THE ROLE OF SALIENCE AND ATTENTION IN CHOICE UNDER RISK:
AN EXPERIMENTAL INVESTIGATION

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ABSTRACT: We conduct two experiments to test the predictions of a recently proposed theory of context-dependent choice under risk called salience theory. The theory predicts that a decision maker’s attention is drawn to precisely defined salient payoffs, and these payoffs are overweighted in the choice process. In our first experiment, subjects choose between risky lotteries and we exogenously manipulate the correlation structure between lotteries; this design feature provides an environment to separate salience theory from expected utility and cumulative prospect theory. In the second experiment, we test whether attention has a causal impact on risky choice. We find two main results. First, the correlation structure between lotteries has a systematic impact on risk taking. This result is predicted by salience theory, but is inconsistent with all parameterizations of expected utility and cumulative prospect theory. Second, we find evidence that manipulating attention through a visual salience channel has a causal, but asymmetric, impact on risky choice.

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I. INTRODUCTION

A key tenet of expected utility theory is that preferences are stable over time and are independent of the context in which choices are presented. These preferences guarantee that choices are consistent across environments and are not affected by context-specific features such as visual cues or the choice set itself. However, starting with Allais (1953), a large body of evidence documents robust violations of context-independent choice. For example, when confronted with a choice between two lotteries with similar expected values, experimental subjects often exhibit a preference reversal: their propensity to take risk depends on whether they are bidding on lotteries or choosing between them (Lichtenstein and Slovic 1971). The systematic nature of these context-independent choice violations suggests that preferences are malleable and influenced by the environment.

Theorists have thus begun to formalize a new class of models where the choice set distorts the relative weights that a decision-maker attaches to attributes of an alternative. Bordalo, Gennaioli and Shleifer (2012) (henceforth BGS) propose the first economic model in this spirit where attention directly influences decision weights, in order to explain context-dependent risk preferences. BGS assume that attention is directed towards salient lottery payoffs, and the decision maker then overweight these payoffs when computing a lottery’s utility. Bordalo, Gennaioli and Shleifer (2013a, 2013b, 2016) use this same core intuition – that attribute weighting is a function of attention and the choice set – to explain context-dependencies in consumer choice, asset pricing, and industrial organization. Other recent models share a similar intuition but assume that the range of utilities across an attribute distorts the associated attribute weight (Koszegi and Szeidl 2013; Cunningham 2013; Bushong, Rabin, and Schwartzstein 2016).

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1 See Camerer (1995) for a review.
2 Earlier work by Rubinstein (1988) and Leland (1994) also propose models of context-dependent choice under risk, though the psychology of these models is not explicitly motivated by attention. Loomes and Sugden (1982) also provide a model driven by attribute-based comparisons, but the interpretation in that work is based on anticipatory regret and rejoicing.
In this paper, we conduct two experiments that allow us to test the psychological mechanisms that drive decision-making under risk according to salience theory. In our first experiment, we vary the state space induced by a choice set of lotteries, while holding constant the payoff distribution of each lottery. This design feature provides a sharp test between salience theory and the leading theories of decision making under risk: expected utility theory and cumulative prospect theory (CPT) (Tversky and Kahneman 1992). In our second experiment, we exogenously manipulate attention through a visual salience channel. This manipulation allows us to test whether attention causally affects risky choice, which is a key assumption of the BGS theory.

To understand how the state space manipulation in our first experiment can provide a sharp test between competing theories of decision-making under risk, we briefly describe the intuition of the BGS model here. A lottery payoff is defined as salient if “it is very different in percentage terms from the payoffs of the other available lotteries (in the same state of the world)” (pg. 1244). A decision-maker’s (DM) attention is then drawn to the salient payoffs, and the DM overweightes the state in which the salient payoffs are delivered. By experimentally manipulating the state space, we change the set of attributes under consideration by the DM, which directly impacts the valuation of each lottery under salience theory. Critically, our state space manipulation holds constant each lottery’s payoff distribution and therefore, it should have no impact on risk taking under any parameterization of expected utility theory or CPT.

Our main result from the first experiment is that risk taking is systematically affected by the correlation between lotteries in a choice set. Each choice set we use is comprised of two lotteries, and is a variant of the choice set typically used in experiments on the Allais paradox. Using a within-subjects design, we find that the propensity to exhibit the Allais paradox changes systematically as we gradually vary the correlation structure between the two lotteries, and the direction of this change in behavior is predicted by salience theory. In contrast, CPT and expected utility make predictions that are independent of the correlation between lotteries in our
experiment, and thus our data are inconsistent with all parameterizations of expected utility theory and CPT.

At the end of the first experiment, we also collect data on risk-taking over high stakes lotteries (with upsides as large as $2,040), where on each trial, a subject chooses between a certain option and a mean-preserving risky lottery. For each trial, salience theory makes a precise prediction about which state is salient, and therefore it predicts on which trials subjects take risk. These data therefore provide a secondary test of salience theory using high stakes decisions, and we find that behavior is broadly consistent with the theory: subjects are significantly more likely to take risk on trials where the risky lottery’s upside is salient compared to trials where the risky lottery’s downside is salient.

These predictions from the BGS theory rely on the assumption that once attention is drawn to a salient state, a subject overweights this state when computing the utility of each lottery. In other words, BGS assumes that attention causally affects preferences. A distinct, although not mutually exclusive, assumption is that preferences causally affect attention allocation. Under this latter assumption, attention is deployed to those attributes or alternatives for which a decision-maker has an ex-ante preference.

In our second experiment, we investigate the direction of causality between preferences and attention. We test whether attention has a causal effect on preferences, as assumed by BGS, by recruiting a sample of three hundred subjects from Amazon Mechanical Turk and asking them to make hypothetical choices between a risky lottery and a certain option. On each trial, there are two states of the world: a gain state (where the risky lottery delivers a gain relative to the certain option) and a loss state (where the risky lottery delivers a loss relative to the certain option). In the control condition, neither state is visually salient. In the treatment, we increase the visual salience of one state by enhancing the visual contrast of the payoff amount and its background color. Importantly, we hold constant the marginal payoff distribution of each lottery in the treatment, just as we did when we varied the correlation structure in Experiment 1. To guide
predictions of the impact of visual salience on risk taking, we generalize the BGS model and allow visual salience to also distort the valuation process. We find that subjects take significantly less risk when we increase the visual salience of the loss state, but we do not find a significant effect on behavior when manipulating the visual salience of the gain state. These results therefore demonstrate that there is a causal, but asymmetric, impact of attention on preferences over risky lotteries in our experiment.

Our paper contributes to a large literature in mathematical psychology, and more recently in behavioral economics, on modeling the relationship between attention and economic choice. Busemeyer and Townsend (1993) propose a model called decision field theory, where random fluctuations in attention bias the decision weight attached to an attribute. Diederich (1997) extends this model to provide more structure on transitions of attention between attributes, while Krajbich et al. (2010) propose the attentional drift diffusion model, which makes predictions about the joint distribution of attention, choice outcomes, and response times. One common feature of these cognitive models of decision-making is that while attention is assumed to influence economic choice, the process that governs attention is taken to be exogenous.

Fortunately, several recent models from the behavioral economics literature have begun to endogenize the attention process as a function of the economic environment (Caplin 2016). The BGS model that we test here is the first to provide this endogenous ex-post attention allocation structure. Koszegi and Szeidl (2013) provide a model where agents focus on attributes that are most different across alternatives, Schwartzstein (2014) studies an agent whose selective attention leads to biased belief updating and Gabaix (2014) builds a general and tractable theory of an agent who chooses attention weights to build a “sparse” model of the world. Cunningham

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3 For recent work that demonstrates the links between economic and perceptual decision-making, see Krajbich, Armel, and Rangel (2010), Summerfield and Tsetsos (2012), Towal et al. (2013), and Frydman and Nave (2016).

4 There is also a large literature in economics on models of rational inattention (Sims 2003). However, these models are fundamentally different in that they assume agents rationally (ex-ante) allocate their scarce attentional resources.
(2013) and Bushong, Rabin, and Schwartzstein (2016) provide related formal models where the choice set endogenously influences decision weights. Our experiment is not designed to distinguish among this particular set of theories (Dertwinkel-Kalt et al. 2016), but is instead meant to provide the first test of the BGS theory applied to decision making under risk.

II. EXPERIMENT 1: THE IMPACT OF CORRELATION ON RISK-TAKING

In our first experiment, we recruit one hundred subjects to the laboratory and we incentivize them to make a series of decisions between two lotteries. We divide this first experiment into two parts, which we refer to as the “Basic Risk Choice Sets” and the “Allais Choice Sets.” We begin with the experimental design of the Basic Risk Choice Sets.

II.A. Experimental Design: Basic Risk Choice Sets

The Basic Risk Choice Sets consist of thirty-five trials where the subject chooses between a risky lottery and a certain option. The risky lottery, \( L = (x, p; y, 1 - p) \) is a mean-preserving spread of the certain option, \( B = (b, 1) \) where \( x > b > y \geq 0 \) and \( p \in (0,1) \). There are thus two states of the world, \( s \in \{gain, loss\} \). We define \( \Pr(S = gain) = p \) because with probability \( p \), the risky lottery delivers a gain relative to the certain payoff, \( b \). The parameter values for all thirty-five trials in the Basic Risk Choice Sets are given in Table I, and a screenshot from one of the trials is shown in Figure I. On each trial, the two lotteries are shown as a pie chart, and each state is characterized by a “slice” of the pie. The colors are always blue and orange on each trial, and they are randomized across the gain and loss states at the subject-trial level; the ordering of the trials is also randomized across subjects. We use the pie chart display in order to make the state space for each lottery explicit and to compare our results with the visual salience treatment we run in our second experiment.
II.B. Experimental Design: Allais Choice Sets

In the Allais Choice Sets part, there are four trials, and on each trial the subject chooses between two lotteries. We design the lotteries to exploit the unique prediction of salience theory that the correlation between lotteries impacts the perception of risk. Specifically, salience theory assumes that a decision-maker distorts the weight attached to a specific attribute, which means that a critical first step in applying the theory is to define the set of attributes. In the domain of risky choice, the set of attributes can be characterized by the state space. We therefore manipulate the state space, which changes the correlation between lotteries and the attribute set induced by the choice problem. Our experimental setting is based on lotteries that are typically used to study the Allais paradox (Allais 1953), and our key innovation is to manipulate the correlation gradually over different choice sets.

In standard examples of the Allais paradox, subjects are asked to choose between two lotteries, \( A_1(z) \) and \( A_2(z) \), in two separate choice problems where only \( z \) varies across the two problems. The specific structure of the lotteries \( A_1(z) \) and \( A_2(z) \) that we use in this experiment is given by:

\[
A_1(z) = (25, 0.33; 0, 0.01; z, 0.66) \\
A_2(z) = (24, 0.34; z, 0.66). \tag{1}
\]

If subjects change their choice between \( A_1(z) \) and \( A_2(z) \) as a function of \( z \), this violates the independence axiom and generates the Allais paradox. Standard examples of the Allais paradox typically present the choice sets as they are shown above in equation (1). In particular, the correlation structure is often left unspecified, perhaps because it has no bearing on choice predictions under many theories, including expected utility and CPT. To test the BGS predictions, we manipulate the correlation between the two lotteries over three different correlation structures, while holding constant the marginal payoff distributions of \( A_1(z) \) and \( A_2(z) \). In other words, we
define the choice set in each problem by $X_c(z) = \{A_1(z), A_2(z)\}_c$, where $c$ represents the correlation between $A_1(z)$ and $A_2(z)$. We vary $c$ over three different values, which we describe in detail below.

In our experiment, the common consequence, $z$, can take on one of two values: 0 or 24. Thus, there are three values of $c$, and two values of $z$, generating a total of six choice problems. In general, a choice set $X_c(z)$ will induce a set of states, $S(c)$, where each state $s \in S(c)$ occurs with probability $p_s$. The joint payoff distribution induced by choice set $X_c(z)$ is given by $J_c(z) = (A_1^s(z), A_2^s(z); p_s))_s^{S(c)}$, which characterizes the probability of each state $s$ and its associated joint payoff. We now develop each of the six choice sets and their associated joint payoff distribution.

**II.B.i. The $z=0$ case**

We begin with our first correlation structure that we define as “perfect” correlation. The correlation is perfect in the sense that when the common consequence, $z=0$, obtains in lottery $A_2(0)$, it also obtains in lottery $A_1(0)$. Under this correlation structure, the joint distribution of $A_1(0)$ and $A_2(0)$ is given by $J_{\text{perfect}} = ((25, 24), 0.33; (0, 24), 0.01; (0, 0), 0.66)$. This generates a state space with three states, and is displayed in Figure II.A.

Our second correlation structure is characterized by “imperfect” correlation. Under this structure, if the common consequence, $z=0$, obtains in lottery $A_2(0)$, it carries information about whether the common consequence obtains in lottery $A_1(0)$, but it does not fully reveal whether this event occurs. Note that there are many different correlation structures that satisfy this criteria. We choose one that is very similar to the perfect correlation structure, except that we introduce a small probability state where the common consequence obtains from $A_2(0)$, but not from $A_1(0)$. Under this correlation structure, the joint distribution of $A_1(0)$ and $A_2(0)$ is given by $J_{\text{imperfect}} = ((25, 24), 0.32; (25, 0), 0.01; (0, 24), 0.02; (0, 0), 0.65)$. This generates a choice set with four states, and is displayed in Figure II.B.
The last correlation structure we use is defined as “uncorrelated”. Under this structure, the payoffs of lotteries \( A_1(0) \) and \( A_2(0) \) are uncorrelated, and the joint distribution of \( A_1(0) \) and \( A_2(0) \) is given by \((25, 24), 0.1122; (25, 0), 0.2178; (0, 24), 0.2278; (0, 0), 0.4422\). This generates a choice set with four states, and is displayed in Figure II.C.

Before moving on to the case where \( z=24 \), it is important to emphasize that for all three choice sets we have just developed, the marginal payoff distributions of \( A_1(0) \) are the same for all choice sets and the marginal payoff distributions of \( A_2(0) \) are the same for all choice sets. This is the main innovation of our experimental design that will allow us to test between competing theories.

**II.B.ii. The \( z=24 \) case**

We now develop the choice sets for each of the three correlation structures when the common consequence takes on the value \( z=24 \). One natural way to proceed is to repeat the case-by-case analysis we described in the previous subsection, but replacing \( z=0 \) with \( z=24 \). Another more efficient approach is to first notice that when \( z=24 \), lottery \( A_2(24) \) is riskless as it generates a payoff of 24 with certainty. Therefore, because lottery \( A_2(24) \) does not generate any variation in payoffs, the realized payoff from lottery \( A_2(24) \) does not contain information about the realized payoff from \( A_1(24) \). In other words, because lottery \( A_2(24) \) is riskless, then for all three correlation structures we obtain the same joint distribution given by: \((25, 24), 0.33; (0, 24), 0.01; (24, 24), 0.66\). This choice set is displayed in Figure II.D. Therefore, we have only one distinct choice set when \( z=24 \), but there are three distinct choice sets when \( z=0 \); all four choice sets are thus shown in Figure II.
II.C. Experimental Procedures

The one hundred subjects we recruited for this experiment were either students from the University of Chicago or residents from the local community. The average age of subjects in this sample was 26.0 (standard deviation: 9.6), 40% were male, 73% had a college degree and 54% had taken a statistics class within the previous five years. The exact sample size and the precise experimental design, including all parameters, were pre-registered before any data collection took place and details of the pre-registration are provided in the Online Appendix.

Each of the one hundred subjects participated in both the Basic Risk Choice Sets and the Allais Choice Sets, completing a total of thirty-nine questions that involved choosing between two lotteries. Upon entering the laboratory, subjects were given instructions and went through a practice problem to become familiar with the experimental software (experimental instructions are provided in the Online Appendix.) Because the dollar amounts are, on average, much larger in the Basic Risk Choice Sets part compared to the Allais Choice Sets part, we first presented the Allais Choice Sets to all subjects. Within each task, the trials were presented in random order and the colors that denote each state were randomized across subjects. At the end of the experiment, one of the thirty-nine questions was randomly selected and subjects were paid according to their decision on that trial.

Subjects were told that there was a 23% chance that each of the four problems in the Allais Paradox Choice Sets would be chosen, and that there was a 0.23% chance that each of the thirty-five problems in the Basic Risk Choice Sets would be chosen. We used this non-uniform distribution of trial selection in order to incentivize all problems, while keeping the expected payout at reasonable levels given the large potential payouts in the Basic Risk Choice Sets (Azrieli, Chambers, and Healy 2014). Once the random trial was selected, and if the subject chose a risky lottery on the selected trial, the random outcome of the risky lottery was determined by the
subject, who rolled a pair of 10-sided die. In addition to the payoff from one random trial, subjects also received a $6 show up fee.

After the subjects completed the experiment, but before receiving their payoffs, we collected demographic information, including gender, education, age, and past courses taken in statistics. The entire experiment lasted approximately forty-five minutes, and the average total earnings, including the show up fee, was $16.82 (minimum: $6, maximum: $36, standard deviation: $12.07).

II.D. Theoretical Predictions for Basic Risk Choice Sets

Under salience theory, risk preferences will be systematically context-dependent. In other words, a subject will exhibit risk-seeking behavior on some trials and risk-averse behavior on other trials. We use the BGS model to generate sharp predictions about the specific trials in which subjects will exhibit risk averse behavior compared to risk seeking behavior. We review this model now.

When confronted with a choice between two lotteries, a subject who is prone to choosing according to salience theory will direct her attention towards the most salient state of the world. The key behavioral implication of this attention allocation is that the subject overweights those states of the world that are most salient. Because there are only two states for each of the Basic Risk Choice Sets, this means that one state will be overweighted relative to the objective state probability, and one state will be underweighted.

To determine which state is theoretically salient, we rely on the definition provided by BGS. BGS define a salience function to be a continuous and bounded function that maps payoffs

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5 Specifically, for a trial in the Basic Risk Choice Set task, rolling the 10-sided die twice generates two integers, $a \in [0, 9]$ and $b \in [0, 9]$. We use these two numbers to construct a variable $Z = (10a + b)$, which takes on integer values in the range $[0, 99]$. If $Z \geq 100(1 - p)$, (where $p$ is the probability of the gain state), then the subject receives the payoff from the gain state; otherwise, she receives the payoff from the loss state. A similar procedure was used for the Allais Paradox Choice Sets, although four die were needed to resolve the outcome of a lottery in choice set $X_{uncorrelated} (0)$. 

into salience measures and that satisfies two properties: ordering and diminishing sensitivity.

Under ordering, the salience of a state is higher when payoff levels within the state are further from the reference level; under diminishing sensitivity, salience decreases as payoff levels rise$^6$.

In what follows, we specialize our analysis to a specific salience function, $\sigma(x^L_s, x^B_s) = \frac{|x^L_s - x^B_s|}{0.1 + |x^L_s| + |x^B_s|}$, where $x^L_s$ denotes the risky lottery payoff in state $s \in \{\text{gain}, \text{loss}\}$ and $x^B_s$ denotes the certain option payoff in state $s \in \{\text{gain}, \text{loss}\}$. While the specific salience function we use here places tighter restrictions on the choice data than are implied by the general properties of ordering and diminishing sensitivity, it provides useful structure in formulating our predictions.

Given the salience function, we say that the gain state is more salient than the loss state if $\sigma(x^L_{\text{gain}}, x^B_{\text{gain}}) > \sigma(x^L_{\text{loss}}, x^B_{\text{loss}})$. Salience distorts the objective probability of each state, where we define the distorted probability of the gain state by $p^*$ (and where the objective probability of the gain state is given by $p$). The subject distorts the odds ratio of the gain state to the loss state as follows:

$$\frac{p^*}{1-p^*} = \frac{\delta[\sigma(x^L_{\text{loss}}, x^B_{\text{loss}})]}{\delta[\sigma(x^L_{\text{gain}}, x^B_{\text{gain}})]} \times \frac{p}{1-p}$$  \hspace{1cm} (2)

Rearranging terms allows us to explicitly solve for the distorted probability $p^*$:

$$p^* = \frac{\delta[\sigma(x^L_{\text{loss}}, x^B_{\text{loss}}) - \sigma(x^L_{\text{gain}}, x^B_{\text{gain}})]}{1 + (\delta[\sigma(x^L_{\text{loss}}, x^B_{\text{loss}}) - \sigma(x^L_{\text{gain}}, x^B_{\text{gain}})] \times \frac{p}{1-p})}$$  \hspace{1cm} (3)

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$^6$ Formally, suppose there are two states $s$ and $s'$. Ordering implies that if $[x^L_s, x^B_s]$ is a subset of $[x^L_{s'}, x^B_{s'}]$ then state $s'$ is more salient than state $s$. Diminishing sensitivity implies that if $x^L_s > 0$ and $x^B_s > 0$, then for any $\epsilon > 0$, state $s$ becomes less salient if $\epsilon$ is added to each payoff $x^L_s$ and $x^B_s$.
In this expression, the parameter $\delta \in (0,1]$ captures the degree to which salience distorts objective probabilities, where this distortion is a smooth increasing function of the difference in salience across states. When $\delta = 1$, there is no probability distortion and $p^* = p$. When $\delta < 1$ the distorted probability of the gain state is larger than its objective probability if and only if

$$\sigma(x_{gain}^L, x_{gain}^B) > \sigma(x_{loss}^L, x_{loss}^B).$$

Given this distortion algorithm, we can now assess how salience impacts decision-making under risk. We assume that the utility of a payoff is given by the value function $v(x) = x$. Subjects compute the value of each alternative under the distorted probabilities, and choose the risky lottery if its value, $m(L)$, exceeds that of the certain option, $m(B)$. In particular, a subject will choose the risky lottery when:

$$m(L) - m(B) > 0 \Rightarrow (p^* \times x) + ((1 - p^*) \times y) - b > 0. \quad (4)$$

We refer to the left-hand side of this inequality as the decision value of the risky lottery, which represents the relative value of choosing the risky lottery compared to the certain option. For the set of gambles in our experiment, the decision value will be positive whenever $p^* > p$, which occurs precisely when the gain state is salient. This leads to our first prediction regarding the distribution of choices as a function of the salience of each state.

**PREDICTION 1:** If subjects make decisions according to salience theory, then risk-taking will be greater when the gain state is salient compared to when the loss state is salient.

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7 This assumes that subjects narrowly frame payoffs, instead of computing utility by first merging the payoff with their total wealth level. We assume that subjects use a reference point of zero when evaluating payoffs.
II.E. Theoretical Predictions for Allais Choice Sets

We now derive the choice predictions under the BGS theory for each of the four Allais Choice Sets (Figure II). Our main objective in this section is to derive predictions for how risk-taking changes as we vary the correlation structure between lotteries. We focus on deriving these predictions because both CPT and expected utility predict that there should be no shift in behavior as the correlation structure changes. As we will show below, salience theory makes sharp predictions about how risk-taking changes as a function of the correlation structure. These distinct predictions therefore provide an environment in which we can separate between the competing theories.

In order to investigate how risk-taking varies with the correlation structure, we compute the decision value of choosing $A_1(z)$ over $A_2(z)$, and then check whether the decision value changes with the correlation structure. To do so, we first generalize the distortion equation in (2) because there are now more than two states induced by each of the Allais Choice Sets. For any two states $s$ and $s'$, with $\Pr(s) = p_s$ and $\Pr(s') = p_{s'}$ the DM distorts the objective odds ratio $\frac{p_s}{p_{s'}}$, to a distorted odds ratio, $\frac{\pi_s}{\pi_{s'}}$, given by:

$$\frac{\pi_s}{\pi_{s'}} = \frac{\delta[\sigma(x_s^{A_1}, x_{s'}^{A_2})]}{\delta[\sigma(x_s^{A_2}, x_{s'}^{A_1})]} \times \frac{p_s}{p_{s'}}. \tag{5}$$

We then normalize the distorted probabilities and generate a set of decision weights given by $\omega_i = \frac{\pi_i}{\sum_s \pi_s}$ for all $i \in S$. When computing decision values we again assume a linear value function, $v(x) = x$. We can now define the decision value of choosing $A_1(z)$ from the choice set $X_c(z) = \{A_1(z), A_2(z)\}_c$ as follows:

$$DV_{A_1(z)}^C = \sum_{s \in S(c)} \omega_s \left( v \left( x_s^{A_1(z)} \right) - v \left( x_s^{A_2(z)} \right) \right) \tag{6}$$
The important aspect to note from equation (6) is that the correlation structure, $c$, has a direct impact on valuation through the state space, $S(c)$. This is the channel through which correlation impacts the perception of risk under salience theory, and we now characterize how risk taking varies under our three different correlation structures. We begin with the case when the two lotteries are uncorrelated. When $z=0$, the joint payoff distribution is given by $((25, 24), 0.1122; (25, 0), 0.2178; (0, 24), 0.2278; (0, 0), 0.4422)$. There are four states induced by this choice set, and we use equation (5) to generate the decision weights $\{\omega_1, \omega_2, \omega_3, \omega_4\}$, which are a function of $\delta$ and are displayed in Figure A.1 in the Online Appendix. Using these decision weights, the decision value of choosing $A_1(0)$ is given by:

$$DV_{A_1(0)}^{uncorrelated} = \sum_{s \in S(uncorrelated)} \omega_s \left( v(x^A_1) - v(x^A_2) \right)$$

$$= \omega_1 \times (25 - 24) + \omega_2 \times (25 - 0) + \omega_3 \times (0 - 24) + \omega_4 \times (0 - 0) \quad (7)$$

Note that because each decision weight, $\omega_s$, is a function of $\delta$, the decision value will also be a function of $\delta$. The black solid line in Figure III.A plots $DV_{A_1(0)}^{uncorrelated}$ for each value of $\delta$.

To check whether salience theory predicts different behavior when the common consequence shifts to $z=24$, we compute the decision value of choosing $A_1(24)$ over $A_2(24)$, again using the weights from equation (5) that are derived in the Online Appendix:

$$DV_{A_1(24)}^{uncorrelated} = \sum_{s \in S(uncorrelated)} \omega_s \left( v(x^A_1) - v(x^A_2) \right)$$

$$= \omega_1 \times (25 - 24) + \omega_2 \times (0 - 24) + \omega_3 \times (24 - 24) \quad (8)$$

The black dashed line in Figure III.A plots $DV_{A_1(24)}^{uncorrelated}$ and we see that it is less than $DV_{A_1(0)}^{uncorrelated}$ for all values of $\delta$. In other words, when the two lotteries are uncorrelated, the
relative utility of choosing $A_1(z)$ over $A_2(z)$ changes as we vary the common consequence, for any salient thinker.

In order to map the decision value into a choice, we assume that the decision value is subject to an independent and additive random shock, which generates stochastic choice (McFadden 2001)\(^8\). In particular, we assume a stochastic choice function such that the probability that a subject chooses $A_1(z)$ is given by, $\Pr(A_1(z) \in \{X_c(z)\}) = \psi(DV_{A_1(z)})$ where $\psi \in (0,1)$ and is strictly increasing. We can now define the probability that a subject exhibits the Allais paradox when the lotteries are uncorrelated as\(^9\)

$$\Pr (\text{choose } \{A_1(0) \text{ and } A_2(24)\}) = \psi(DV_{A_1(0)}^{uncorrelated}) \times (1 - \psi(DV_{A_1(24)}^{uncorrelated})).$$

The next step is to characterize how this probability of exhibiting the Allais paradox varies when the correlation structure changes. Because the probability is a function of the decision values, we proceed by computing decision values under the two remaining correlation structures. When the lotteries are imperfectly correlated and $z=0$, the choice set $X_{imperfect}(0)$ induces a joint distribution of payoffs given by $((25, 24), 0.32; (25, 0), 0.01; (0, 24), 0.02; (0, 0), 0.65)$. Figure III.B. shows that for all values of $\delta$, the decision value is larger when $z=0$ compared to when $z=24$; this indicates that the relative utility of choosing $A_1(z)$ over $A_2(z)$ is again a function of the common consequence. More importantly for our purposes, by comparing Figure III.B. with Figure III.A, we see that $DV_{A_1(0)}^{imperfect} < DV_{A_1(0)}^{uncorrelated}$ for all $\delta$. In other words, for any salient thinker, the relative utility of choosing lottery $A_1(0)$ over $A_2(0)$ is higher when the

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\(^8\) For a review of the literature on stochastic binary choice over lotteries, see Wilcox (2008). The theoretical foundation of stochastic choice is an active area of research. Besides the random utility model interpretation, other theories of stochastic choice include deliberate randomization (Fudenberg, Ijima, and Strzalecki (2015); Agranov and Ortoleva (2015)) and bounded rationality, which can be derived from neurobiological constraints on the choice process (Fehr and Rangel (2011); Webb (2015); Woodford (2016)). We also note that stochastic choice is not a necessary condition to generate the predictions we derive below. At the end of this section we discuss an alternative condition based on heterogeneity in $\delta$ that can also be used to generate similar qualitative predictions.

\(^9\) Technically, the probability of a choice reversal is defined as $\Pr (\{A_1(0), A_2(24)\} \cup \{A_1(24), A_2(0)\})$, which includes the violation where a subject chooses $A_1(24)$ and $A_2(0)$. However, we restrict our definition of the Allais paradox to the more common violation of expected utility as the event where a subject chooses $A_1(0)$ and $A_2(24)$. **
two lotteries are uncorrelated compared to when they are imperfectly correlated. On the other hand, when \( z=24 \) the choice sets do not vary with the correlation structure, which implies that

\[
DV_{A_1(24)}^{\text{imperfect}} = DV_{A_1(24)}^{\text{uncorrelated}}.
\]

Therefore, as we shift from uncorrelated lotteries to imperfectly correlated lotteries, there is a systematic decrease in the probability of choosing lottery \( A_1(0) \), but the probability of choosing lottery \( A_1(24) \) remains constant. The overall effect is that the shift in correlation decreases the probability of exhibiting the Allais paradox, which leads to Prediction 2A.

PREDICTION 2A: For any salient thinker, the propensity to exhibit the Allais paradox is lower when the lotteries are imperfectly correlated, compared to when the lotteries are uncorrelated.

The final step in our analysis is to derive predictions for the case where the two lotteries exhibit perfect correlation. In this case, when \( z=0 \), the choice set \( X_{\text{perfect}}(0) \) induces a joint distribution of payoffs given by \((25, 24), 0.33; (0, 24), 0.01; (0, 0), 0.66\). Figure III.C provides the decision value of choosing \( A_1(0) \) over \( A_2(0) \) for all values of \( \delta \), and we see that under this correlation structure, the decision value does not vary with the common consequence. Moreover, by comparing Figure III.C with Figure III.B, we see that

\[
DV_{A_1(0)}^{\text{perfect}} < DV_{A_1(0)}^{\text{imperfect}},
\]

which means that the relative value of choosing lottery \( A_1(0) \) over \( A_2(0) \) is higher when the two lotteries are imperfectly correlated compared to when they are perfectly correlated. On the other hand, we again have the result that for \( z=24 \), the decision value does not vary with the correlation structure and thus,

\[
DV_{A_1(24)}^{\text{perfect}} = DV_{A_1(24)}^{\text{imperfect}}.
\]

These two results imply that the shift from imperfect to perfect correlation will decrease the probability of choosing lottery \( A_1(0) \), but it will not affect the probability of choosing lottery \( A_1(24) \). The overall effect generates a decrease in the probability of exhibiting the Allais paradox.
PREDICTION 2B: For any salient thinker, the propensity to exhibit the Allais paradox is lower when the lotteries are perfectly correlated, compared to when the lotteries are imperfectly correlated.

In summary, we find that BGS does predict different levels of risk taking as we shift the correlation structure, even though the marginal payoff distribution of each lottery remains constant. Specifically, as the correlation shifts from uncorrelated lotteries to perfectly correlated lotteries, there is a monotonic decrease in the propensity to exhibit the Allais paradox. While we assumed that our subjects exhibit stochastic choice, we note that this is not necessary to generate the prediction of monotonicity. If instead there is sufficient heterogeneity in $\delta$ across the subject pool, then even under deterministic choice, BGS still generates the prediction of monotonicity. Critically, the monotonicity prediction differs sharply from that of expected utility and CPT. Under each of these theories, risk taking should remain constant as the correlation structure varies. In this basic sense, our experimental design allows use to separate these competing theories.

II.F. Results from Basic Risk Choice Sets

Overall, subjects choose the risky lottery on 41.1% of trials in the Basic Risk Choice Sets. Table II.A presents the average risk taking results disaggregated by trial, where each cell corresponds to a different trial$^{10}$. Each column characterizes the probability of the gain state and each row characterizes the expected value of the risky lottery (and, by design, of the certain option). The shaded cells correspond to those trials for which the gain state is salient.

Table II.B provides results from a formal test of Prediction 1, where the dependent variable in each regression is a dummy variable that takes on the value 1 if the subject chose the

---

$^{10}$ Due to a software error, we failed to record data on one trial for thirty-three subjects (trial 32 in Table I), and thus these trials are excluded from the subsequent analyses in this experiment.
risky lottery and EconSal is a dummy that takes on the value 1 if the gain state is salient. Column (1) shows that subjects are significantly more likely to take risk when the gain state is salient (49.8%) compared to when the loss state is salient (34.1%). Column (2) adds a subject fixed effect, which controls for heterogeneity in overall risk taking levels across subjects, and the results are similar to those in column (1). Columns (3) and (4) provide results when using a logistic regression and a mixed effects logistic regression, respectively. The mixed effects logistic regression includes both a random slope and a random intercept, which allows for variation across subjects in both overall levels of risk taking and the weight attached to salience. Across all four specifications, the coefficient on EconSal is significantly positive at \( p < 0.001 \). These results therefore support Prediction 1.

Another basic pattern that is evident from Table II.A is that for each of the seven probabilities of the gain state (each column of the table), subjects exhibit nearly a 100% increase in risk taking as the expected value increases from $20 to $60. This pattern is easier to see through the data visualization shown in Figure IV. Salience theory can deliver this prediction because the probability weighting function is context-dependent. In other words, for two trials that have the same objective probability of the gain state, the distorted probabilities can still differ if the expected values of the lottery differ.

Figure V shows this context-dependent property of the weighting function for the five different levels of expected value in our design, generated with two different salience parameter values: \( \delta = 0.2 \) and \( \delta = 0.6 \). The dashed black line denotes the 45-degree line, which crosses each weighting curve at a different point, indicating that the shift from overweighting to underweighting objective probabilities is a function of average payoff levels. It is important to emphasize that in both panels of Figure V, the average payoff level, \( b \), is not a free parameter that generates different shapes of the weighting function; on the contrary, \( b \) is endogenous and is fully pinned down by the choice set on each trial in our experiment. For example, on trials in which the expected value is $20, the loss state is always salient (because of the salient $0 downside) and
therefore the probability of the gain state is always underweighted. In contrast, when \( \delta = 0.2 \) and the expected value of the lottery is $60, objective probabilities are overweighted in the range (0, 0.4).

One interesting aspect of these context-dependent weighting functions is that they resemble the inverse S-shaped probability weighting function from prospect theory. Indeed, within this class of gambles (and when payoffs are positive), the weighting function generated by salience theory preserves the key aspects of prospect theory’s overweighting of small probabilities and underweighting of large probabilities. One can also see that by comparing Panel A and Panel B, the degree of context dependence is heavily influenced by the parameter \( \delta \). When \( \delta = 0.6 \), the probability weighting function is relatively stable, and can be approximated by a single curve, as in prospect theory. However, when \( \delta = 0.2 \), probability weights are strongly dependent on context. This suggests that prospect theory’s ability to explain the data will depend on the local thinking parameter \( \delta \). Fortunately, the second part of our experiment on the Allais Choice Sets provides a more general, parameter-free test between salience theory and CPT.

**II.G. Results from Allais Choice Sets**

The results in the previous section indicate that BGS can explain some variation in risk taking between a risky lottery and a certain option. However, the data we presented in the previous section do not violate expected utility nor are they inconsistent with CPT. In order to separate these two theories from salience theory, we now turn to the results from the Allais Choice Sets.

Recall that salience theory predicts that, holding constant the payoff distribution of each lottery, there should be a systematic shift in risk taking as the correlation between lotteries changes. Specifically, Prediction 2A states that the propensity to exhibit the Allais paradox should decrease when shifting from uncorrelated lotteries to imperfectly correlated lotteries;
Prediction 2B states that the propensity to exhibit the Allais paradox should decrease when shifting from imperfect correlation to perfect correlation.

We start by reporting the propensity to choose lottery $A_1(z)$ for each of the different correlation structures. For all values of $\delta \in (0,1)$, BGS predicts that $DV^{uncorrelated}_{A_1(0)} > DV^{imperfect}_{A_1(0)} > DV^{perfect}_{A_1(0)}$. The data is broadly consistent with this prediction as the proportion of subjects who choose lottery $A_1(0)$ decreases from 51% to 41% as the lotteries shift from uncorrelated to imperfectly correlated ($p = 0.07$, one-tailed $t$-test). Second, the propensity to choose lottery $A_1(0)$ decreases from 41% to 20% as the lotteries shift from imperfectly correlated to perfectly correlated ($p < 0.001$, one-tailed $t$-test).

Using these choice results, we can now compute the proportion of subjects that exhibit the Allais paradox under each correlation structure, which provides a direct test of Predictions 2A and 2B. Figure VI shows that there is indeed a monotonic relationship between the propensity to exhibit the Allais paradox and the correlation structure. The propensity to exhibit the Allais paradox decreases from 49% to 36% as the lotteries shift from uncorrelated to imperfectly correlated ($p = 0.024$, one-tailed $t$-test), which supports prediction 2A. As the lotteries switch from imperfectly correlated to perfectly correlated, the propensity decreases from 36% to 15% ($p < 0.001$, one-tailed $t$-test), which is consistent with prediction 2B.

Table III displays more detailed tests of Predictions 2A and 2B using a variety of regression models. In the first column, we run the following OLS regression:

\[
y_{i,t} = \alpha + \beta_1Uncorrelated_t + \beta_2PerfectCorrelation_t + \epsilon_{i,t} \tag{9}
\]
where each observation is at the subject-trial level, and the dependent variable, $y_{i,t}$, takes on the value 1 if subject $i$ exhibited the Allais paradox on trial $t$.\textsuperscript{11} Uncorrelated is a dummy that takes on the value 1 if the trial belongs to the condition where the two lotteries are uncorrelated; PerfectCorrelation is a dummy that takes on the value 1 if the trial belongs to the condition where the two lotteries are perfectly correlated. The omitted experimental condition is the imperfect correlation condition, and the constant therefore provides the propensity to exhibit the Allais paradox when the lotteries are imperfectly correlated. In this regression framework, for any salient thinker, Prediction 2A implies that $\beta_1 > 0$ and Prediction 2B implies that $\beta_2 < 0$.

The point estimates in column (1) of Table III confirm the basic difference in means results from above, as $\beta_1$ is significantly positive and $\beta_2$ is significantly negative. Column (2) adds a subject fixed effect that controls for heterogeneity across subjects in the overall propensity to exhibit the Allais paradox. We run a logistic regression in column (3), and a mixed effects logistic regression in column (4) that includes a random intercept and a random slope on each of the two dummy variables. Overall, the results from each of the four specifications support both Prediction 2A and Prediction 2B, and they demonstrate that the propensity to exhibit the Allais paradox declines monotonically as the lotteries shift from uncorrelated to perfectly correlated.

Although the data from this part of the experiment consist of only four binary choice sets per subject, it is worth emphasizing how starkly different the predictions between BGS, CPT and expected utility are for these four questions. Because expected utility and CPT only take as input the marginal payoff distribution of each lottery, both theories predict that there are no differences in the propensity to exhibit the Allais paradox as the correlation structure changes. The data in Figure VI are therefore inconsistent with the predictions from all parameterizations of expected utility and CPT, and the data demonstrate that the state space is an important component that shapes the perception of risk.

\textsuperscript{11} The Allais paradox is defined as choosing lottery $A_1$ when $z=0$ and choosing lottery $A_2$ when $z=24$. Thus, each observation in this regression uses a subject’s decision from two choice sets, one when $z=0$ and one when $z=24$, to code the Allais paradox.
III. EXPERIMENT 2: CAUSAL EFFECT OF ATTENTION ON RISKY CHOICE

In our first experiment, we found two pieces of evidence that support predictions of the BGS model: 1) risk taking is greater when a risky lottery’s upside is salient compared to when its downside is salient, and 2) risk taking depends systematically on the correlation between lotteries. A key feature of the psychology that generates these predictions is that salient attributes are overweighted when computing the utility of a lottery. In other words, BGS assumes that attention causally affects preferences. A distinct – although not mutually exclusive – assumption is that preferences causally affect attention allocation. Under this latter assumption, attention is drawn towards alternatives for which the DM has an *ex-ante* preference. In our second experiment, we test whether attention has a causal impact on risky choice by manipulating the *visual* salience of a state.

To illustrate the distinction between economic salience (modeled in BGS) and visual salience (not explicitly modeled in BGS), recall that a lottery payoff that is extreme compared to the magnitude of other payoffs is economically salient; however, this same lottery payoff may not be *visually* salient if, for example, it is displayed in faint gray font against a light background. We use a visual salience manipulation in this experiment as a channel for exogenously shifting attention, which provides a test of causality.

To guide our predictions of the impact of visual salience on risk taking, we extend the BGS model to incorporate visual salience. Although we incorporate this extra source of salience into the BGS model, we note that visual salience is likely to also interact with other theories of risky choice (such as CPT) and that the assumption that attention causally affects preferences is not unique to BGS. Our objective in this second experiment is simply to provide a test of whether attention causally affects preferences over risky lotteries. We describe the theory, experimental design, and results in the next three subsections.
III.A. Theoretical Background and Predictions

We begin with the same framework that we used to generate predictions for the Basic Risk Choice Sets in section II.D. When a DM is given the choice between a certain option, \( B = (b, 1) \) and a mean preserving risky lottery, \( L = (x, p; y, 1 - p) \), where \( x > b > y \), the gain state is realized with probability, \( p \), and the objective probability distribution is distorted by:

\[
\frac{p^*}{1-p^*} = \frac{\delta[\sigma(x_{loss} - x_{loss})]}{\delta[\sigma(x_{gain} - y_{gain})]} \times \frac{p}{1-p}, \tag{10}
\]

Because BGS only model economic salience in their theory, we refer to the first term on the right-hand side as the “economic salience distortion factor.”

However, it is well known that two types of factors attract attention: top-down and bottom-up factors. Top-down factors are cognitive and are related to goal-directed behavior (Connor, Egeth, Yantis 2004; Knudsen 2007; Milosavljevic and Cerf 2008), such as obtaining monetary payoffs. Therefore, the economic salience that BGS use belongs to this first set of factors. On the other hand, bottom-up or “stimulus-based” factors, such as accessibility or visual salience of information, can involuntarily attract attention. These bottom-up factors are also important for economic choice because it has been shown that they can override one’s voluntary goals and intentions (Milosavljevic, Navalpakkam, Koch and Rangel 2012) and influence economic choice (Towal, Mormann and Koch 2013). We make the distinction between “top-down” economic salience (which is affected exclusively by monetary outcomes), and “bottom up” visual salience, and propose that both types of salience influence information processing and risky choice.

To formalize this argument, we generalize the BGS model by adding a “visual salience distortion factor” to the distortion equation in (10). In particular, if the visual salience of the gain state is increased, e.g., by making the payoff of the gain state visually “pop out”, we expect this to
distort the objective probability, \( p \), upwards. Conversely, if the visual salience of the loss state is increased, we expect this to distort \( p \) downwards. The following equation generalizes the distortion algorithm to include both economic salience and visual salience, where \( p^{**} \) now reflects the distorted probability of the gain state taking into account both sources of salience:

\[
\frac{p^{**}}{1-p^{**}} = \frac{\delta^{\mu x(x_{\text{loss}})}_{\delta^{x_{\text{gain}}}} (1-p)}{\delta^{\mu x(x_{\text{gain}})}_{\delta^{x_{\text{loss}}}} (1-p^{**})} \times \frac{p}{1-p}
\]

(11)

We refer to this model that takes into account both sources of salience as the full salience model. Here, \( 1_{\text{gain}} \) is an indicator function taking on the value 1 when the gain state is visually salient. In contrast, \( 1_{\text{loss}} \) is an indicator function taking on the value 1 when the loss state is visually salient. \( \mu \in \mathbb{R} \) is a parameter that controls the degree to which visual salience distorts objective probabilities. When \( \mu = 0 \), the first term on the right side vanishes and the distortion is exclusively a function of economic salience. Similarly, when neither state is visually salient, both indicator functions take on the value 0, and the first term on the right side vanishes.

The decision value of the risky lottery under the full salience model is computed just as before, except we now use the fully distorted probability distribution. We again assume a value function given by, \( v(x) = x \), which implies that the fully distorted decision value of the risky lottery is given by:

\[
DV_{\text{full}} = p^{**} \times v(x) + (1-p^{**}) \times v(y) - v(b)
\]

\[
= p^{**} \times x + (1-p^{**}) \times y - b
\]

(12)

If visual salience operates through our hypothesized full salience model, and if the gain state is made visually salient, then \( p^{**} > p^* \). This will increase \( DV_{\text{full}} \) and lead to an increase in
risk taking. Conversely, when the loss state is made visually salient, $p^{**} < p^*$, which will decrease $DV_{full}$ and lead to a decrease in risk taking. This leads to our final set of predictions:

**PREDICTION 3A:** If attention causally affects preferences, then if the loss state is made visually salient, risk taking will decrease compared to a baseline condition in which neither state is visually salient.

**PREDICTION 3B:** If attention causally affects preferences, then if the gain state is made visually salient, risk taking will increase compared to a baseline condition in which neither state is visually salient.

**III.B. Experimental Design**

To test Predictions 3A and 3B, we collect data from an additional three hundred subjects through Amazon Mechanical Turk (mTurk), which is an online data collection platform. One advantage of mTurk over a laboratory environment is the ability to collect data from a larger and more diverse pool of subjects; the disadvantage is that the remote nature of the data collection reduces experimental control. The mTurk platform has become increasingly popular in economic research (Olea and Strzalecki 2014; Ambuehl, Niederle, and Roth 2015; Lian, Ma, Wang 2016), and there is evidence that it provides response quality that is similar to that in lab experiments (Casler, Bickel, and Hackett 2013).\(^{12}\)

The subjects we recruit from mTurk make decisions over the same thirty-five trials from the Basic Risk Choice Sets in Experiment 1, for which the parameter values are given in Table I. In contrast to the incentive structure in Experiment 1, our subjects from mTurk make hypothetical

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\(^{12}\) The mTurk platform consists of “requesters” who hire “workers” to complete jobs in exchange for monetary compensation. After a worker completes a job, the requester decides based on the quality of the job whether to approve the job for compensation. Before hiring a worker, a requester can filter potential workers based on the worker’s historical approval rate. In order to ensure high quality data collection, we restrict participation to individuals who have an approval rate of 95% or higher and who reside in the US.
choices and are paid $1.50 for completing the task.\textsuperscript{13} We employ a within subjects design with three conditions that are shown in Figure VII. The control condition is identical to the Basic Risk Choice Sets design used in Experiment 1. In the Gain treatment, we increase the visual salience of the gain state by making both the background color and font of the loss state more faint. Specifically, we increase the transparency of the color and font of the loss state to 60%, which makes the gain state “pop out” (since we keep the transparency of the gain state at 0%). Conversely, in the Loss treatment, we increase the transparency of the gain state to 60%, which makes the loss state “pop out” (since we keep the transparency of the loss state at 0%). We randomize these conditions at the trial-subject level.

The experiment was pre-registered on Aspredicted.org, and contains details on the sample size, number of conditions, and predictions to be tested. The details of the pre-registration are given in the Online Appendix. The average age of subjects in this sample was 37.4 (standard deviation: 11.0), 57% were male, 73% had college degrees and a vast majority (86%) had not taken a statistics class in the past five years.

\textit{III.C. Results from Visual Salience Experiment}

Before turning to a formal test of Predictions 3A and 3B, we first present the average levels of risk-taking across the three experimental conditions\textsuperscript{14}. The overall pattern of risk-taking is very similar to the results we obtain in the Basic Risk Choice Sets task in the laboratory from Experiment 1. First, in the control condition, the probability of choosing the risky lottery increases from 30.5% when the loss state is economically salient to 47.9% when the gain state is

\textsuperscript{13} Because subjects in this experiment make decisions over the same set of thirty-five trials as in the Basic Risk Choice Sets in experiment 1, we are able to formally test whether risk-taking is systematically different on mTurk compared to risk-taking in the lab. In the Online Appendix, we show that risk taking is very similar across the two samples, suggesting that the difference in incentives does not have a major impact on behavior.

\textsuperscript{14} We excluded 7 of the 300 subjects because they completed the entire task in a very short amount of time (under 200 seconds) and were unlikely paying sufficient attention to the task. Additionally, due to a software glitch we lost one trial for fifty-three of our subject (trial 3 in Table 1), and so these trials are not included in any subsequent analyses.
economically salient ($p < 0.001$). We find similar effects in the treatment conditions; in the Gain treatment, the probability of choosing the risky lottery increases from 30.7% when the loss state is economically salient to 46.2% when the gain state is economically salient ($p < 0.001$). In the Loss treatment, the probability of choosing the lottery increases from 28.5% when the loss state is economically salient to 45.3% when the gain state is economically salient ($p < 0.001$).

Table IV provides results from formal tests of predictions 3A and 3B. In Column (1) we run an OLS regression where the dependent variable is a dummy that takes on the value 1 if the subject chooses the risky lottery; EconSal is a dummy equal to 1 if the gain state is economically salient, GainTreat is a dummy that takes on the value 1 if the trial is in the Gain treatment, and LossTreat is a dummy that takes on the value 1 if the trial is in the Loss treatment. The intercept therefore provides the average level of risk taking in the control condition for trials where the loss state is economically salient. Prediction 3A states that risk taking should be lower in the Loss treatment compared to the control condition; Prediction 3B states that risk taking should be higher in the Gain treatment compared to the control condition.

The results in columns (1) – (3) provide support for Prediction 3A, as the coefficient on the LossTreat variable is significantly negative in each specification. Columns (1) and (2) provide results from an OLS model, and we find that the average level of risk taking is reduced by 2.2% when the loss state is made visually salient. This result is robust to a mixed effects logistic specification, which allows for heterogeneity across subjects in the response to manipulating the visual salience of the loss state. In columns (4) – (7) we provide subsample analysis where we split the data into those trials where the gain state is economically salient and those trials where the loss state is economically salient. The strength of the effect becomes smaller, likely due to the smaller sample size, but the results remain significant at the 10% level in all four specifications. It is also worth noting that the relative strength of the visual salience effect is much smaller than the strength of the economic salience effect. For example, the coefficient on the EconSal variable in column (2) indicates that the marginal effect of making the gain state economically salient is a
16.6% increase in risk taking. The marginal effect of making the loss state visually salient is approximately one-sixth of this size.

While we find a significant effect in the Loss treatment, our results do not support Prediction 3B as there is no significant effect on risk taking when increasing the visual salience of the gain state. In all seven specifications of Table IV, the coefficient on the GainTreat variable is not statistically different from zero. Our data therefore indicate that there is an asymmetric impact of visual salience on risk taking. One possibility for this asymmetric result is that the visual salience distortion factor (equation (11)) may itself be asymmetric, potentially because there is a risk-taking “ceiling” above which any visual salience manipulation has no impact. We discuss this asymmetric result in more detail in the conclusion section.

In summary, we find that the basic risk taking results in the control condition replicate the risk taking results we find in the laboratory in Experiment 1. The visual salience manipulation results are asymmetric as we find that risk taking is significantly reduced when the loss state is made visually salient, but we do not find a treatment effect on risk taking when the gain state is made visually salient. Our data therefore provide some, but not perfect, support for the assumption that attention causally affects risk-taking.

IV. CONCLUSION

In this paper, we use data on lottery choices to test the BGS model of decision-making under risk. The main contribution of the paper is to provide an experimental test that can separate expected utility theory, cumulative prospect theory, and salience theory. The key innovation in our first experiment that enables us to separate these theories is straightforward: by changing only the correlation structure in the Allais Choice Sets task, we create an environment where behavior should not differ across the choice sets under either expected utility theory or cumulative prospect theory. In contrast, BGS predicts that there will be a systematic shift in risk taking across the
different correlation structures. Overall, the data provide support for this novel prediction of the BGS theory, but these significant shifts in the Allais paradox are inconsistent with all parameterizations of CPT and expected utility.

In our second experiment, we test whether attention has a causal impact on risky choice. Our data provide some evidence in favor of this direction of causality, as we find that increasing the visual salience of the loss state causes a significant decrease in risk taking. At the same time, we do not find a significant effect on risk taking when manipulating the visual salience of the gain state. As discussed in the previous section, one possibility for this asymmetric result is that the visual salience distortion factor is itself asymmetric. Another possibility is that the visual salience manipulation was stronger for the loss treatment compared to the gain treatment. In particular, the average probability of the gain state in our experiment is much smaller than the average probability of the loss state (the gain state is typically characterized by a low probability and high payoff). Because our manipulation operates through making a visual representation of the state more salient (where the size of the visual representation is proportional to the state probability), the visual salience treatment may have had a larger effect in the Loss treatment compared to the Gain treatment. This would make it harder to detect a treatment effect in the Gain treatment compared to the Loss treatment. However, this explanation is clearly post-hoc, and further research is needed on the visual salience distortion factor to determine if it is differentially sensitive to losses compared to gains.

Returning to the results from the first experiment, one reason we were able to perform a direct test of the BGS theory is because our experimental design makes the state space of each problem explicit. Because the state space forms the foundation for the predictions of choice under risk according to BGS, it was necessary to explicitly present the correlation structure to our subjects15. A potential criticism of the BGS theory is that in many applied settings, only the

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15 Birnbaum (2004) provides a similar but distinct argument for the Allais paradox whereby a decision-maker violates the assumption of “coalescing.” While coalescing is concerned with the presentation mode
marginal payoff distributions are known (to the decision-maker and the researcher), and the correlation structure is unknown. Hence, in these scenarios, it is difficult to apply the BGS theory. While this criticism is certainly valid, the data we present here suggest that the correlation structure is a critical factor in shaping risk attitudes, and it may be misguided to discard the correlation structure as an input to the perception of risk.

In their original paper, BGS suggest that when the correlation structure is left unspecified, a decision maker perceives the lotteries within a choice set to be uncorrelated. Such an assumption can explain the robustness of the Allais paradox when the correlation structure is not specified, since salience theory predicts the Allais paradox will arise when the two lotteries are uncorrelated. Our data provide some extra support for this assumption and offer a potential reason why a DM’s default perception is that lotteries are uncorrelated. As mentioned in the experimental design section for the Allais Choice Sets, there are many (in fact, infinite) distinct correlation structures that are consistent with the marginal payoff distributions of lotteries $A_1(0)$ and $A_2(0)$. There is, of course, only one correlation structure where the two lotteries are statistically independent. This leads us to conjecture that when the state space is not explicitly defined, a decision-maker defaults to perceiving the unique correlation structure characterized by statistical independence.

This is certainly not the only mechanism by which an unspecified correlation structure can impact risk-taking. For example, it is possible that the decision-maker integrates over a distribution of potential correlation structures. The conjecture in the previous paragraph is a special case of this mechanism, where the prior puts full mass on the singleton correlation structure of statistical independence. It is also likely that the perception of the state space – and more generally the “consideration set” – is governed by those attributes and states of a decision problem that receive the most attention (Caplin, Dean, and Leahy 2016). Given the importance of each lottery’s marginal distribution, salience theory is, in part, concerned with the presentation mode of the joint distribution of lotteries.
that the state space has in explaining risk-taking over binary lottery choice, we believe that understanding the perception of correlation is an important step for future research.

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UNIVERSITY OF MIAMI SCHOOL OF BUSINESS
REFERENCES


Table I. Each row represents a single trial in the Basic Risk Choice Sets part of Experiment 1. In each trial a subject is given the choice between a risky lottery \((x, p; y, (1-p))\) and a certain option with payoff \(b\), where \(x > b > y\).

<table>
<thead>
<tr>
<th>Trial Number</th>
<th>x</th>
<th>y</th>
<th>b</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2000</td>
<td>0</td>
<td>20</td>
<td>0.01</td>
</tr>
<tr>
<td>2</td>
<td>400</td>
<td>0</td>
<td>20</td>
<td>0.05</td>
</tr>
<tr>
<td>3</td>
<td>100</td>
<td>0</td>
<td>20</td>
<td>0.2</td>
</tr>
<tr>
<td>4</td>
<td>61</td>
<td>0</td>
<td>20</td>
<td>0.33</td>
</tr>
<tr>
<td>5</td>
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<td>0</td>
<td>20</td>
<td>0.4</td>
</tr>
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<td>0</td>
<td>20</td>
<td>0.5</td>
</tr>
<tr>
<td>7</td>
<td>30</td>
<td>0</td>
<td>20</td>
<td>0.67</td>
</tr>
<tr>
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<td>2010</td>
<td>10</td>
<td>30</td>
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<tr>
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<td>410</td>
<td>10</td>
<td>30</td>
<td>0.05</td>
</tr>
<tr>
<td>10</td>
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<td>0.2</td>
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<td>10</td>
<td>30</td>
<td>0.33</td>
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<td>12</td>
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<td>10</td>
<td>30</td>
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<tr>
<td>13</td>
<td>50</td>
<td>10</td>
<td>30</td>
<td>0.5</td>
</tr>
<tr>
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<td>40</td>
<td>10</td>
<td>30</td>
<td>0.67</td>
</tr>
<tr>
<td>15</td>
<td>2020</td>
<td>20</td>
<td>40</td>
<td>0.01</td>
</tr>
<tr>
<td>16</td>
<td>420</td>
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<td>40</td>
<td>0.05</td>
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<td>20</td>
<td>40</td>
<td>0.33</td>
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<td>19</td>
<td>70</td>
<td>20</td>
<td>40</td>
<td>0.4</td>
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<tr>
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<td>20</td>
<td>40</td>
<td>0.5</td>
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<tr>
<td>21</td>
<td>50</td>
<td>20</td>
<td>40</td>
<td>0.67</td>
</tr>
<tr>
<td>22</td>
<td>2030</td>
<td>30</td>
<td>50</td>
<td>0.01</td>
</tr>
<tr>
<td>23</td>
<td>430</td>
<td>30</td>
<td>50</td>
<td>0.05</td>
</tr>
<tr>
<td>24</td>
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<td>0.2</td>
</tr>
<tr>
<td>25</td>
<td>91</td>
<td>30</td>
<td>50</td>
<td>0.33</td>
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<tr>
<td>26</td>
<td>80</td>
<td>30</td>
<td>50</td>
<td>0.4</td>
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<tr>
<td>27</td>
<td>70</td>
<td>30</td>
<td>50</td>
<td>0.5</td>
</tr>
<tr>
<td>28</td>
<td>60</td>
<td>30</td>
<td>50</td>
<td>0.67</td>
</tr>
<tr>
<td>29</td>
<td>2040</td>
<td>40</td>
<td>60</td>
<td>0.01</td>
</tr>
<tr>
<td>30</td>
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<td>40</td>
<td>60</td>
<td>0.05</td>
</tr>
<tr>
<td>31</td>
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<td>0.2</td>
</tr>
<tr>
<td>32</td>
<td>101</td>
<td>40</td>
<td>60</td>
<td>0.33</td>
</tr>
<tr>
<td>33</td>
<td>90</td>
<td>40</td>
<td>60</td>
<td>0.4</td>
</tr>
<tr>
<td>34</td>
<td>80</td>
<td>40</td>
<td>60</td>
<td>0.5</td>
</tr>
<tr>
<td>35</td>
<td>70</td>
<td>40</td>
<td>60</td>
<td>0.67</td>
</tr>
</tbody>
</table>
**Table II.** Table II.A provides the proportion of subjects who choose the risky lottery over the certain option in the Basic Risk Choice Sets in Experiment 1. Each row of the table corresponds to the expected value of the lottery (and of the certain option). Each column corresponds to the probability of the gain state. The shaded cells correspond to those trials where the gain state is salient, and the non-shaded cells correspond to those trials where the loss state is salient. Table II.B provides results from a regression where the dependent variable is a dummy that takes the value 1 if the subject chose the risky lottery, and EconSal is a dummy that takes on the value 1 if the gain state is salient. In columns (1), (2), and (3), standard errors are clustered at the subject level and shown in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

### Table II.A.

*Proportion of Risk Seeking Subjects*

<table>
<thead>
<tr>
<th>Expected value b</th>
<th>$60</th>
<th>$50</th>
<th>$40</th>
<th>$30</th>
<th>$20</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.55</td>
<td>0.47</td>
<td>0.43</td>
<td>0.48</td>
<td>0.31</td>
</tr>
<tr>
<td></td>
<td>0.53</td>
<td>0.51</td>
<td>0.53</td>
<td>0.44</td>
<td>0.32</td>
</tr>
<tr>
<td></td>
<td>0.54</td>
<td>0.49</td>
<td>0.49</td>
<td>0.48</td>
<td>0.29</td>
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<tr>
<td></td>
<td>0.60</td>
<td>0.51</td>
<td>0.41</td>
<td>0.49</td>
<td>0.20</td>
</tr>
<tr>
<td></td>
<td>0.49</td>
<td>0.46</td>
<td>0.45</td>
<td>0.32</td>
<td>0.27</td>
</tr>
<tr>
<td></td>
<td>0.55</td>
<td>0.45</td>
<td>0.39</td>
<td>0.40</td>
<td>0.10</td>
</tr>
<tr>
<td></td>
<td>0.40</td>
<td>0.32</td>
<td>0.39</td>
<td>0.32</td>
<td>0.12</td>
</tr>
</tbody>
</table>

### Table II.B.

<table>
<thead>
<tr>
<th>dependent variable: risky choice</th>
<th>(1) OLS</th>
<th>(2) OLS</th>
<th>(3) Logit</th>
<th>(4) Mixed Effects Logit</th>
</tr>
</thead>
<tbody>
<tr>
<td>EconSal</td>
<td>0.157***</td>
<td>0.157***</td>
<td>0.649***</td>
<td>0.773***</td>
</tr>
<tr>
<td></td>
<td>(0.028)</td>
<td>(0.028)</td>
<td>(0.113)</td>
<td>(0.174)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.341***</td>
<td>0.341***</td>
<td>-0.661***</td>
<td>-0.784***</td>
</tr>
<tr>
<td></td>
<td>(0.020)</td>
<td>(0.013)</td>
<td>(0.090)</td>
<td>(0.111)</td>
</tr>
<tr>
<td>Observations</td>
<td>3,467</td>
<td>3,467</td>
<td>3,467</td>
<td>3,467</td>
</tr>
<tr>
<td>Subject Fixed Effects</td>
<td></td>
<td></td>
<td>x</td>
<td></td>
</tr>
<tr>
<td>(Pseudo) R²</td>
<td>0.025</td>
<td>0.032</td>
<td>0.019</td>
<td></td>
</tr>
</tbody>
</table>
Table III. Regression results from the Allais Choice Sets in Experiment 1. Each column provides results from a regression where the dependent variable is a dummy that takes the value 1 if the subject exhibits the Allais paradox. Uncorrelated is a dummy that takes on the value 1 if the lotteries are uncorrelated and Perfect Correlation is a dummy that takes on the value 1 if the lotteries are perfectly correlated. The omitted experimental condition is the imperfect correlation condition. In columns (1), (2), and (3), standard errors are clustered at the subject level and shown in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

<table>
<thead>
<tr>
<th>dependent variable: Allais paradox</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OLS</td>
<td>OLS</td>
<td>Logit</td>
<td>Mixed Effects Logit</td>
</tr>
<tr>
<td>Uncorrelated</td>
<td>0.13**</td>
<td>0.13**</td>
<td>0.535**</td>
<td>0.591*</td>
</tr>
<tr>
<td></td>
<td>(0.065)</td>
<td>(0.065)</td>
<td>(0.269)</td>
<td>(0.174)</td>
</tr>
<tr>
<td>Perfect Correlation</td>
<td>-0.21***</td>
<td>-0.21***</td>
<td>-1.159***</td>
<td>-3.182*</td>
</tr>
<tr>
<td></td>
<td>(0.061)</td>
<td>(0.061)</td>
<td>(0.355)</td>
<td>(1.915)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.36***</td>
<td>0.36***</td>
<td>-0.575***</td>
<td>-0.636***</td>
</tr>
<tr>
<td></td>
<td>(0.048)</td>
<td>(0.036)</td>
<td>(0.209)</td>
<td>(0.239)</td>
</tr>
<tr>
<td>Observations</td>
<td>300</td>
<td>300</td>
<td>300</td>
<td>300</td>
</tr>
<tr>
<td>Subject Fixed Effects</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>(Pseudo) R²</td>
<td>0.088</td>
<td>0.132</td>
<td>0.074</td>
<td></td>
</tr>
</tbody>
</table>
**Table IV.** The table provides regressions where the dependent variable is a dummy that equals 1 if the subject chose the risky lottery in Experiment 2. EconSal is a dummy that takes on the value 1 if the gain state is economically salient, GainTreat is a dummy that takes on the value 1 if the gain state is visually salient, and LossTreat is a dummy that takes on the value 1 if the loss state is visually salient. In the OLS regressions, standard errors are clustered at the subject level. The mixed effects logit regressions contain a random intercept and random slopes on all explanatory variables. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

<table>
<thead>
<tr>
<th>dependent variable: risky choice</th>
<th>Full Sample</th>
<th>Gain State Economically Salient</th>
<th>Loss State Economically Salient</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) OLS</td>
<td>(2) OLS</td>
<td>(3) Mixed Effects Logit</td>
</tr>
<tr>
<td>EconSal</td>
<td>0.166***</td>
<td>0.166***</td>
<td>0.781***</td>
</tr>
<tr>
<td></td>
<td>(0.017)</td>
<td>(0.016)</td>
<td>(0.102)</td>
</tr>
<tr>
<td>GainTreat</td>
<td>-0.007</td>
<td>-0.005</td>
<td>-0.041</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.011)</td>
<td>(0.062)</td>
</tr>
<tr>
<td>LossTreat</td>
<td>-0.023*</td>
<td>-0.022**</td>
<td>-0.160***</td>
</tr>
<tr>
<td></td>
<td>(0.012)</td>
<td>(0.011)</td>
<td>(0.063)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.309***</td>
<td>0.308***</td>
<td>-1.028***</td>
</tr>
<tr>
<td></td>
<td>(0.015)</td>
<td>(0.010)</td>
<td>(0.086)</td>
</tr>
<tr>
<td>Observations</td>
<td>10,202</td>
<td>10,202</td>
<td>10,202</td>
</tr>
<tr>
<td>Subject Fixed Effects</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.030</td>
<td>0.038</td>
<td>0.001</td>
</tr>
</tbody>
</table>
FIGURE I: Sample Choice Trial from the Basic Risk Choice Sets in Experiment 1. Each state of the world is characterized by a color in the pie chart. The size of each “slice” of the pie chart corresponds to the probability of the state, which is summarized in the top left corner of the screen.
FIGURE II: Allais Choice Sets from Experiment 1. Each of the four choice sets is presented to subjects in pie chart form. For each pie chart, the colors denote the different states and letters denote the different lotteries. The size of each “slice” of the pie chart corresponds to the probability of the state, which is summarized on the top left corner of each screen. Panel A: the choice set when \( z=0 \) and lotteries are perfectly correlated. Panel B: the choice set when \( z=0 \) and lotteries are imperfectly correlated. Panel C: the choice set when \( z=0 \) and lotteries are uncorrelated. Panel D: the choice set when \( z=24 \) (for any correlation structure). Colors are randomized at the subject-trial level.
FIGURE III: Theoretical Decision Values for Allais Choice Sets as a Function of Correlation Structure. Each panel displays the decision value of choosing lottery $A_1(z)$ as a function of $\delta$ and the common consequence, $z$. Panel A displays the decision value curves when the lotteries are uncorrelated. Panel B displays the decision value curves when the lotteries are imperfectly correlated. Panel C displays the decision value curve when the lotteries are perfectly correlated. In Panel C, there is only one curve because the decision value is independent of the common consequence when the lotteries are perfectly correlated.
FIGURE IV: Proportion of Subjects who Choose the Risky Lottery in the Basic Risk Choice Sets part of Experiment 1. Each cell corresponds to a single trial.
FIGURE V: Context-Dependent Probability Weighting Function. Panel A generates the weighting function using $\delta = 0.2$ while Panel B is generated using $\delta = 0.6$. The black dashed line is the 45-degree line. Each different colored line is the probability weighting function conditional on the average payoff level in the Basic Risk Choice Sets. The probability weights are generated using the salience function, $\sigma(x^L, x^R) = \frac{|x^L - x^R|}{0.1 + |x^L| + |x^R|}$, and the two properties that characterize choice sets in the Basic Risk Choice Sets: 1) the choice set contains a risky lottery with a two-outcome support and a mean-preserving certain option and 2) the downside of the risky lottery is fixed at $(b-20)$, where $b$ denotes the payoff of the certain option.
FIGURE VI: Results from the Allais Choice Sets. Figure displays the percentage of subjects who exhibit the Allais paradox for each of the three different correlation structures.
FIGURE VII: Example Trial from Experiment 2. The figure displays the choice set in each of the three experimental conditions in Experiment 2. Panel A shows the choice set in the control condition. Panel B shows the choice in the Gain treatment, where the visual transparency of the loss state is increased relative to the control condition. Panel C shows the choice set in the Loss treatment, where the visual transparency of the gain state is increased relative to the control condition.
1. Computing Decision Weights

1.1 Solving for decision weights with $N$ states

In this section we compute the decision weights used in the Allais Choice Sets part of Experiment 1. Recall that for any two states $s$ and $\bar{s}$, with $\Pr(s) = p_s$ and $\Pr(\bar{s}) = p_{\bar{s}}$ the subject distorts the odds ratio $\frac{p_s}{p_{\bar{s}}}$ to $\frac{\omega_s}{\omega_{\bar{s}}}$, using the following distortion equation:

$$\frac{\omega_s}{\omega_{\bar{s}}} = \frac{\delta[\sigma(x_1^s, x_2^s)]}{\delta[\sigma(x_1^{\bar{s}}, x_2^{\bar{s}})]} \times \frac{p_s}{p_{\bar{s}}} \quad (E1)$$

We then normalize the distorted probabilities into unique decision weights by imposing:

$$\sum_s \omega_s = 1 \quad (E2)$$

With $N$ states, the decision weights can be solved with an $N \times N$ system of equations given by:

$$\omega_1 = \frac{\delta[\sigma(x_1^{A_1}, x_2^{A_2})]}{\delta[\sigma(x_1^{A_1}, x_1^{A_2})]} \times \frac{p_1}{p_2} \times \omega_2$$

$$\omega_1 = \frac{\delta[\sigma(x_3^{A_1}, x_2^{A_2})]}{\delta[\sigma(x_1^{A_1}, x_1^{A_2})]} \times \frac{p_1}{p_3} \times \omega_3$$

$$\vdots$$

$$\omega_1 = \frac{\delta[\sigma(x_N^{A_1}, x_2^{A_2})]}{\delta[\sigma(x_1^{A_1}, x_1^{A_2})]} \times \frac{p_1}{p_N} \times \omega_N$$

$$\sum_s \omega_s = 1$$
1.2 Solving for decision weights when lotteries are uncorrelated:

Here we solve for the decision weights in the case when lotteries $A_1(0)$ and $A_2(0)$ are uncorrelated and $z=0$. Under this correlation structure, there are four states with the following objective probability distribution:

$$(p_1, p_2, p_3, p_4) = (0.1122, 0.2278, 0.2178, 0.4422).$$

The joint payoff distribution of $A_1(0)$ and $A_2(0)$ is given by $((25, 24), 0.1122; (0, 24), 0.2278; (25, 0), 0.2178; (0, 0), 0.4422)$. To compute the decision weights, we solve the system given by:

$$\omega_1 = \frac{\delta_{24,1}}{\delta_{49,1}} \times \frac{0.1122}{0.2278} \times \omega_2$$

$$\omega_1 = \frac{\delta_{25,1}}{\delta_{49,1}} \times \frac{0.1122}{0.2178} \times \omega_3$$

$$\omega_1 = \frac{\delta^0_{1}}{\delta_{49,1}} \times \frac{0.1122}{0.4422} \times \omega_4$$

$$1 = \omega_1 + \omega_2 + \omega_3 + \omega_4$$

Note that the unknowns, $(\omega_1, \omega_2, \omega_3, \omega_4)$ are a function of the parameter $\delta$, and thus in figure A.1 we display the solution to this equation by plotting the decision weights against $\delta$. When $\delta = 1$, there is no distortion of probabilities, and the decision weights coincide with objective probabilities, such that:

$$(\omega_1, \omega_2, \omega_3, \omega_4) = (0.1122, 0.2278, 0.2178, 0.4422).$$
1.3 Solving for decision weights when lotteries are imperfectly correlated:

When lotteries $A_1 (0)$ and $A_2 (0)$ are imperfectly correlated, there are four states of the world with objective probability distribution:

$$(p_1, p_2, p_3, p_4) = (0.02, 0.65, 0.01, 0.32).$$

The joint payoff distribution of $A_1 (0)$ and $A_2 (0)$ is given by ((0, 24), 0.02; (0, 0), 0.65; (25, 0), 0.01; (25, 24), 0.32). To compute the decision weights, we solve the system given by:

$$
\omega_1 = \frac{\delta^{0\cdot0}}{\delta^{24.1}} \times \frac{0.02}{0.65} \times \omega_2
$$

$$
\omega_1 = \frac{\delta^{25.1}}{\delta^{24.1}} \times \frac{0.02}{0.01} \times \omega_3
$$

$$
\omega_1 = \frac{\delta^{49.1}}{\delta^{24.1}} \times \frac{0.02}{0.32} \times \omega_4
$$

$$
1 = \omega_1 + \omega_2 + \omega_3 + \omega_4
$$
Again, the decision weights \((\omega_1, \omega_2, \omega_3, \omega_4)\) are a function of the parameter \(\delta\), and thus in Figure A.2 we display the solution to this equation by plotting the decision weights against \(\delta\). When \(\delta = 1\), there is no distortion of probabilities, and the decision weights coincide with objective probabilities, such that:

\[
(\omega_1, \omega_2, \omega_3, \omega_4) = (0.02, 0.65, 0.01, 0.32).
\]

![Figure A.2 Decision weights when lotteries are imperfectly correlated.](image)

1.4 Solving for decision weights when lotteries are perfectly correlated:

When lotteries \(A_1(0)\) and \(A_2(0)\) are perfectly correlated, there are only three states of the world with objective probability distribution, \((p_1, p_2, p_3) = (0.01, 0.66, 0.33)\). The joint payoff distribution of \(A_1(0)\) and \(A_2(0)\) is given by \((0, 24), (0, 0), (0.01, 0.66), (25, 0), (0.33)\). To compute the decision weights, we solve the system given by:
\[
\omega_1 = \frac{\delta^{0.1} 24}{24} \times 0.01 \times 0.66 \times \omega_2 \\
\omega_1 = \frac{\delta^{0.1} 24}{24} \times 0.01 \times 0.33 \times \omega_3 \\
1 = \omega_1 + \omega_2 + \omega_3
\]

The decision weights \((\omega_1, \omega_2, \omega_3)\) are a function of the parameter \(\delta\), and in Figure A.3 we display the solution to this equation by plotting the decision weights against \(\delta\). When \(\delta = 1\), there is no distortion of probabilities, and the decision weights coincide with objective probabilities, such that \((\omega_1, \omega_2, \omega_3) = (0.01, 0.66, 0.33)\).

**Figure A.3** Decision weights when lotteries are perfectly correlated.

1.5 Solving for decision weights when \(z=24\):

When \(z=24\), the two lotteries \(A_1(24)\) and \(A_2(24)\) induce a state space with three states and objective probability distribution, \((p_1, p_2, p_3) = (0.01, 0.66, 0.33)\). The joint payoff distribution of \(A_1(24)\) and \(A_2(24)\) is given by \(((0, 24), 0.01; (24, 24), 0.66; (25, 0),\)
0.33). Note that the only difference between this joint payoff distribution and that of the case when \( z=0 \) and lotteries are perfectly correlated, are the payoffs in State 2. However, the two choice sets induce the same system of equations used to compute decision weights:

\[
\omega_1 = \frac{\delta_{6.1}}{\delta_{24.1}} \times \frac{0.01}{0.66} \times \omega_2
\]

\[
\omega_1 = \frac{\delta_{25.1}}{\delta_{24.1}} \times \frac{0.01}{0.33} \times \omega_3
\]

\[1 = \omega_1 + \omega_2 + \omega_3\]

Therefore, for all \( \delta \in (0,1] \), the decision weights \((\omega_1, \omega_2, \omega_3)\) are identical to those shown in Figure A.3.

2. Comparing risk-taking in the incentivized laboratory experiment to risk-taking on mTurk

In this section we compare the behavior of subjects in the laboratory (Experiment 1) to the behavior of subjects on mTurk (Experiment 2). Specifically, we compare risk taking among the Basic Risk Choice Sets in Experiment 1 to risk taking in the control condition in Experiment 2. We find that there is no major qualitative difference in overall risk taking levels: subjects choose the risky lottery on 41.1\% of trials in the laboratory compared to 38.7\% on mTurk.

We then formally compare, across the two samples, the degree to which subjects rely on economic salience when making their decisions. Table A.1 provides evidence that there is no systematic difference in the sensitivity to economic salience across those subjects who face the Basic Risk Choice Sets in the laboratory, compared to those subjects who face the same choice sets on mTurk (in the control condition). In Table A.1, Mturk is a dummy that takes on the value 1 if the subject is from Mturk. We see that neither the coefficient on Mturk, nor the coefficient on the interaction between Mturk and EconSal is significantly different from zero. While this analysis does not rule out the possibility that incentives can affect the visual salience treatment, the fact that economic salience has a much larger effect on risk taking compared to visual salience (Table IV) provides us with confidence that overall risk taking levels are unlikely to exhibit a major qualitative shift if incentives were shifted.
Table A.1: Comparing risk taking results from the laboratory experiment and the mTurk experiment.

<table>
<thead>
<tr>
<th>dependent variable: risky choice</th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OLS</td>
<td>Logit</td>
</tr>
<tr>
<td>EconSal</td>
<td>0.157***</td>
<td>0.649***</td>
</tr>
<tr>
<td></td>
<td>(0.028)</td>
<td>(0.113)</td>
</tr>
<tr>
<td>Mturk</td>
<td>-0.036</td>
<td>-0.163</td>
</tr>
<tr>
<td></td>
<td>(0.026)</td>
<td>(0.116)</td>
</tr>
<tr>
<td>EconSal*Mturk</td>
<td>0.018</td>
<td>0.092</td>
</tr>
<tr>
<td></td>
<td>(0.035)</td>
<td>(0.142)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.341***</td>
<td>-0.661***</td>
</tr>
<tr>
<td></td>
<td>(0.020)</td>
<td>(0.090)</td>
</tr>
<tr>
<td>Observations</td>
<td>6,938</td>
<td>6,938</td>
</tr>
<tr>
<td>Subject Fixed Effects</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Pseudo) R²</td>
<td>0.029</td>
<td>0.022</td>
</tr>
</tbody>
</table>
3. Pre-registration documents for Experiment 1 and Experiment 2

CONFIDENTIAL - FOR PEER-REVIEW ONLY

Salience Experiments - August 2016 (#994)

Created: 08/16/2016 11:40 PM (PT)
Shared: 12/21/2016 08:32 PM (PT)

This pre-registration is not yet public. This anonymized copy (without author names) was created by the author(s) to use during peer-review. A non-anonymized version (containing author names) will become publicly available either when an author makes it public, or three years from the “Shared” date at the top of this document (whichever comes first). Until that time the contents of this pre-registration are confidential.

1) What’s the main question being asked or hypothesis being tested in this study?
Can salience theory better explain decision making under risk compared to expected utility theory or prospect theory?

2) Describe the key dependent variable(s) specifying how they will be measured.
There are 2 parts to the experiment. In the first part, subjects will be asked to answer an Allais paradox question in three separate conditions, for a total of four questions (there are 2 questions per condition, but 1 question is the same in all three conditions, and hence, is asked only once).

In the 2nd part of the experiment, subjects will be given 35 questions, which consist of a choice between a certain option and a mean-preserving spread. The dependent variable in all 39 questions (4 from part 1 + 35 from part 2) will consist of a binary variable which codes for choice between the two gambles.

3) How many and which conditions will participants be assigned to?
In the first part of the experiment, all subjects will be assigned to all three conditions. Hence, the first part is a within-subjects design. The three conditions are characterized by the correlation structure of the state space: 1) uncorrelated 2) imperfectly correlated and 3) perfectly correlated.

In the second part, all subjects complete the 35 gamble choices.

4) Specify exactly which analyses you will conduct to examine the main question/hypothesis.
In the first part of the experiment, we will compute for each subject, whether he/she exhibits the Allais paradox in each of the three conditions. The main analyses will be to test whether, within subjects, 1) the propensity to exhibit the Allais paradox increases from the perfectly correlated condition to the imperfectly correlated condition and 2) the propensity to exhibit the Allais paradox increases from the imperfectly correlated condition to the uncorrelated condition.

The state space for the uncorrelated condition (ζ=0) is given by: [(0,0), (25,24), (0,24), (25,0)] with associated probabilities (.4422,.1122,.2278,.2178).

The state space for the perfectly correlated condition (ζ=0) is given by: [(25,24), (0,24), (0,0)] with associated probabilities (.33,.01,.66).

The state space for the imperfectly correlated condition (ζ=0) is given by: [(0,0), (25,24), (0,24), (25,0)] with associated probabilities (.65,.32,.02,.01).

5) Any secondary analyses?
We will also estimate the structural parameters of the salience model using data from the 2nd part (the 35 gambles).

We will also test whether individual differences in the 1st and 2nd part of the task are correlated. Specifically, we will test whether individual differences in the degree to which the state space modulates the Allais paradox, correlates with the propensity to choose the risky option when the gain state is salient.

6) How many observations will be collected or what will determine sample size? No need to justify decision, but be precise about exactly how the number will be determined.
We will collect N=100 subjects.

7) Anything else you would like to pre-register? (e.g., data exclusions, variables collected for exploratory purposes, unusual analyses planned?)
1) Gender
2) Education level
3) Age
4) College major
5) # of stats courses taken

8) Have any data been collected for this study already?
No, no data have been collected for this study yet

Verify authenticity: http://aspredicted.org/blind.php/?x=d2da62
1) What's the main question being asked or hypothesis being tested in this study?
Does visual salience bias economic risk-taking? In particular, does it bias risk-taking as a function of which state is made visually salient?

2) Describe the key dependent variable(s) specifying how they will be measured.
Subjects will be asked to choose between a certain option and a mean-preserving spread in 35 trials. The dependent variable is a binary variable which codes whether the subject took the risky option or not.

3) How many and which conditions will participants be assigned to?
There are 3 conditions, and the experiment will use a within-subjects design.

1) Control condition
2) Gain Treatment
3) Loss Treatment

In the control condition, each of the two states is equally visually salient (blue and orange colors are counterbalanced).

In the Gain treatment condition, the Gain state will be made visually salient (again, blue and orange “background” colors will be counterbalanced).

In the Loss treatment condition, the Loss state will be made visually salient (again, blue and orange “background” colors will be counterbalanced).

4) Specify exactly which analyses you will conduct to examine the main question/hypothesis.
We will test whether risk taking is greater in the gain treatment condition compared to the control condition.

We will test whether risk taking is smaller in the loss treatment condition compared to the control condition.

5) Any secondary analyses?
We will estimate the parameters of a “full salience” model, which extends the Bordalo, Gennaioli, Shleifer (2012) model to include visual salience.

6) How many observations will be collected or what will determine sample size? No need to justify decision, but be precise about exactly how the number will be determined.
N=300 subjects will be collected on Amazon MTurk.

7) Anything else you would like to pre-register? (e.g., data exclusions, variables collected for exploratory purposes, unusual analyses planned?)
No

8) Have any data been collected for this study already?
No, no data have been collected for this study yet

Verify authenticity: http://aspredicted.org/blind.php/?x=ex43nx
4. Experimental Instructions

4.1 Experimental Instructions and Practice Problem for Experiment 1

Thank you for agreeing to take part in this experiment on decision-making. For your participation, you will receive $6. In addition, you will have the opportunity to earn more money throughout the experiment.

The experiment will be split into two parts, Part 1 will have 4 questions, and Part 2 will have 35 questions.

For each question in the experiment, you will be presented with two gamble options, and you'll be asked to choose one of them. Your payment at the end of the experiment will depend on your decisions.

At the end of the experiment, one of the questions will be randomly selected and you will be paid according to your choice and the outcome of the randomly selected gamble.

The chance that each question in Part 1 will be selected to be paid is 23%. The chance that each question in Part 2 will be selected to be paid is 0.23%. Because any question in the experiment can randomly be selected to be paid, it is important to answer each question carefully. Before you begin, you will go through a practice problem to make sure you understand the instructions.

To continue, please click the button labeled ">>".
PRACTICE QUESTION

The following is a practice problem to make sure you understand the setup. This will not count for real money.

Please choose between the two options L and M described in the wheel shown below. One of the colors on the wheel will be randomly selected. The chance that each color is selected is given by:

Blue: 22%
Orange: 11%
Green: 67%

The amount of money you win depends on two things: 1) which option you choose and 2) which color of the wheel is randomly selected. For example, if the color blue is randomly selected and you chose option L, you would win $18, but if you chose option M, you would win $0.

Please choose your answer by clicking on one of the options below and then hit the ">>" button.

OPTION L

OPTION M
4.2 Experimental Instructions and Practice Problem for Experiment 2

Thank you for agreeing to take part in this survey on decision-making. There are 35 questions in this survey.

In each question, you will be presented with two gamble options, and you'll be asked which one you would choose. Please answer the questions as if you were playing the gambles for real money.

To continue, please click the button labeled ">>".
Before we begin, here is an example of the type of problem you will see.

Which of the following two gambles would you choose? The amount you win depends on which gamble you choose, and which of the two colors is randomly selected by the computer. The chance that each color is selected is given by the numbers above the pie chart. In this example, there is a 40% chance the blue color is selected, and a 60% chance the orange color is selected. Please select either Option D or Option G.

Blue: 40%  Orange: 60%

D: $30  G: $50  D: $80  G: $50