcard (with a retail value of \$2.50 at the college bookstore, which was not revealed to subjects), and consequently indicating whether they would switch their choice for a monetary compensation. The compensation ranged from 1 cent to 50 cents.

¹⁹The main experiment had counterbalanced the order of options in Q1, Q2, and Q5. In this experiment, treatment C changed the order of options in Q3 to provide a robustness check.

Table 5: Robustness Study

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

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.

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 cent 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.²⁰ 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:

²⁰Subjects 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.

- “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.”

Thus, it seems that differences across preferences for non-instrumental information indeed maps onto differential desires to manage anticipatory emotions.²¹ Psychologists have categorized people who prefer to keep their expectations low as “defensive pessimists”, and those who prefer to have high hopes as “strategic optimists” (Norem and Cantor, 1986, Showers 1992). This categorization separates people’s differences in coping strategies from dispositional optimism and dispositional pessimism (Scheier and Carver, 1985). There is considerable heterogeneity documented in the use of strategic optimism and defensive pessimism as regulatory strategies. For example, Siegel and Scrimshaw (2000) report that some of the HIV patients coping with anxiety would “anticipate or expect bad news as a way of mentally preparing themselves for negative events. For example, in anticipation of a contact with their doctor in which they might be receiving news about a T-cell count taken earlier or information about some symptom they were experiencing, some men would defensively assume that the news would be bad.” On the other hand, some of the patients tried to keep their hopes up in order to cope with anxiety by actively identifying and pondering about the long-term survivors of the illness. ”By identifying others who were infected years before they

²¹When 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.”

believed they had been, and who were still living, they were able to feel reassured that they could also expect to live for at least several more years.” Currently, the psychology literature does not offer correlates of personality traits that could help predict whether a person prefers to keep their expectations high or low in anxiety provoking situations.

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 (unconditional) 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).²²

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.²³

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.²⁴

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.

²²Recall 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.

²³Machina (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.

²⁴Our 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.

We consider the predictions of models that specifically assume recursivity and can address preferences for skewness.²⁵ 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 $u_1 \circ u_2^{-1}$ 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 $(x, y) \succ_{.5} (\prec_{.5})(y, x)$ whenever $x \leq y$.*

In Figure 4, 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. This means that individuals with these preferences would prefer to learn nothing at all to learning just a little information about the state; in other words utility initially declines when moving to the northeast of $(.5, .5)$ in (p, q) space.

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 $\epsilon < \epsilon'$, $(.5, .5) \succ_{.5} (.5 + \epsilon, .5 + \epsilon)$.*

²⁵Eliasz and Spiegel (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 4 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 preferences 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.²⁶

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

Thus, as in the previous prediction, individuals with preferences in the class considered by Dillenberger and Segal (2015) must prefer to learn nothing at all to learning just a little information about the state; utility initially declines when moving to the northeast of $(.5, .5)$ in (p, q) space.

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 Kőszegi 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; equivalently sized changes in beliefs have

²⁶Note 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%.

the same effect on utility regardless of the initial level of belief. Thus, individuals will be indifferent (given a prior of .5) between signal structures (x, y) and (y, x) .

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 form is flexible enough to be applied to other settings and can generate not only a preference for gradual resolution of information, but also a preference for one-shot resolution of information, depending on the parameterization. Thus, their preferences can generate behavior very similar to KR. We believe it is important to test the general implications of their functional form, as it represents an easily adaptable alternative to many of the other existing models. EFK present two functional forms. One they describe as capturing surprise, the other as capturing suspense; both have strong symmetry assumptions regarding how beliefs effect payoffs. Thus, we obtain the same prediction as in Kőszegi 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 $(.5, .5)$. Thus, these represent situations where the decision-maker prefers to learn nothing at all to learning just a little information about the state.

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 4 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 .²⁷

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.²⁸ 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

²⁷Recall 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.

²⁸We 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.

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. Thus, our data rules out indifference curves as represented in Panels E and F of Figure 4.

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 ϵ close enough to .5. We find no evidence for this type of preference for clumping.²⁹ Our 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. This prediction of the models is represented in Panels G and H of Figure 4. In contrast to this prediction, 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); these types of preferences are represented in the first row of Figure 4. The Kreps-Porteus 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 $V_1(l) = \sum_{x \in l} u_1(x)l(x) = \sum_{x \in l} x^\rho l(x)$ while $V_2(l) = \sum_{x \in l} u_2(x)l(x) = \sum_{x \in l} x^\alpha l(x)$. In this case, the local utility function is convex if and only if $u_1(u_2^{-1}(x))$ is convex — or $x^{\frac{\rho}{\alpha}}$ 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. Because individuals have a preference for early resolution and for positively skewed information structures their indifference curves cannot take the form of Panels A, B or D of Figure 4. However, the data is consistent with indifference curves represented in Panel C, which reflect 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

²⁹One potential objection is that perhaps we did not set ϵ close enough to 0. In fact, simple calibrations show the power of our test, where $\epsilon = .05$. Suppose preferences in V_1 and V_2 both have a disappointment aversion representations (u_i, β_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 β_2 (i.e., $0 \geq \beta_2 \leq 100$), β_1 must be less than .01, or in other words, people must be ‘almost’ expected utility over gambles that resolve now.

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.

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, ES 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 (1997), Ahlbrecht and Weber (1997), Lovallo and Kahneman (2000) and Brown and Kim (2013) generally find a preference for early rather than late resolution of information.³⁰ 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, van Winden, Krawczyk, Hopfensitz (2011) find that subjects invest more in a risky investment if

³⁰One caveat is that many of these studies either ask hypothetical questions or examine demand for information in contexts where information may be instrumentally valuable.

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 information, 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 Zimmerman (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 investment, they tend to invest less in that option and favor a safe investment where such information 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. Chew, Miao and Zhong (2015) explicitly address this concern, and find that (in general) individuals prefer compound lottery structures that feature full early resolution to most other compound lottery structures.

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. Such 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. Research investigating the degree to which typical elicited values for information confound instrumental and intrinsic preferences can also help in understanding the extent to which policies need to take into both motives.

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

- [1] Mohammed Abdellaoui, Peter Klibanoff, and Lætitia Placido. Experiments on compound risk in relation to simple risk and to ambiguity. *Management Science*, 2013.
- [2] Mohammed Abdellaoui, Olivier l’Haridon, and Antoine Nebout. Probability weighting in recursive evaluation of two-stage prospects. Technical report, Working Paper, 2015.
- [3] Martin Ahlbrecht and Martin Weber. Preference for gradual resolution of uncertainty. *Theory and Decision*, 43(2):167–185, 1997.
- [4] Larbi Alaoui. The value of useless information. Working paper, Department of Economics and Business, Universitat Pompeu Fabra, 2012.
- [5] Marianne Andries and Valentin Haddad. Information aversion. In *Society for Economic Dynamics 2014 Meeting Paper*, volume 1091, 2014.
- [6] Dariush Arai. Temporal resolution of uncertainty in risky choices. *Acta psychologica*, 96(1):15–26, 1997.
- [7] Yaron Azrieli, Christopher P Chambers, and Paul J Healy. Incentives in experiments with objective lotteries. Working paper, 2012.
- [8] Charles Bellemare, Michaela Krause, Sabine Kröger, and Chendi Zhang. Myopic loss aversion: Information feedback vs. investment flexibility. *Economics Letters*, 87(3):319–324, 2005.

- [9] Roland Bénabou. Groupthink: Collective Delusions in Organizations and Markets. *Review of Economic Studies*, 80(2):429–462, 2013.
- [10] David Blackwell. Comparison of experiments. In *Proceedings of the second Berkeley symposium on mathematical statistics and probability*, volume 1, pages 93–102, 1951.
- [11] Lindsley G Boiney. The effects of skewed probability on decision making under ambiguity. *Organizational Behavior and Human Decision Processes*, 56(1):134–148, 1993.
- [12] Alexander L Brown and Hwagyun Kim. Do individuals have preferences used in macro-finance models? an experimental investigation. *Management Science*, 60(4):939–958, 2013.
- [13] Marcus Brunnermeier and Jonathan Parker. Optimal expectations. *American Economic Review*, 95:4, 2005.
- [14] Andrew Caplin and Kfir Eliaz. Aids policy and psychology: A mechanism-design approach. *RAND Journal of Economics*, pages 631–646, 2003.
- [15] Andrew Caplin and John Leahy. Psychological expected utility theory and anticipatory feelings. *The Quarterly Journal of Economics*, 116(1):55–79, 2001.
- [16] Andrew Caplin and John Leahy. The supply of information by a concerned expert. *The Economic Journal*, 114(497):487–505, 2004.
- [17] S Cerreia, F Maccheroni Vioglio, and M Marinacci. A new look at local expected utility. Working paper, 2014.
- [18] Soo Hong Chew and Joanna L Ho. Hope: An empirical study of attitude toward the timing of uncertainty resolution. *Journal of Risk and Uncertainty*, 8(3):267–288, 1994.
- [19] Robin P Cubitt, Chris Starmer, and Robert Sugden. On the validity of the random lottery incentive system. *Experimental Economics*, 1(2):115–131, 1998.
- [20] Mark Dean and Pietro Ortoleva. Is it all connected? a testing ground for unified theories of behavioral economics phenomena. Working paper, 2015.
- [21] David Dillenberger. Preferences for one-shot resolution of uncertainty and Allais-type behavior. *Econometrica*, 78(6):1973–2004, 2010.
- [22] David Dillenberger and Uzi Segal. Skewed noise. Technical report, 2015.
- [23] David Eil and Justin M Rao. The good news-bad news effect: asymmetric processing of objective information about yourself. *American Economic Journal: Microeconomics*, 3(2):114–138, 2011.
- [24] Kfir Eliaz and Andrew Schotter. Paying for confidence: An experimental study of the demand for non-instrumental information. *Games and Economic Behavior*, 70(2):304–324, 2010.
- [25] Kfir Eliaz and Ran Spiegler. Can anticipatory feelings explain anomalous choices of information sources? *Games and Economic Behavior*, 56(1):87–104, 2006.
- [26] Jeffrey Ely, Alexander Frankel, and Emir Kamenica. Suspense and surprise. *Forthcoming in Journal of Political Economy*, 2013.

- [27] Larry G Epstein and Stanley E Zin. Substitution, risk aversion, and the temporal behavior of consumption and asset returns: A theoretical framework. *Econometrica*, pages 937–969, 1989.
- [28] Larry G Epstein and Stanley E Zin. Substitution, risk aversion, and the temporal behavior of consumption and asset returns: An empirical analysis. *Journal of Political Economy*, pages 263–286, 1991.
- [29] Ido Erev and Ernan Haruvy. Two-stage lotteries and the value of unresolved uncertainty. *Marketing Letters*, 21(2):149–162, 2010.
- [30] Armin Falk and Florian Zimmermann. Beliefs and utility: Experimental evidence on preferences for information. Working paper, Working Paper, 2014.
- [31] Ananda R Ganguly and Joshua Tasoff. Fantasy and dread: the demand for information and the consumption utility of the future. *Claremont McKenna College Robert Day School of Economics and Finance Research Paper*, 2014.
- [32] Simon Grant, Atsushi Kajii, and Ben Polak. Intrinsic preference for information. *Journal of Economic Theory*, 83(2):233–259, 1998.
- [33] Faruk Gul. A theory of disappointment aversion. *Econometrica*, 59(3):667–86, May 1991.
- [34] Yoram Halevy. Ellsberg revisited: An experimental study. *Econometrica*, 75(2):503–536, 2007.
- [35] Mitchell Hoffman. Overconfidence at work and the evolution of beliefs: Evidence from a field experiment. Working paper, University of California, Berkeley, 2011.
- [36] Charles A Holt. Preference reversals and the independence axiom. *The American Economic Review*, pages 508–515, 1986.
- [37] Botond Köszegi and Matthew Rabin. Reference-dependent consumption plans. *The American Economic Review*, 99(3):909–936, 2009.
- [38] Martin G Kocher, Michal Krawczyk, and Frans van Winden. let me dream on! anticipatory emotions and preference for timing in lotteries. *Journal of Economic Behavior and Organization*, 98:29–40, 2014.
- [39] Botond Köszegi. Health anxiety and patient behavior. *Journal of health economics*, 22(6):1073–1084, 2003.
- [40] David M Kreps and Evan L Porteus. Temporal resolution of uncertainty and dynamic choice theory. *Econometrica*, pages 185–200, 1978.
- [41] Dan Lovallo and Daniel Kahneman. Living with uncertainty: attractiveness and resolution timing. *Journal of Behavioral Decision Making*, 13(2):179, 2000.
- [42] Mark J Machina. “Expected utility” analysis without the Independence axiom. *Econometrica*, pages 277–323, 1982.
- [43] Carmen Menezes, Charles Geiss, and John Tressler. Increasing downside risk. *The American Economic Review*, pages 921–932, 1980.

- [44] Markus M Mobius, Muriel Niederle, Paul Niehaus, and Tanya S Rosenblat. Managing self-confidence: Theory and experimental evidence. Working paper, National Bureau of Economic Research, 2011.
- [45] Sendhil Mullainathan and Andrei Shleifer. The market for news. *American Economic Review*, pages 1031–1053, 2005.
- [46] Julie K Norem and Nancy Cantor. Anticipatory and posthoc cushioning strategies: Optimism and defensive pessimism in risky situations. *Cognitive Therapy and Research*, 10(3):347–362, 1986.
- [47] Emily Oster, Ira Shoulson, and E. Ray Dorsey. Optimal expectations and limited medical testing: Evidence from huntington disease. *American Economic Review*, 103(2):804–30, 2013.
- [48] Ignacio Palacios-Huerta. The aversion to the sequential resolution of uncertainty. *Journal of Risk and uncertainty*, 18(3):249–269, 1999.
- [49] John Quiggin. A theory of anticipated utility. *Journal of Economic Behavior & Organization*, 3(4):323–343, 1982.
- [50] Michael F Scheier and Charles S Carver. Optimism, coping, and health:assessment and implications of generalized outcome expectancies. *Health psychology*, 4(3):219, 1985.
- [51] Nikolaus Schweizer and Nora Szech. Optimal revelation of life-changing information. Working paper, 2013.
- [52] Uzi Segal. Two-stage lotteries without the reduction axiom. *Econometrica*, pages 349–377, 1990.
- [53] Carolin Showers. *Anticipatory Cognitive Strategies: The Positive Side of Negative Thinking*. University of Michigan, 1986.
- [54] Carolin Showers. Compartmentalization of positive and negative self-knowledge: Keeping bad apples out of the bunch. *Journal of Personality and Social Psychology*, 62(6):1036, 1992.
- [55] Karolynn Siegel and Eric W Schrimshaw. Perceiving benefits in adversity: Stress-related growth in women living with hiv/aids. *Social Science & Medicine*, 51(10):1543–1554, 2000.
- [56] Chris Starmer and Robert Sugden. Does the random-lottery incentive system elicit true preferences? an experimental investigation. *The American Economic Review*, pages 971–978, 1991.
- [57] Jules H Van Binsbergen, Jesús Fernández-Villaverde, Ralph SJ Koijen, and Juan Rubio-Ramírez. The term structure of interest rates in a dsge model with recursive preferences. *Journal of Monetary Economics*, 59(7):634–648, 2012.
- [58] Frans Van Winden, Michal Krawczyk, and Astrid Hopfensitz. Investment, resolution of risk, and the role of affect. *Journal of Economic Psychology*, 32(6):918–939, 2011.
- [59] Hans-Martin Von Gaudecker, Arthur Van Soest, and Erik Wengström. Heterogeneity in risky choice behavior in a broad population. *The American Economic Review*, pages 664–694, 2011.
- [60] Florian Zimmermann. Clumped or piecewise? evidence on preferences for information. *Management Science*, 61(4):740–753, 2014.