Contingent Reasoning in Risky Choice*

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Abstract

Decisions under risk that stem from shared rather than mutually independent sources are ubiquitous in financial decision-making. In insurance choice, plans on the menu present positively correlated lotteries. This paper experimentally induces contingent reasoning in choice under risk. Using prize wheels to illustrate the correlation between lotteries, I vary whether subjects sequentially learn the outcomes of states or individual lotteries. Eye-tracking data reveal that experimental treatments altered evaluation procedures. I find causal evidence that statewise comparisons prompt more risk-averse choices. Implications are significant since insurance policy designers can extract surplus from consumers by emphasizing trade-offs between premiums and deductibles.

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1 Introduction

Purchasing insurance is a cornerstone of economic rationality for risk-averse individuals seeking to hedge their risks. Field and experimental evidence, however, suggest that people may commonly and excessively overinsure against potential losses (Cutler & Zeckhauser, 2004; Kunreuther & Pauly, 2006). Notably, individuals tend to overpay for insurance against low-probability risks, such as appliance failures or aviation indidents. Further, individuals prefer insurance plans with low deductibles even when the additional cost of insuring small losses is very high (Johnson, Hershey, Meszaros, & Kunreuther, 1993; Sydnor, 2010). Some possible explanations for overinsuring have been attributed to the portrayal of specific or tangible risks as opposed to when risks remain unmentioned (Gennaioli & Shleifer, 2010; Johnson et al., 1993), menu effects for when people are unsure of their preferences (Kamenica, 2008), and subjectively high claim rates, or rather, overweighting of small probabilities of the claim rates (Tversky & Kahneman, 1992). This paper examines another possible factor, namely information acquisition procedures in the evaluation of insurance plans. As I will show using eye-tracking techniques, I exogenously direct subjects' attention to the state space in correlated risky choice to study the effects of different heuristics that inherently induce or limit contingent reasoning. The results of the experiment suggest that subjects become more risk-averse when evaluating lotteries statewise compared to when they assess them holistically. Implications are significant since insurance policy designers can extract surplus from consumers by emphasizing trade-offs between premiums and deductibles.

Choice processes in the evaluation of different insurance plans may be shaped by the formulation of the decision problem, which is a channel that has posited significant concern for theories of choice (Thaler & Sunstein, 2021; Tversky & Kahneman, 1988). To give some intuition to this discussion, consider a traveler who is booking a flight ticket and is faced with a decision on whether to purchase flight insurance at check-out. Such insurance tends to cover a host of adverse events, some of which may include compensation for delayed flights, hotel expenses for overnight stays and damaged or lost personal items. In deliberating whether to purchase flight insurance, a traveler may either evaluate the two options independently or recognize the underlying (positive) correlation between them and assess trade-offs across contingent states – namely, the payoffs under loss and no-loss. From an ex-post perspective, a traveler prefers to have purchased insurance only if loss occurs. The extent to which a traveler engages these evaluation methods in decision-making is endogenous though choice-processes are likely influenced by the presentation or formulation of the

possibility to purchase flight insurance. In this paper, I make use of an exogenous manipulation in lottery display that varies whether subjects sequentially learn the outcomes of states or individual lotteries, allowing me to study the impact of contingent reasoning on decisions under risk. Patterns from eye-tracking data show experimental treatments generated strong variation in the way alternative lotteries are contrasted against one another. Notably, contingent reasoning modulates gaze allocation by drawing attention to states in which safe lotteries are preferred thus prompting more risk-averse choices.

When lotteries are correlated, the salience theory of choice under risk (Bordalo, Gennaioli, & Shleifer, 2012) or regret theory (Loomes & Sugden, 1987) construct the state space based on the arisal of payoffs in different contingencies. Crucially, these theories make an implicit assumption that agents attend to the underlying correlation though it is largely unobservable how this information is processed. For instance, in an experimental investigation of correlation-sensitive theories using choice reversals (Castillo & Vitaku, 2023), preference reversals become pronounced when the correlation is made more apparent. Related, augmenting an experimental test of salience theory with eye-tracking techniques, Alós-Ferrer and Ritschel (2022) examine how subjects process decisions by presenting lotteries in a 2×2 quadrant.[1] In such settings, people might follow different heuristics that predict specific transition patterns between outcomes. For example, the lexicographic heuristic prescribes attention towards first determining the most likely outcome of each lottery and choosing the option with the better outcome. If both outcomes are equal, it suggests determining the second most likely outcome of each lottery and choosing the option with the better (second most likely) outcome, and the heuristic proceeds in this manner until a decision is reached. The maximax heuristic prescribes a simple rule of choosing the lottery with the highest outcome while the minimax prescribes choosing the lottery with the highest minimum outcome (see Fiedler and Glöckner (2012) for a summary of alternative attention heuristics).[2] Studying the effects of

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[1]Their findings suggest the number of transitions between outcomes corresponding to different states does not coincide with payoff saliency. Less salient states receive more attention than more salient states highlighting a puzzling pattern that people may be more attentive to payoffs in contingencies that are harder to differentiate than those whose outcomes are easily discernible. This pattern is also found by Frydman and Mormann (2018) who show that subjects do not pay more attention to the state that is theoretically the most salient. These results, however, are in line with evidence from psychology and neuroscience showing that more similar stimuli are harder to differentiate and require more attention (Dashiell, 1937; Moyer & Landauer, 1967).

[2]In the same vein, analyzing subjects' eye-movements while playing a series of two-person, simultaneous one-shot games in normal form, Devetag, Di Guida, and Polonio (2016) find subjects use simple decision rules such as "choose the strategy with the highest average payoff" or "choose the strategy leading to an attractive and symmetric outcome" without (optimally) incorporating knowledge on the opponent's behavior. Later on, using similar games, Zonca, Coricelli, and Polonio (2019) showed that after less sophisticated players are exposed to decision rules that highlighted others' incentives, equilibrium response rates increased thus showing that subjects can improve their level of strategic thinking with training.

such heuristics on risky choice is problematic since these data suffer from selection bias as subjects endogenously decide how to allocate their gaze. One possibility is to dynamically display features of the decision environment so as to prod a decision-maker toward a particular decision rule.[3] To this end, I exogenously direct subjects' attention to the state space of correlated lotteries, thereby enabling causal identification of the effect of contingent reasoning on decisions under risk.

In other related work, Arieli, Ben-Ami, and Rubinstein (2011) present subjects with binary choice lotteries in tabular format and track choice procedures using eye-tracking technology. In their setting, each lottery offers a prize with a given probability. They find choice procedures are affected by the difficulty of expectation calculations suggesting decision-makers are more likely to compare probability and payoff attributes separately as opposed to evaluating lotteries holistically when calculations are difficult. Indeed, a substantial body of research suggests individuals often rely on simple decision rules to streamline intricate calculations (Gigerenzer & Gaissmaier, 2011; Gigerenzer & Goldstein, 1996; Simon, 1978).

More broadly, correlation is ubiquitous in financial decision-making extending well beyond insurance plan choice. Understanding the myriad of asset return correlations is essential in modern portfolio theory for a risk-averse investor aiming to minimize variance for a given expected return (Markowitz, 1952). Related, understanding the structure of correlations can help exploit arbitrage opportunities,[4] or avoid dominated choices in instances where an asset is dominated by a continuum of allocations in other negatively correlated assets (Eyster & Weizsacker, 2016).

The rest of the paper proceeds as follows: the next section summarizes the nature of a common insurance decision problem, section 3 outlines the experimental design, section 4 describes a simple choice-process model and derives predictions, section 5 presents results from the experiment and section 6 concludes.

2   Insurance Decision Problem

In this section, I summarize a typical insurance decision problem for an agent who is faced with a choice between different insurance premium plans that offer varying deductibles and no co-insurance. Such plans are commonly found in different types of insurance including automobile, home or weather insurance. For example, it may be mandatory for one to purchase at least a basic

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[3]Further, it is possible to examine the effect of visual fixations on choices by exogenously manipulating the visual saliency of the decision environment through color saturation or hue.

[4]Consider the trivial case of two foreign currency exchange kiosks offering different exchange rates for the same pair of currencies.

insurance policy if leasing or renting a vehicle. A renter's insurance may be legally required by a landlord prior to move in. A farmer may seek to purchase weather index insurance to protect against potential losses due to extreme weather. In these circumstances a minimum insurance premium policy is typically offered alongside other plans. These plans present lower deductibles in the event of a loss or accident at the expense of paying a higher premium. Mathematically, a choice problem with n such plans can be expressed as follows:

- $Plan_1$: $(w - c_1, \, 1 - p; \, w - c_1 - d_1, \, p)$

- $Plan_2$: $(w - c_2, \, 1 - p; \, w - c_2 - d_2, \, p)$

  $\ldots$

- $Plan_n$: $(w - c_n, \, 1 - p; \, w - c_n - d_n, \, p)$

where w represents wealth, loss occurs with probability p, and $c_i > 0$ and $d_i > 0$ denote the cost of premium and deductible for plan i, respectively. Assuming $Plan_1$ offers minimum coverage, the policies are offered such that $c_1 < c_2 < \cdots < c_n$ and $d_n < d_{n-1} < \cdots < d_1$. In what follows, I will describe trade-offs between any two adjacent plans i and $i + 1$ for $1 \leq i \leq n - 1$. For two such plans, $c_i < c_{i+1}$ and $d_{i+1} < d_i$. Also, $c_{i+1} + d_{i+1} < c_i + d_i$ for otherwise plan $i + 1$ is first-order stochastically dominated. Higher premium policies are offered by emphasizing significant savings on deductibles in the event of a loss at a relatively small cost of a higher premium: i.e., $c_{i+1} - c_i < d_i - d_{i+1}$. Comparing the four outcomes, it must be that $c_i < c_{i+1} < c_{i+1} + d_{i+1} < c_i + d_i$. Note, plan $i + 1$ has a lower variance than plan i for any $p \in (0, 1)$; this can be observed by the fact that $[c_{i+1}, c_{i+1} + d_{i+1}]$ is a subset of $[c_i, c_i + d_i]$. It must also be true that the expected value of plan $i + 1$ is lower than the expected value of plan i for otherwise it would not be profitable for an insurance policymaker to offer plan $i + 1$. Hence, plan $i + 1$ offers a lower expected value, lower variance option compared to plan i. A risk-neutral expected utility maximizer prefers plan i and a sufficiently risk-averse agent prefers plan $i + 1$. There are a couple of noteworthy observations:

i) a risk-neutral (or risk-seeking) agent prefers minimum coverage (i.e., $Plan_1$), and

ii) more risk-averse agents prefer higher coverage (i.e., more expensive plans).

Given these implications and how plans differ in profitability for an insurance policymaker, profits are increasing as policyholders become more risk-averse.

2.1 Contingent Reasoning

As discussed in section 1, it is largely unobservable how a decision-maker may choose between different insurance plans. Plans on the menu present positively correlated lotteries as illustrated in section 2. Importantly, the choice process is endogenous as to whether an agent evaluates options independently or assesses trade-offs across contingent states. As I will show in the next section, I exogenously direct subjects' attention to the state space of correlated lotteries to test the effect of contingent reasoning on choice under risk.

3 Experimental Design

In this section, I summarize the implementation of the experiment. First, I describe the one-shot risky choice problem that was selected from a list. Then I describe treatments that intend to induce or limit contingent reasoning. The experiment was computerized using o-Tree (Chen, Schonger, & Wickens, 2016). Subjects underwent a 9-point eye-tracking calibration routine before the experiment began that was repeated up to three times until the gaze calibration result printed an 'excellent' score.[5] A total of 303 undergraduate students participated in the experiment.[6] A session lasted, on average, about 15 minutes including calibration time. Experimental earnings were converted at a rate of 1 Experimental Dollar = $0.50. Average earnings were $16.29 (sd=3.134) which includes a $10 participation fee.

3.1 Choice Problems

Subjects were presented with one incentivized binary choice problem that determined their earnings. I opted to elicit risk preferences from a single choice problem to make the decision salient.[7] Subjects initially underwent two practice, unincentivized choice problems presented in a random order which were meant to illustrate how earnings are determined. Then, each subject faced *only one* of the

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[5]A 24″ screen showed the stimuli with a resolution of 1920×1080 pixels. Subjects' eye-movements were recorded using either Tobii Pro Fusion or Tobii Pro Spectrum, which were embedded on the computer screens. Eye-tracking data were recorded using iMotions software which determines the quality of gaze calibration based on a score (out of 100) that depends on accuracy (mean gaze offset) and precision (standard deviation of samples). A high score corresponds with minimal gaze offsets and near perfect precision. An 'excellent' gaze calibration result requires a score that is above 80. Eye-tracking data were collected at a sampling rate of 120 Hz (i.e., 120 observations per second).

[6]Sample size was chosen without an a priori power analysis and based on budget constraints.

[7]Even if choices are not resolved so as to eliminate income effects, subjects might still fail to consider choice problems in isolation when one of many decisions is randomly chosen and resolved for payment at the end of the experiment. Nonetheless, accounting for order effects can address this issue.

two choice problems presented in Table 1 which was used to determine one's earnings from the experiment.[8]

Panel A shows a positively correlated problem which resembles a choice between different insurance premium plans as illustrated in section 2 where the unlikely state pays out lower earnings. (*Favorable Odds.*) Lottery S has a lower expected value and a lower variance than Lottery R. A sufficiently risk-averse agent prefers Lottery S, and a risk-neutral or risk-seeking agent prefers Lottery R. In Panel B, Lottery R is a mean-preserving spread of Lottery S which pays $8 with certainty. (*Equal Odds.*) While a risk-neutral agent is indifferent between the two lotteries, a risk-averse agent prefers Lottery S and a risk-seeking agent prefers Lottery R.

Table 1: BINARY CHOICE PROBLEMS

A. *Favorable Odds*

State	Probability	Lottery S	Lottery R
1	0.1	$8	$0
2	0.9	$16	$20

B. *Equal Odds*

State	Probability	Lottery S	Lottery R
1	0.5	$8	$0
2	0.5	$8	$16

3.2 Treatments

Upon arriving at the lab and signing a consent form, subjects were randomly seated in front of a computer equipped with eye-tracking technology. At the beginning of a session, each subject was randomly assigned to one of two treatments using a block design: *Sequential Lotteries* or *Sequential States*. I presented lotteries on spinning wheels since sectors of a circle provide a straightforward illustration for describing states. I implemented correlation of outcomes by making separate wheels spin at the same rate and stop at the same angle (see Figures 1 and 2).[9] *Sequential Lotteries* aims to limit contingent reasoning during evaluation by presenting each lottery individually for 7 seconds before subjects make a choice. *Sequential States* aims to induce contingent reasoning by presenting each state individually for 7 seconds before subjects make a choice.

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[8]Practice choices can be found in the Appendix.

[9]Recall, subjects first underwent two practice choices to understand lotteries are correlated. A similar sequence of images followed for the *Equal Odds* problem before subjects chose one of the two lotteries. A video animation of the treatments is available upon request. Lottery presentations of other problems can be found in the Appendix.
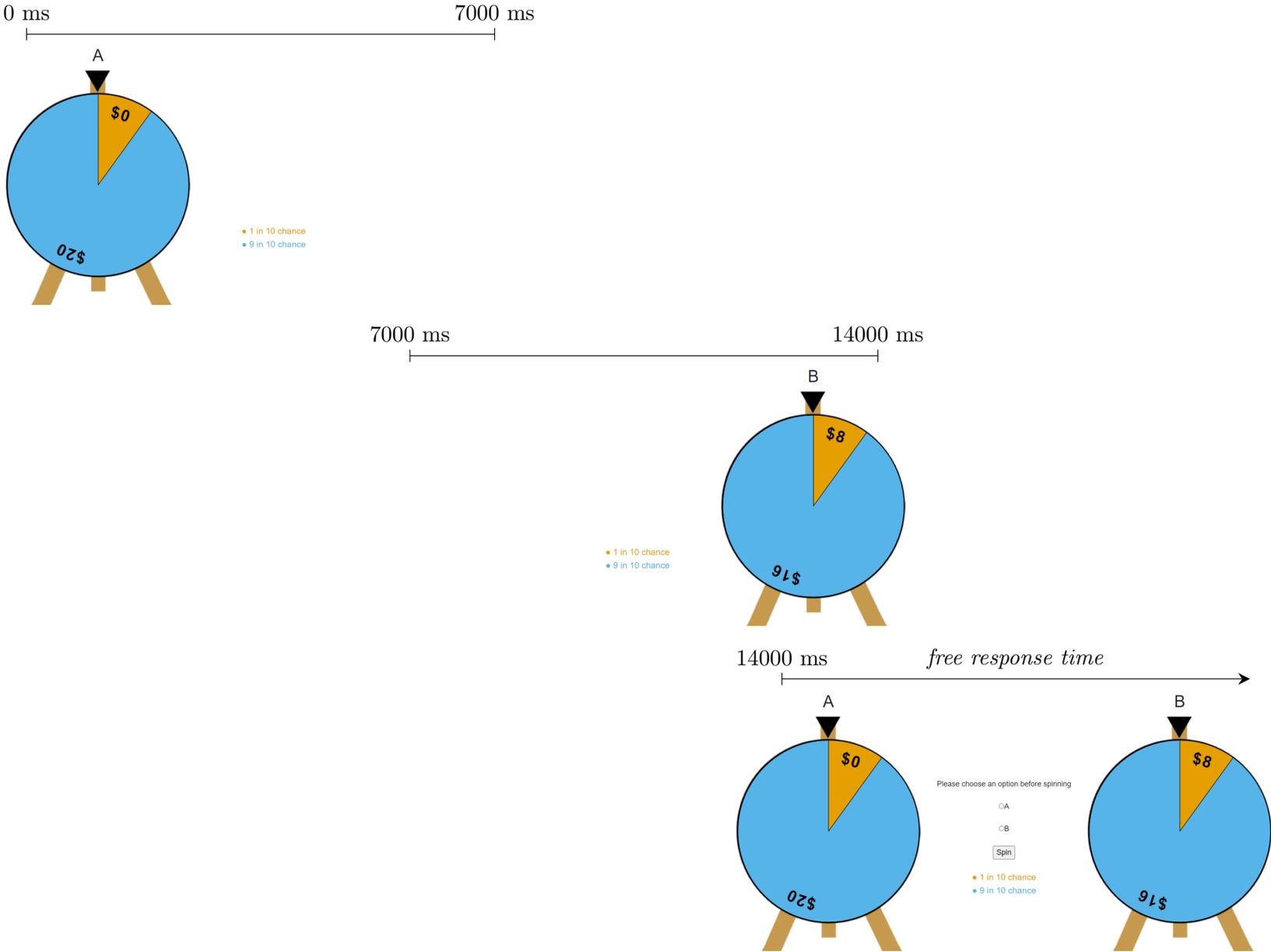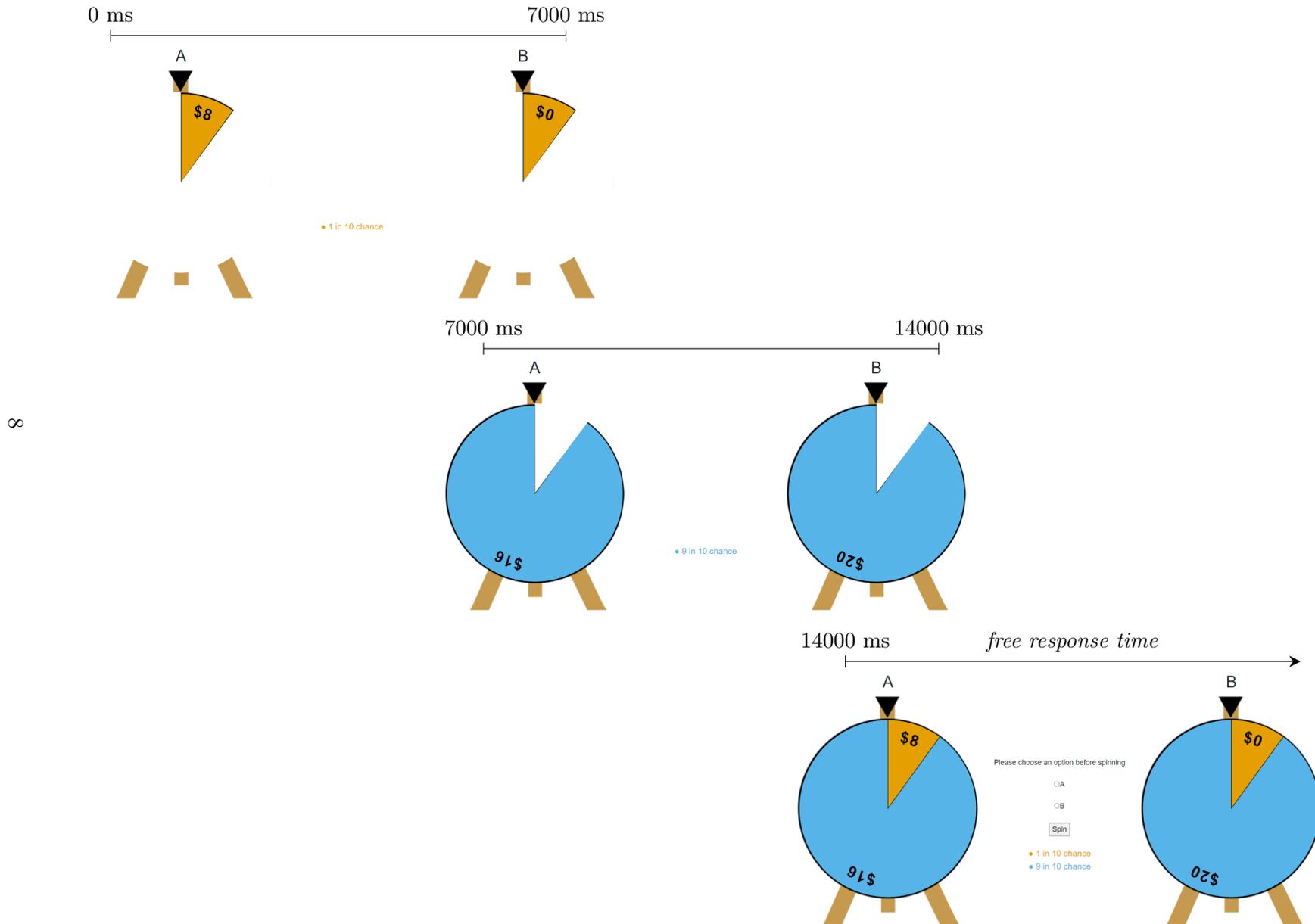
Figure 1: SEQUENTIAL LOTTERIES

Figure 2: SEQUENTIAL STATES

A distinct color was used to depict each state.[10] Colors of states, the order of lotteries, and the order of states were randomized at the subject-trial level to account for biases in subjects potentially finding a particular color more appealing than the other, and tendency to read from left-right and top-bottom.

4 A Model of Dual Choice Processes

This section introduces a model of choice processes in evaluating correlated lotteries. When faced with choosing between correlated lotteries, it is largely or completely unobservable how an agent may attend to the underlying correlation. Specifically, an agent may assess trade-offs between lotteries conditional on state-specific outcomes, or may evaluate each lottery independently, considering only the payoffs and their corresponding probabilities. The model is intended to integrate the dual nature of these procedures.

Consider a finite set of states of the world, S. Each state $s \in S$ occurs with objective probability $\pi_s \in [0,1]$ such that $\sum_{s \in S} \pi_s = 1$. An agent is faced with a choice between two lotteries where each lottery $i \in \{R, S\}$ gives a payoff $x_s^i \in \mathbb{R}$ in state s. Valuation of lottery i is:

$$V_i = \sum_{s \in S} [\pi_s + \mathbb{1}_{\{statewise\}}(\pi_s \cdot \omega_s^i - \pi_s)] \cdot u(x_s^i) \tag{1}$$

where $\mathbb{1}_{\{statewise\}}$ is an indicator variable for whether an agent compares lotteries by state-specific outcomes, $\pi_s \cdot \omega_s^i$ is the distorted probability which deviates from the objective probability π_s discussed below, and $u(\cdot)$ is assumed to be an increasing utility function.

The intuition underlying probability distorting under statewise comparisons captures the perceived relevance of outcomes based on contingent reasoning. That is, an agent may consider a state relevant to the extent that its realization alters the outcome as a consequence of the agent's lottery choice. By normalizing $\sum_{s \in S} \pi_s \cdot \omega_s^i = 1$ and defining $\omega_s^i = \frac{\delta^{k_s^i}}{\sum_r \delta^{k_r^i} \cdot \pi_r}$ where $\delta \in (0,1)$ represents the degree of local thinking as in salience theory, $k_s^i \in \{1, ..., |S|\}$ denotes the salience ranking of state s for lottery i where lower k_s^i indicate higher salience. The salience ranking is determined through a salience function θ which assigns a non-negative number (relevance) to each state s which depends on the outcomes of the two lotteries in that state, $\theta(x_s^R, x_s^S)$. This function is symmetric for binary lottery choices, $\theta(x_s^R, x_s^S) = \theta(x_s^S, x_s^R)$. I assume the salience function $\theta(x_s^R, x_s^S)$ is a continuous and

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[10]Colors were chosen from colorblind-friendly palettes (Wong, 2011). It is estimated that roughly 4% of the world population suffers from at least one of three main types of color blindness (Deeb, 2005).

bounded function that has the following properties:

A1: If $x_s^R = x_s^S$, $\theta(x_s^R, x_s^S) = 0$

A2: For $x_s^R = x_s^S$ and $k > 0$, $\frac{\partial \theta(x_s^R, x_s^S + k)}{\partial k} = \frac{\partial \theta(x_s^R + k, x_s^S)}{\partial k} > 0$

A3: If $x_s^i \geq 0$ for $i \in \{R, S\}$, then for any $k > 0$, $\theta(x_s^R + k, x_s^S + k) < \theta(x_s^R, x_s^S)$.

In words, an agent perceives a state to be irrelevant if the realization of that state has no impact on the outcome as a consequence of the agent's choice (A1). An agent perceives the relevance of such states to be increasing in the outcome of one of the two lotteries (A2). The final property is adopted from the Weber-Fechner law (*diminishing sensitivity* in salience theory) which implies that the perceived difference between outcomes decreases as their absolute magnitude increases (A3).

4.1 Predictions

For both problems in the experiment, probability distorting under contingent reasoning can be summarized by a weight $\epsilon > 0$, which is added (subtracted) to (from) the objective probability of the perceptually most (least) salient state. By the properties of the model, the valuation contrast between lotteries R and S in the *Favorable Odds* problem can be expressed as:

$$V_R - V_S = \underbrace{[0.1 + \mathbb{1}_{\{statewise\}}(\epsilon)][u(0) - u(8)]}_{\text{State 1: } S \succ R} + \underbrace{[0.9 - \mathbb{1}_{\{statewise\}}(\epsilon)][u(20) - u(16)]}_{\text{State 2: } R \succ S}, \qquad (2)$$

and the valuation contrast between lotteries R and S in the *Equal Odds* problem can be expressed as:

$$V_R - V_S = \underbrace{[0.5 + \mathbb{1}_{\{statewise\}}(\epsilon)][u(0) - u(8)]}_{\text{State 1: } S \succ R} + \underbrace{[0.5 - \mathbb{1}_{\{statewise\}}(\epsilon)][u(16) - u(8)]}_{\text{State 2: } R \succ S}. \qquad (3)$$

In both choice problems, the valuation contrast is unequivocally affected in favor of Lottery S when comparing lotteries in a statewise fashion by the mere observation that more (less) weight is attached to the state in which Lottery S (R) is preferred. Whether an agent would choose the same lottery in the two frames, however, is sensitive to both risk preferences and ϵ.[11] By appealing to random assignment to balance individual differences, I derive the following prediction based on the intent of treatments to induce or limit contingent reasoning.

Prediction 1 (Choices). Subjects will choose Lottery S more frequently under *Sequential States* than *Sequential Lotteries*.

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[11]For instance, in the *Equal Odds* problem, a risk-averse agent prefers Lottery S under both frames. A risk-neutral agent, however, is indifferent between the two lotteries when not comparing lotteries in a statewise fashion but would strictly prefer Lottery S when doing so since the *perceived* expected value of Lottery R would be less than $8.

When faced with a choice between multi-attribute alternatives, it has been argued that attention governs the relative weighting of those attributes (Busemeyer & Townsend, 1993; Maier, Raja Beharelle, Polanía, Ruff, & Hare, 2020; Roe, Busemeyer, & Townsend, 2001). Indeed, gaze allocation tends to reflect attribute weights with more gaze to higher-weighted attributes across a host of two-alternative, two-attribute preferential tasks (Amasino, Sullivan, Kranton, & Huettel, 2019; Yang & Krajbich, 2023). At the same time, research using eye-tracking to study binary choice consistently reveals a gaze bias effect: options looked at longer during the decision-making process are more likely to be chosen (Armel, Beaumel, & Rangel, 2008; Shimojo, Simion, Shimojo, & Scheier, 2003; Smith & Krajbich, 2018; Thomas, Molter, Krajbich, Heekeren, & Mohr, 2019). Hence, provided that choice procedures affect decisions, we should observe a treatment difference in gaze allocation at the state or lottery level.

Prediction 2a (State-level gaze difference). The proportion of gaze allocated to payoffs of the state in which Lottery S is preferred will be greater under *Sequential States* than *Sequential Lotteries*.

Prediction 2b (Lottery-level gaze difference). The proportion of gaze allocated to payoffs of Lottery S will be greater under *Sequential States* than *Sequential Lotteries*.

5   Results

This section studies the effect of contingent reasoning in choice under risk. I describe the sample first. Then I analyze risky choices. I finish by discussing patterns behind eye-tracking data and tie them back to subjects' choices.

5.1   Sample Description

A total of 303 undergraduate students participated in the experiment. Males comprise 45.2% of the sample and the average age of participants is around 20 years old. Data were collected at the Human Behavior Lab at Texas A&M University during 2024. Table 2 presents means of observable characteristics by treatment. None of the differences are significant under conventional levels (two-sided t-tests, $p > 0.1$).

11

Table 2: Description of Sample by Treatment

| | Treatment | | |
	Seq. Lotteries	Seq. States	p-value
age	20.095	20.000	0.581
	(1.425)	(1.566)	
male	0.463	0.442	0.724
	(0.500)	(0.498)	
N	147	156	303

Notes: Standard deviations reported in parentheses. p-values are based on two-sided t-tests.

5.2 The Effect of Contingent Reasoning in Choice Under Risk

As described in section 3.1, each subject was faced with a single choice problem that was randomly selected from a list. In each problem, the safe lottery offers a lower variance than the risky lottery, and either an equal or a lower expected value. Figure 3 shows the proportion choosing lottery S by choice problem and when the two problems are pooled.[12] In the *Favorable Odds* problem, subjects in the *Sequential States* condition are 10.5 percentage points more likely to choose the safe lottery than those in the *Sequential Lotteries* condition (two-sided t-test, $p = 0.176$). Similarly, in the *Equal Odds* problem, subjects in the *Sequential States* condition are 8 percentage points more likely to choose the safe lottery (two-sided t-test, $p = 0.335$). While these results are not statistically significant under conventional levels, they suggest a similar pattern. After the two problems are pooled, we observe meaningful evidence that subjects choose safe lotteries more frequently under the *Sequential States* than the *Sequential Lotteries* condition (9.6 percentage points; two-sided t-test, $p = 0.088$). Table 3 confirms that this result is robust to the inclusion of demographic and choice problem controls.

Patterns across two different choice problems suggest subjects become more risk-averse when they sequentially learn the outcomes of states compared to outcomes of individual lotteries. The next section examines, and verifies, that the exogenous manipulation in lottery display altered evaluation procedures which ultimately affected choices.

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[12]While the model makes signed predictions, I report two-sided tests to be conservative.

Figure 3: Probability of Choosing Lottery S by Choice Problem

Figure 3: PROBABILITY OF CHOOSING LOTTERY S BY CHOICE PROBLEM
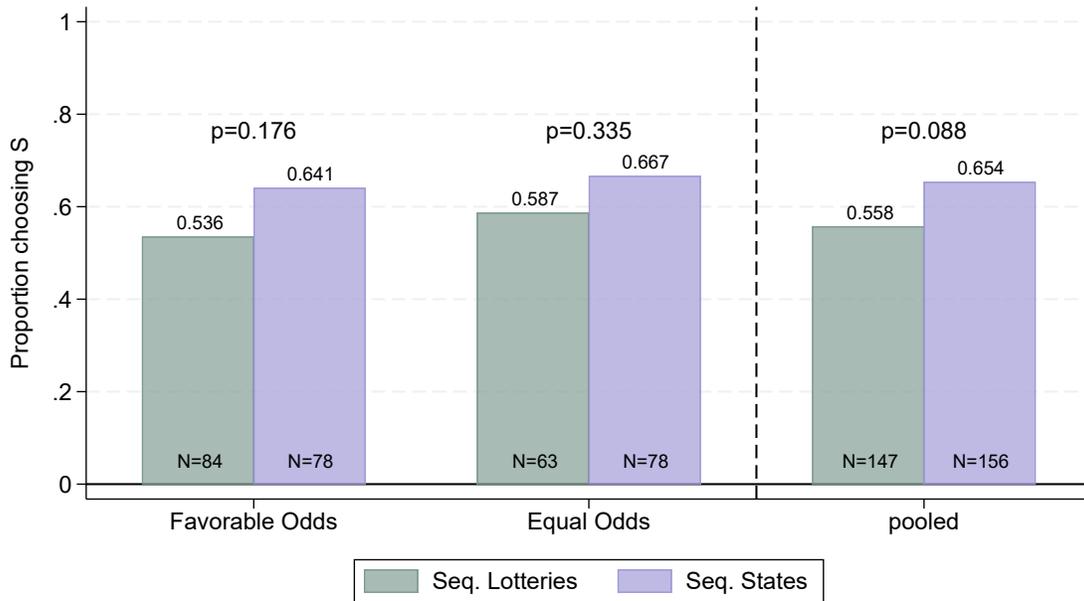
Note: p-values are based on two-sided t-tests.

Table 3: REGRESSION OF CHOOSING A SAFE LOTTERY ON TREATMENT ASSIGNMENT

	(1)	(2)	(3)
Seq. States	0.093	0.097	0.094
	(0.056)	(0.056)	(0.056)
	[0.098]	[0.087]	[0.097]
Favorable Odds	-0.038		-0.037
	(0.056)		(0.057)
	[0.500]		[0.509]
constant	0.580	0.460	0.495
	(0.052)	(0.380)	(0.384)
	[0.000]	[0.227]	[0.199]
Demographics	No	Yes	Yes
N	303	303	303

Notes: Dependent variable equals one if a subject chose lottery S, zero otherwise. Standard errors reported in parentheses. p-values in brackets.

5.2.1 Evidence from Eye-Tracking Data

Recall, at the beginning of each session, subjects underwent a 9-point eye-tracking calibration routine that was repeated up to three times until the gaze calibration result printed an 'excellent' score.[13] To capture gaze allocation and eye-movements between different payoffs, I constructed *Areas of Interest* (AOIs) around each outcome (187×79 pixels per AOI); see Figure 4 for visual representations. Transitions between payoffs of the same state (horizontal) correspond to comparing lotteries in a statewise fashion, and transitions between payoffs of the same lottery (vertical) correspond to holistic, i.e. option-wise evaluations.[14] Figure 5 shows the distribution of transitions in the two treatments by type. We observe significantly more horizontal transitions in the *Sequential States* (mean=11.56) than the *Sequential Lotteries* (mean=4.17) condition (Kolmogorov-Smirnov test, $p < 0.001$; two-sided t-test, $p < 0.001$), which already suggest the randomly assigned treatments altered choice procedures. In evaluating lotteries holistically, we observe significantly more vertical transitions in the *Sequential Lotteries* (mean=12.34) than the *Sequential States* (mean=7.81) condition (Kolmogorov-Smirnov test, $p < 0.001$; two-sided t-test, $p < 0.001$). The data so far suggest the randomly assigned treatments generated strong variation in the way alternative lotteries are contrasted against one another.

Given the observed treatment effect on subjects' choices, we should also observe a treatment difference in gaze allocation toward payoffs. Figure 6 summarizes gaze allocation by choice problem based on state and lottery levels. Panel A shows the mean proportion of gaze allocated to payoffs of the most salient state, i.e. payoffs of the state in which Lottery S is preferred. Although not statistically significant under conventional levels, we observe that across both choice problems subjects in the *Sequential States* condition allocate a greater proportion of their gaze to payoffs of the state in which Lottery S is preferred. After the two problems are pooled, *Sequential States* shows a 4.1 percentage-point greater proportion than *Sequential Lotteries* (two-sided t-test, $p = 0.145$; Wilcoxon rank-sum test, $p = 0.153$). Further, we observe that across both treatments subjects allocate a greater proportion of their gaze to payoffs of the state in which Lottery S is preferred in the *Equal Odds* problem, which coincides with Lottery S being chosen more frequently in the *Equal Odds* problem under both treatments. Taken together, these patterns suggest contingent reasoning

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[13]268 out of 303 subjects passed the calibration routine. Subjects who were unable to be calibrated were told that the failed calibration attempts were not their fault. There are no meaningful treatment differences in age (two-sided t-test, $p = 0.927$) or gender (proportion male; two-sided t-test, $p = 0.600$) for subjects with eye-tracking data.

[14]Transitions between top-left and bottom-right (or vice versa) payoffs, and bottom-left and top-right (or vice versa) payoffs correspond to diagonal transitions. For calculating gaze allocations and transitions, I omitted gaze points that were not in any of the four AOIs.

Figure 4: Areas of Interest (AOIs) and Possible Transitions between Payoffs (H-horizontal, V-vertical, D-diagonal)

A. *Favorable Odds*
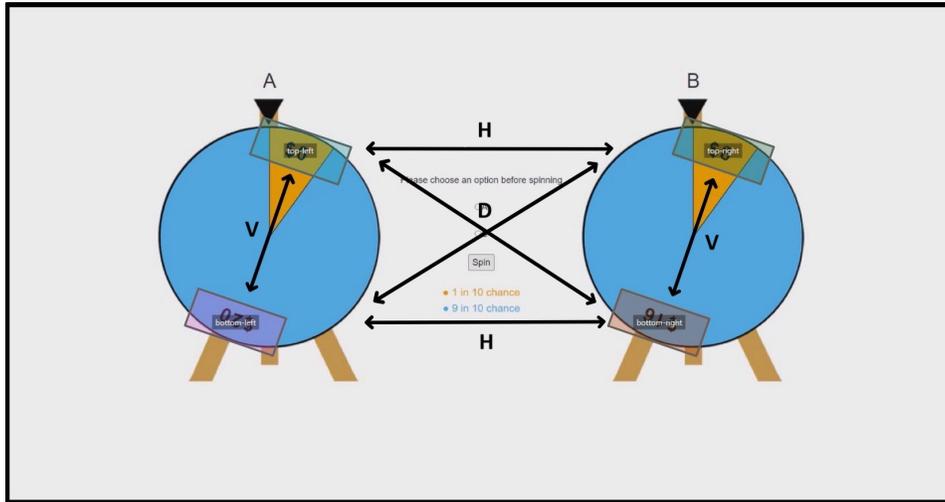
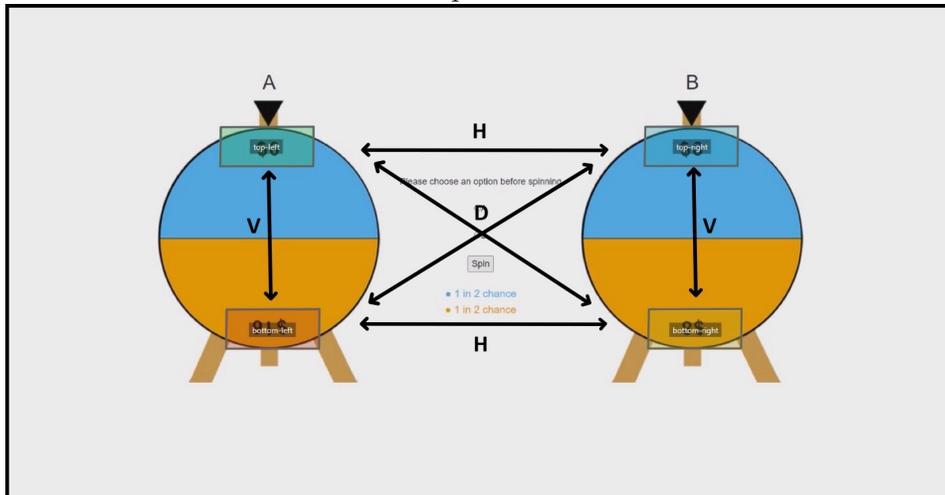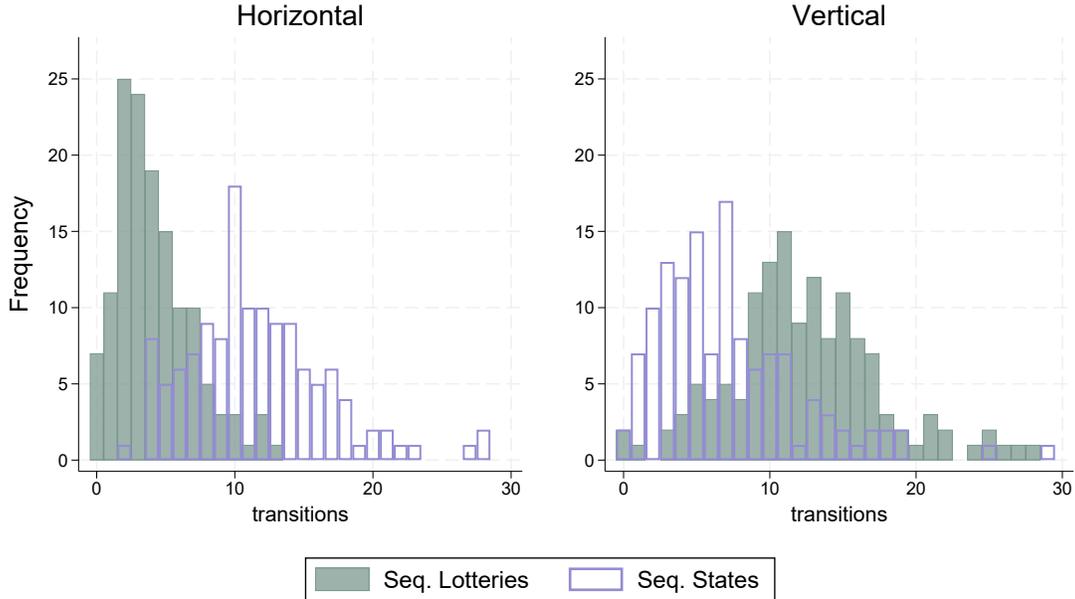B. (*Alternative*) *Favorable Odds*
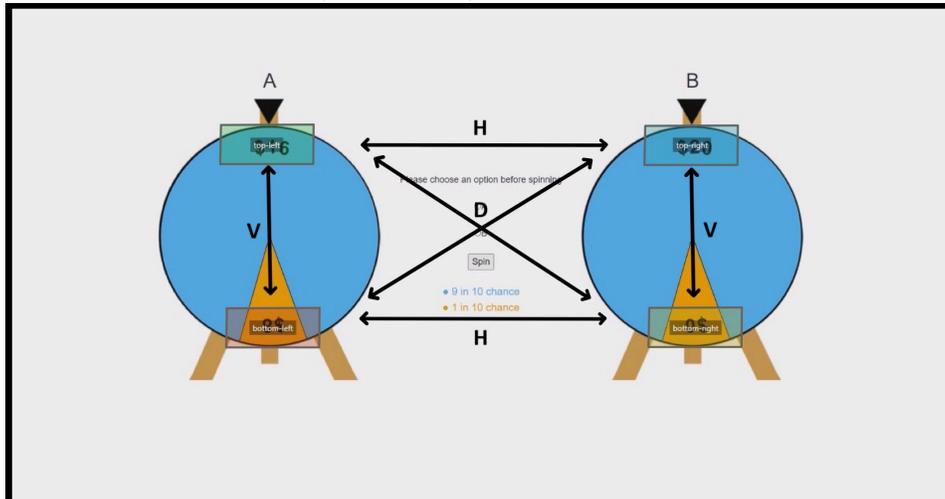
C. *Equal Odds*

Figure 5: Distribution of Transitions between Payoffs by Type

Notes: The distribution of vertical transitions is censored at 30. One outlier with a total of 94 transitions in the *Sequential States* condition is not shown.

attracted gaze to states in which safe lotteries are preferred thus prompting more risk-averse choices.

Applying the alternative-level gaze bias effect in the present context is not straightforward since subjects likely did not evaluate lotteries independently in neither treatment as suggested by patterns of state-level gaze differences. Panel B shows that across both choice problems, lottery-level gaze differences are in line with Prediction 2b albeit not statistically significant. Surprisingly, across both treatments, subjects allocate a lower proportion of their gaze to payoffs of Lottery S in the *Equal Odds* problem and yet Lottery S is chosen more frequently in this problem under both treatments. These patterns combined with the observed state-level gaze differences together suggest smaller lottery-level than state-level gaze effects on correlated risky choice (Yang & Krajbich, 2023).

Table 4 summarizes transitions between payoffs by type for each problem to further elucidate how choice procedures modulated gaze allocation toward payoffs. Horizontal transitions suggest the within-subject difference in comparing payoffs of the state in which Lottery S versus Lottery R is preferred is greater under *Sequential States* in both problems albeit treatment differences are not significant using Wilcoxon rank-sum tests (0.70 transitions, *Favorable Odds*, $N = 147$, $p = 0.368$; 1.58 transitions, *Equal Odds*, $N = 121$, $p = 0.194$).[15] After the two problems are pooled, the

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[15]Signed tests in the direction of the prediction yield $p = 0.184$ and $p = 0.097$ in the *Favorable Odds* and *Equal Odds* problems, respectively.
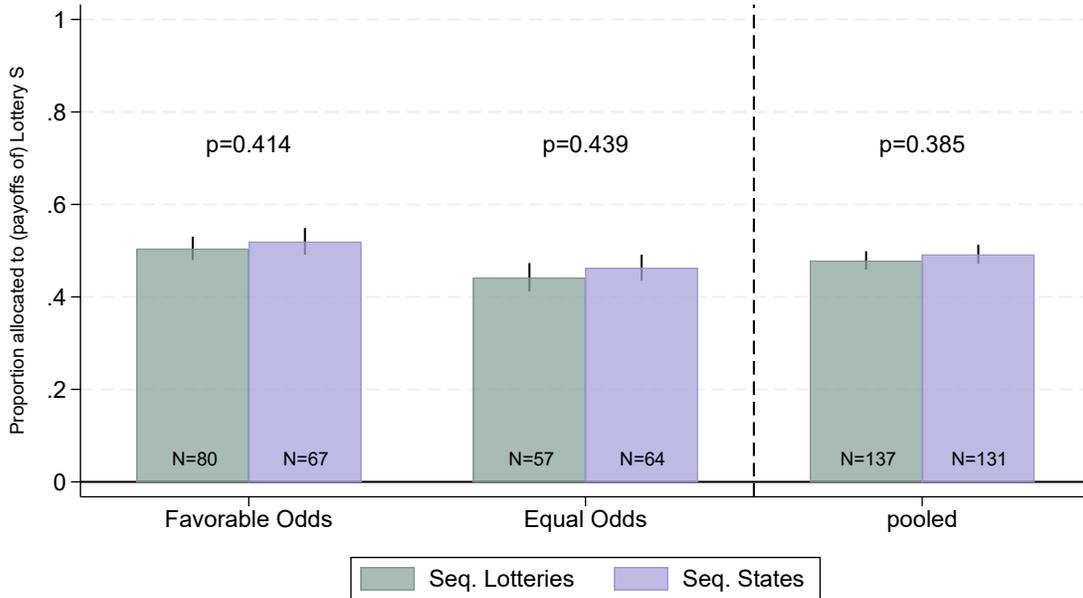
Figure 6: Gaze Allocation by Choice Problem

A. *State-Level Gaze Differences*
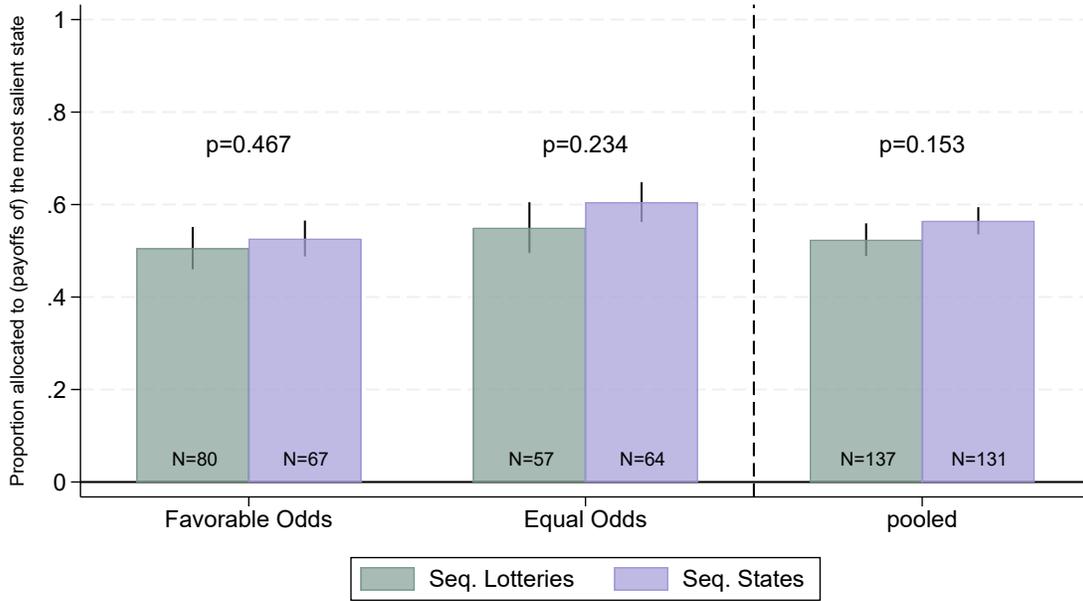
Notes: error bars represent 90% confidence intervals. p-values are based on Wilcoxon rank-sum tests.

B. *Lottery-Level Gaze Differences*

Notes: error bars represent 90% confidence intervals. p-values are based on Wilcoxon rank-sum tests.

evidence in line with the prediction that this difference will be greater under *Sequential States* becomes meaningful (1.18 transitions; Wilcoxon rank-sum test, $p = 0.097$). Overall, these patterns align well with the differences in state-level gaze allocation. Vertical transitions suggest there is no

treatment difference in subjects comparing the payoffs of one lottery more than of the other in the *Favorable Odds* problem (Wilcoxon rank-sum test, $N = 147$, $p = 0.484$), while the within-subject difference in comparing the payoffs of Lottery S versus Lottery R based on vertical transitions is significantly greater under *Sequential States* in the *Equal Odds* problem (2.31 transitions, Wilcoxon rank-sum test, $N = 121$, $p = 0.040$).

Table 4: SUMMARY OF TRANSITIONS

A. Horizontal Transitions by Choice Problem and State

	Favorable Odds			Equal Odds		
	s_1: $\theta(0,8)$	s_2: $\theta(20,16)$	$s_1 - s_2$	s_1: $\theta(0,8)$	s_2: $\theta(16,8)$	$s_1 - s_2$
Seq. Lotteries	2.15	2.11	0.04	2.40	1.63	0.77
Seq. States	6.16	5.42	0.74	6.94	4.59	2.35

B. Vertical Transitions by Choice Problem and Lottery

	Favorable Odds			Equal Odds		
	Lottery S	Lottery R	$S - R$	Lottery S	Lottery R	$S - R$
Seq. Lotteries	6.78	6.24	0.54	5.35	6.05	-0.70
Seq. States	4.16	3.81	0.35	4.63	3.02	1.61

As mentioned in section 1, a decision-maker elects how to disperse attention in evaluating lotteries, and this raises endogeneity concerns when estimating the effects of visual attention on choices. To address this issue, we can causally estimate the effect of statewise comparisons, i.e. minimum number of horizontal transitions corresponding to distinct states,[16] on choices using treatment assignment as an instrumental variable (IV) given the exogenously generated variation in evaluation procedures having been attained.

Treatment assignment provides a valid instrument as it is arguably related to choices only through its relationship to eye movements. Second, it is correlated with horizontal transitions but not correlated with observed (or unobserved) characteristics as subjects were randomly assigned to treatments. The model was estimated using two-stage least squares (2SLS) by first regressing the endogenous variable on the instrument and then including the fitted values obtained from this regression in the second stage. Table 5 provides estimates of results obtained from the second stage. We observe that an additional statewise comparison increases the likelihood of choosing a safe lottery by 5.1 percentage points ($p = 0.018$), which remains robust to the inclusion of demographic controls.

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[16]For example, if the number of eye-movements between payoffs in the first and second state are 5 and 7, respectively, these transitions would comprise a total of 5 statewise comparisons.

Table 5: IV Regressions (2SLS) of the Effect of Horizontal Transitions on Choosing S

	(1)	(2)
$\widehat{\text{statewise}}$	0.051	0.052
	(0.022)	(0.022)
	[0.018]	[0.018]
constant	0.520	0.453
	(0.050)	(0.392)
	[0.000]	[0.248]
Demographics	No	Yes
N	268	268

Notes: Dependent variable equals one if a subject chose lottery S, zero otherwise. $\widehat{\text{statewise}}$ represents the fitted values of the number of state-wise comparisons obtained from the first stage. Standard errors reported in parentheses. p-values in brackets.

6   Conclusion

This paper presents experimental evidence suggesting contingent reasoning in correlated risky choice prompts more risk-averse decisions. Eye-tracking data show contingent reasoning attracts gaze to perceptually most relevant states thus affecting the valuation contrast in favor of safe lotteries. Implications are significant since insurance policy designers can extract surplus from consumers by emphasizing trade-offs between premiums and deductibles. Field evidence suggests insurance firms may use this strategy by presenting a pre-selected (recommended) plan, and highlighting differences in premiums and deductibles between alternative plans and the default option. In the experiment, binary choice lotteries were offered in the gain domain. Future studies could examine whether similar patterns are observed in the loss domain, and whether results replicate when subjects are faced with more than two options, i.e. with ternary or quaternary choice problems, to enhance the generalizability of the findings. The exogenous manipulation in lottery display through dynamic presentation presents a novel method in prodding different heuristics in decision-making. Importantly, dynamic presentation may allow a researcher to causally estimate the effects of different decision rules provided exogenous variation in evaluation procedures is attained.

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Appendix

Instructions and Protocol

<u>Page 1 (read out loud)</u>

INTRODUCTION

This is an experiment in economic decision making. If you pay attention to these instructions, you can earn a significant amount of money. Please turn off/silence your phones and put them away; otherwise, you may be asked to leave. If you have any questions, please raise your hand and a staff member will come to assist you. Your earnings will depend on your decisions and luck. Experimental dollars will be converted at a rate of $1 (Experimental Dollar) = 50 cents. These earnings will be paid in addition to your $10 show-up payment.

INSTRUCTIONS

In this experiment, you will be asked to pick one of two options (Option A or Option B). Your payment will be based on the outcome of your choice.

First, you will be asked to make choices in 2 practice rounds. During these rounds, you get to see how your earnings are determined. Your earnings will not depend on the outcomes of the practice choices – these are meant to illustrate how the experiment works. Then, you will be asked to make a choice in 1 round based on which your payment will be determined.

This is not a test, and there are no right or wrong answers. For each choice, please choose the option that you prefer.

If you have any questions, please raise your hand.

—————————————————————**Practice Choices**—————————————————————

<u>Page 4</u>

Now that you had the opportunity to learn how earnings are determined, you will be asked to make a choice in 1 round.

The outcome of this round will determine your earnings. Please click *Next* to continue.

—————————————————————**Incentivized Choice**—————————————————————

<u>Page 6</u>

Please answer the following questions.

1. What is your age?

   $\rightarrow$

2. What is your gender?

   $\rightarrow$ Male, Female, Other (please specify):

<u>Page 7</u>

(*Summary of subject earnings*)

Choice Problems

Table A1: Practice Choices (% chose A)

				Choice 1	
State	Probability	A	B	Sequential Lotteries	Sequential States
1	0.5	8	5	51.0% (N=147)	45.5% (N=156)
2	0.5	14	19		

				Choice 2	
State	Probability	A	B	Sequential Lotteries	Sequential States
1	0.1	7	3	36.7% (N=147)	32.7% (N=156)
2	0.9	15	18		

Table A2: Incentivized Choices (% chose A)

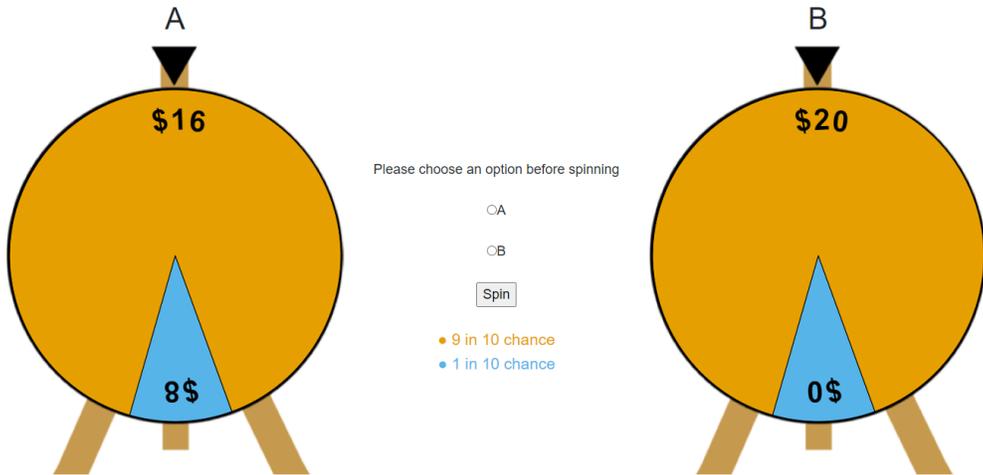|				**Choice 1**	
State	Probability	A	B	Sequential Lotteries	Sequential States
1	0.5	8	0	58.7% (N=63)	66.7% (N=78)
2	0.5	8	16		
				OR	
State	Probability	A	B	Sequential Lotteries	Sequential States
1	0.1	8	0	53.6% (N=84)	64.1% (N=78)
2	0.9	16	20		

Lottery Presentations

Figure A1: Incentivized Problems

A. *Favorable Odds*
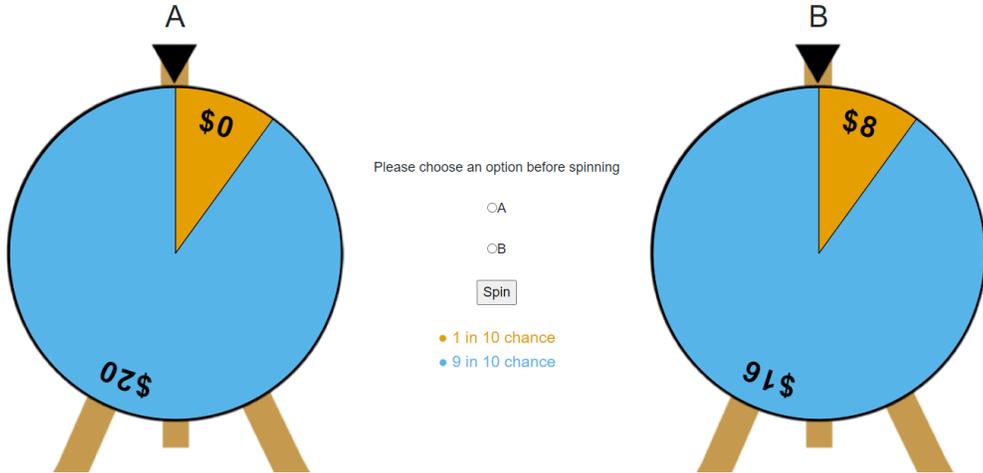
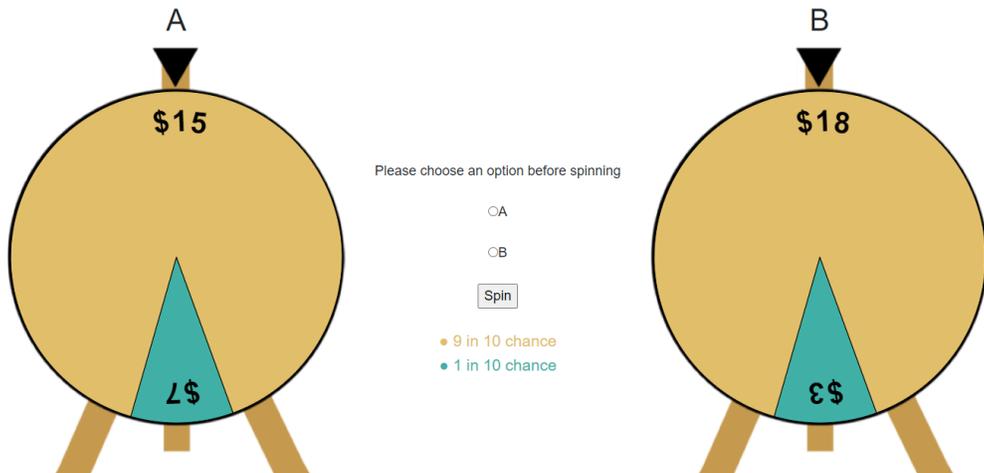

B. (*Alternative*) *Favorable Odds*

C. *Equal Odds*

Figure A2: Practice Problems

A. *10-90 Lotteries*

Please choose an option before spinning

○ A

○ B

[Spin]

● 1 in 10 chance
● 9 in 10 chance
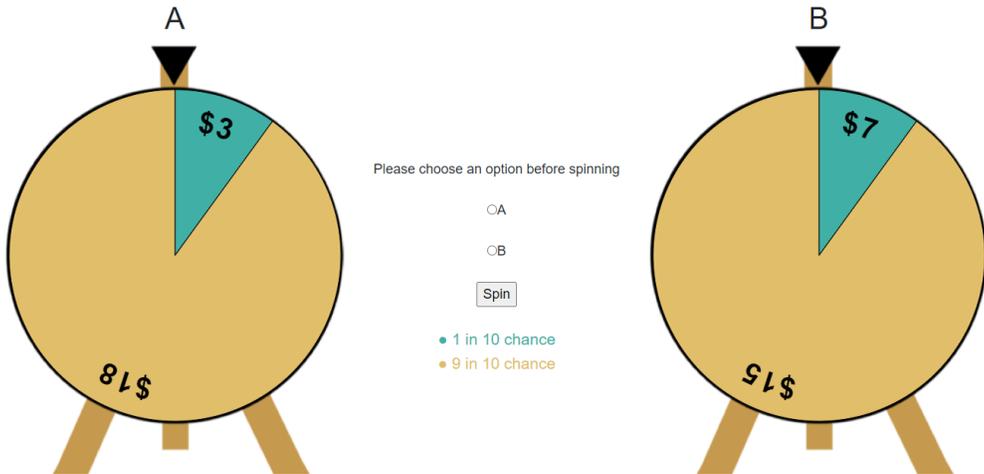
B. (*Alternative*) *10-90 Lotteries*

Please choose an option before spinning

○ A

○ B

[Spin]

● 9 in 10 chance
● 1 in 10 chance

C. *50-50 Lotteries*

Please choose an option before spinning

○ A

○ B

[Spin]

● 1 in 2 chance
● 1 in 2 chance