Salience in Choice Under Risk: An Experimental Investigation*

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Abstract

In choosing between lotteries, Bordalo, Gennaioli, and Shleifer (2012) postulate agents overweight states that are more salient. We manipulate the correlation between lotteries to test if changes in behavior predicted by salience obtain. Under highly controlled experimental conditions, and contrary to salience theory, we find mixed evidence that correlation affects choice behavior. The evidence in favor of salience improves when we manipulate the choice architecture to make the correlation more apparent.

JEL classification: D81, D87

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1 Introduction

Several authors have argued that in choosing among lotteries agents might be sensitive to the underlying correlation of outcomes (e.g., Bordalo et al., 2012; Loomes & Sugden, 1982; Quiggin, 1994). These authors differ in the way they model agents' reactions to this correlation (Lanzani, 2022). In this paper, we provide a non-parametric test of correlation-sensitive preferences in decisions under risk and its conformity to theoretical predictions. Our main finding is that subjects are sensitive to the underlying correlation of outcomes, but that this correlation is not always apparent to subjects nor is the reaction to it always consistent with theory.

We show that salience (and regret) theory can be tested by varying the correlation between outcomes across lotteries. The test is completely non-parametric and relies only on preferences being strictly monotonic over money. To provide a robust test of correlation-sensitive preferences, we explore a wide range of lotteries. Crucially, to account for the possibility that correlation is not a salient feature of the environment, we manipulate the framing of lotteries to make it apparent. By keeping constant the size of the state space, combined probabilities of outcomes, and the number of states in which an outcome occurs, any choice reversals we observe cannot be attributed to event-splitting effects. In this context, expected utility theory and prospect theory cannot explain preference reversals.

These theories produce choice reversals by affecting utility contrasts between alternative lotteries. The extant research on decision times reports two patterns. First, judgment errors are more likely to occur whenever comparisons are harder to make, i.e., when the contrast between choices is smaller. Second, harder decisions take more time to make than easier ones. Both these patterns have been found in decisions under risk (Alos-Ferrer & Garagnani, 2022; Moffatt, 2005; Mosteller & Nogee, 1951). We augment our design to include decision times and explore if choice reversals are due to preference reversals using the approach developed by Alós-Ferrer, Fehr, and Netzer (2021). We confirm the significance of the choice reversal coefficients using response time data which show that the observed patterns are qualitatively robust (Liu & Netzer, 2023).

Choice reversals occur only when the correlation is made apparent and for lotteries with equal expected payoffs and lotteries that can be ordered by first-order stochastic dominance. The choice reversals we observe are consistent with salience theory in the first case but not in the second. These choices also reject either globally concave or convex regret theory. We exploit decision times to explore if choice reversals are consistent with preference reversals. We find decision time reversals consistent with preference reversals. This suggests that agents are sensitive to the correlation of outcomes but that correlation is not a salient feature of the decision problem. How subjects react to the correlation is not always predicted by existing theories. Our design cannot determine if the evidence consistent with correlation-sensitive preferences is a lower or upper bound effect since attention is not observable. Additional experiments would help elucidate the patterns we report.

Related Literature. There are a few papers that focus on salience in risky choices. Frydman and Mormann (2016) experimentally gauge the observed malleability of the Allais paradox and use pairs of lotteries whose marginal distributions are kept constant, but their joint distributions are changed. Nielsen, Sebald, and Sørensen (2018) experimentally investigate the salience theory of choice under risk by designing risky-choice treatments in which subjects are endowed with some amount of money and can only wager a portion of it between two assets, a riskier one and one that is safer. Their setup is such that the state-dependent wealth consequences of any amount bet are the same for the different treatments. The authors make assumptions on the shape of the salience function and rely on the notion of *just-noticeable differences* to distinguish which one of two states is more salient. They find support for salience theory under these assumptions. Alós-Ferrer and Ritschel (2022) investigate the implications of salience theory for the classical preference reversal phenomenon by presenting subjects with binary lottery choices and then eliciting monetary valuations. Following the choice task, they elicit monetary valuations for a lottery by manipulating the salience of payoffs through the presence or absence of an alternative lottery. Each lottery has two outcomes, each occurring with a different probability. The authors found no support for the salience theory via eye movements, and their choice data lend moderate to little support to salience theory explaining preference reversals. Addressing concerns raised by Lichtenstein and Slovic (1971) that the primary cause of preference reversals is due to individuals processing information differently when making choices and when making valuations, Loomes, Starmer, and Sugden (1989) find support in favor of a convex regret function in an experiment that separately uses i) only choice problems and ii) choice and reservation price elicitations in a traditional sense (à la Grether & Plott, 1979). A convex regret function in the generalized form (Loomes & Sugden, 1987) makes similar predictions to salience theory as shown by Herweg and Müller (2021).

Other related work investigates first-order stochastically dominated (FOSD) choices. Violations of first-order stochastic dominance are framing effects, which expected utility theory and cumulative prospect theory cannot account for. Dertwinkel-Kalt and Köster (2015) propose a version of salience theory that unravels the underlying mechanism triggering such effects and which can explain the impact of event- and attribute-splitting on choices. They investigate binary lottery choices that are dominance-ordered, which were originally studied by Birnbaum and Navarrete (1998) and Birnbaum (2005). Choices were presented in a list format and assumed to be independent. They observed most of the dominance violations in problems where lotteries differed in both attributes: probabilities and outcomes. When there was no differentiation between lotteries in the probability attribute, a significant drop in FOSD choices was observed. We, however, observe FOSD choices when there is no differentiation in the probability attribute between two lotteries. For the most part, monotonicity with respect to first-order stochastic dominance is a widely accepted principle in decision theory, as pointed out by Quiggin (1990), Wakker (1993), and Starmer (2000), among others.[1] While under certain conditions of probability distortion salience theory could predict FOSD choices, salience theory cannot rationalize dominated choices for the problems we study. Our exercise shows that dominated choices in correlated lotteries may stem from failures of isolating the consideration of individual lotteries, or alternatively evaluating the CDFs of individual lotteries one at a time.

The paper is organized as follows: in the next section we briefly introduce the salience theory of choice under risk, section 3 summarizes the implementation and predictions, in section 4 we present our results and we conclude in section 5.

2 Salience Theory

BGS proposed a theory of choice among lotteries in which the decision maker's attention is drawn to salient outcomes. This leads a decision maker to a context-dependent representation of lotteries in which objective probabilities are distorted in favor of states whose payoffs are more salient. 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 $\sum_{s \in S} \pi_s = 1$. A decision-maker chooses among two lotteries (L_1, L_2) where each lottery $i = 1, 2$ gives a payoff $x_s^i \in \mathbb{R}$ in state s. In BGS, valuation of lottery i is:

$$V(L_i) = \sum_{s \in S} \pi_s^j \cdot u(x_s^i) \tag{1}$$

where π_s^j is the distorted probability which deviates from the objective probability π_s and $u(\cdot)$ is assumed to be an increasing utility function. For the purpose of the experiment, it suffices to know that salience increases the perceived odds of states that are more salient and decreases the

[1] For a recent challenge to this view see Dembo, Kariv, Polisson, and Quah (2021).

perceived odds of states that are less salient. All the results in the paper are independent of the particular way probabilities are distorted.

The salience ranking is determined through a salience function σ which assigns a real number (the salience) to each state s which depends on the outcomes of the two lotteries in that state, $\sigma(x_s^1, x_s^2)$. The salience function is symmetric for binary lottery choices, $\sigma(x_s^1, x_s^2) = \sigma(x_s^2, x_s^1)$. The salience of state s for lottery L_i, $i = 1, 2$ is a continuous and bounded function $\sigma(x_s^i, x_s^{-i})$ that satisfies two key properties:

$(i.)$ *ordering*, which states that if the range of payoffs of one state is contained within the range of payoffs of another state, the former state is less salient. Formally, if for states s, $\tilde{s}$ we have that $[x_s^{min}, x_s^{max}] \subseteq [x_{\tilde{s}}^{min}, x_{\tilde{s}}^{max}]$, then $\sigma(x_s^i, x_s^{-i}) < \sigma(x_{\tilde{s}}^i, x_{\tilde{s}}^{-i})$, and

$(ii.)$ *diminishing sensitivity*, which states that adding a positive constant to a state with only positive outcomes will generate a less salient state. Formally, if $x_s^i > 0$ for $i = 1, 2$ then for any $\epsilon > 0$, $\sigma(x_s^i + \epsilon, x_s^{-i} + \epsilon) < \sigma(x_s^i, x_s^{-i})$.[2]

3 Experimental Design

This section presents testable implications of the salience theory that we implement in our experiments. In particular, we show that ordering and diminishing sensitivity coupled with increasing utility over money can be used to generate choice reversals in a predictable way. We rely on the fact that salience theory allows for preferences to depend on the correlation between alternative outcomes (see Lanzani, 2022).

3.1 Choice Reversals

Consider lotteries $A = (\$8, 0.5; \$12, 0.5)$ and $B = (\$5, 0.5; \$15, 0.5)$, where lottery B is a mean-preserving spread of lottery A. Salience theory predicts that the choice between these two lotteries depends on whether outcomes are correlated or not. The outcomes are correlated if a flip of a coin determines simultaneously if lottery A pays \$8 and lottery B pays \$5 or if lottery A pays \$12 and lottery B pays \$15. The outcomes are uncorrelated if one coin flip determines if lottery A pays \$8 or \$12, and a different coin flip determines if lottery B pays \$5 or \$15.

Consider the case in which lottery A pays \$8 every time lottery B pays \$5, and lottery A pays \$12 every time lottery B pays \$15. The difference in payoffs between lotteries A and B is always 3

[2] A third and final property, *reflection*, states that the salience of a state does not change between gains and losses. This property is not relevant to our purposes since we present subjects with lotteries only in the gain domain.

Table 1: Correlation across alternatives

Positive correlation			Negative correlation		
A\B	\$5	\$15	A\B	\$5	\$15
\$8	0.5	0	\$8	0	0.5
\$12	0	0.5	\$12	0.5	0

in absolute terms. Since outcomes \$5 and \$8 are a translation of outcomes \$12 and \$15, diminishing sensitivity implies that the state that pays \$5 and \$8 is more salient. In this case, an agent will overestimate the probability of this state and choose lottery A if:

$$p(u(8) - u(5)) + q(u(12) - u(15)) \geq 0, \text{for some } p, q \text{ such that } p > q, p + q = 1. \quad (2)$$

Suppose instead that lottery A pays \$8 every time lottery B pays \$15, and lottery A pays \$12 every time lottery B pays \$5. The difference in payoffs between lotteries A and B is always 7 in absolute terms. Since outcomes \$5 and \$12 are a translation of outcomes \$8 and \$15, diminishing sensitivity implies that the state that pays \$5 and \$12 is more salient. In this case, an agent will overestimate the probability of this state and choose lottery A if:

$$p(u(12) - u(5)) + q(u(8) - u(15)) \geq 0, \text{for some } p, q \text{ such that } p > q, p + q = 1. \quad (3)$$

We note that the probability weights attributed to the outcomes of Lottery B are always the same, but they are different for Lottery A. In the first presentation, a payoff of \$8 is overweighted while in the second presentation, a payoff of \$12 is overweighted. According to salience theory, lottery A looks more attractive in the second presentation than in the first presentation. Table 1 illustrates that the only difference in the choices between lotteries A and B is the correlation of outcomes. All the lotteries in our study follow a similar pattern.

We can now derive conditions for choice reversals. In particular, consider a choice reversal from choice Lottery B in the first presentation and Lottery A in the second presentation. This is equivalent to changing the sign of equation (2). Adding up equations (2) and (3), and using some simple algebra, we find that a necessary condition for this choice reversal is the following inequality:

$$(p - q)(u(8) - u(12)) \leq 0. \quad (4)$$

Since salience implies that $p - q \geq 0$, we conclude that the inequality holds if preferences are monotone in lottery prizes.[3] In our example, salience and payoff monotonicity can produce a preference reversal from lottery B to lottery A, but not a preference reversal from lottery A to lottery B. Note that choice reversals are not expected if the outcomes of lottery A and lottery B are not correlated. When lotteries are not correlated, the ordering of outcomes is irrelevant since the state space corresponds to the product of all possible prizes. Choice reversals are therefore not expected if lottery outcomes are not correlated.

Table 2 shows six pairs of lotteries where we can use a version of (4) to rationalize choice reversals in a predictable way.[4] The lotteries are chosen so that salience can explain choosing lottery B in pair i and lottery A in choice j, but not the opposite. We attain this result by making sure that the permutation of lottery prizes does not alter the salience ranking of states for Lottery B. In every lottery in Table 2, the most salient state is always 1, followed by state 2 and then state 3. Salience and payoff monotonicity can also explain choosing Lottery B in choice i and Lottery A in choice j for pairs 2 and 3 in Table 2.[5] Finally, in panel D, lottery A is first-order stochastically dominated by lottery B. Salience theory cannot rationalize dominated choices in these pairs.[6]

Table 2 presents the lotteries used in the experiment to test for choice reversals.[7] The expected value of lottery A is lower than the expected value of lottery B in pairs 1 and 2. The expected value of lottery A is higher than the expected value of lottery B in pairs 3, 4, and 5. In panel B, lottery B is a mean-preserving spread of lottery A and each lottery has two outcomes. In panel C, lottery B is a mean-preserving spread of lottery A and each lottery has four outcomes. In panel D, lottery A is first-order stochastically dominated by Lottery B.

Calibration: The conditions derived above are necessary, but not sufficient to produce choice reversals. Choice reversals are likely sensitive to individual risk attitudes and the strength of salience itself. Table 2 therefore explores a large range of payoffs to avoid the possibility of false negatives. Ex-ante, we expect that the effects of salience should be easier to detect whenever subjects are close to indifference between lottery A and lottery B. As we will explain later, we will use decision times to measure whether Lottery A and Lottery B are perceptually closer to each

[3] This is a necessary but not sufficient condition for preference reversals.

[4] The pairs are 1, 4, 5, 6, 7 and 8.

[5] The argument is only slightly more complicated. The condition for a choice reversal from lottery B to lottery A is: $p(u(\pi_1) - u(\pi_3)) + q(u(\pi_2) - u(\pi_1)) + r(u(\pi_3) - u(\pi_2)) \leq 0$, for $p > q > r, p + q + r = 1$. Dividing this equation by $p > 0$ shows that the inequality holds if preferences are monotone in prizes since $\frac{q}{p}, \frac{r}{p} \leq 1$.

[6] Salience theory cannot explain a choice reversal from lottery B in choice i to lottery A in choice j if preferences are strictly monotone. Assuming weakly increasing anomalous utility preferences, such a reversal can be rationalized if utility is flat for payoffs between \$15 and \$26 in pair 9, and between \$7 and \$19 in pair 10.

[7] We implemented two additional lotteries that do not involve preference reversals. We do not include those lotteries in the current analysis.

other. We can derive predictions according to salience theory based on the underlying correlation.

Prediction 1a: (Uncorrelated). Lottery A is equally likely to be chosen in choices i and j for all pairs when lotteries are uncorrelated.

Prediction 1b: (Correlated). Lottery A is more likely to be chosen in choice j for all pairs when lotteries are correlated.

Table 2: Equiprobable State Problems. A state is denoted by π_i for correlated conditions. For each pair, salience theory predicts subjects choose lottery A more frequently in choice j than in choice i when lotteries are correlated.

A. Three Equiprobable States

		Lottery A			Lottery B		
Pair	Choice	π_1	π_2	π_3	π_1	π_2	π_3
1	i	10	9	13	2	14	11
	j	13	9	10	2	14	11
2	i	9	10	14	1	18	11
	j	14	9	10	1	18	11
3	i	9	10	15	1	18	17
	j	15	9	10	1	18	17
4	i	8	11	16	0	17	22
	j	11	8	16	0	17	22
5	i	8	11	17	0	18	24
	j	11	8	17	0	18	24

B. Mean Preserving Spreads - Two Equiprobable States

		Lottery A		Lottery B	
Pair	Choice	π_1	π_2	π_1	π_2
6	i	8	12	5	15
	j	12	8	5	15
7	i	18	22	15	25
	j	22	18	15	25

C. Mean Preserving Spreads - Four Equiprobable States

		Lottery A				Lottery B			
Pair	Choice	π_1	π_2	π_3	π_4	π_1	π_2	π_3	π_4
8	i	7	9	11	13	1	3	17	19
	j	11	13	7	9	1	3	17	19

D. First Order Stochastic Dominance - Three or Four Equiprobable States

		Lottery A			Lottery B		
Pair	Choice	π_1	π_2	π_3	π_1	π_2	π_3
9	i	4	15	26	27	5	16
	j	4	26	15	27	5	16

		Lottery A				Lottery B			
Pair	Choice	π_1	π_2	π_3	π_4	π_1	π_2	π_3	π_4
10	i	1	7	13	19	20	2	8	14
	j	1	19	7	13	20	2	8	14

3.2 Correlation awareness

The discussion so far assumes agents care about the correlation between lottery outcomes and *do* perceive whether lottery outcomes are correlated or not. That is, salience theory makes the implicit assumption that agents notice such correlation. It stands to reason, however, that effects consistent with salience theory under correlation will be stronger the more apparent the correlation between outcomes is. As we will show in the next section, we will stress test for salience by making the correlation between outcomes more apparent. This gives the next prediction.

Prediction 2 (Correlation awareness). Salience effects are invariant to presentation effects.

3.3 Decision times

Salience theory produces choice reversals by affecting utility contrasts between alternative lotteries. The extant research on decision times reports two patterns. First, judgment errors are more likely to occur whenever comparisons are harder to make, i.e., when the contrast between choices is smaller. This pattern is referred to as the *psychometric function*. Second, harder decisions take more time to make than easier decisions. This pattern is referred to as the *chronometric function* (see Alós-Ferrer et al., 2021). Both these patterns have been found in decisions under risk (Alos-Ferrer & Garagnani, 2022; Moffatt, 2005; Mosteller & Nogee, 1951).

These regularities furnish additional implications of salience theory. We should expect the effect of salience to be larger whenever subjects are closer to indifference. The existence of a *chronometric function* suggests that harder choices are those that take longer to make. However, salience itself might make decisions harder making interpretation difficult.

Equation (4) summarizes the change in contrast between lotteries due to salience. That contrast is lowest in pairs 1-5, followed by pairs 6-8, and highest for pairs 9-10. Choice reversals can be rationalized by salience theory by only relying on the property of *diminishing sensitivity* in mean-preserving spread pairs, and by relying on both *diminishing sensitivity* and *ordering* for the rest of the pairs. If salience affects the contrast between lotteries, we expect a within-subject change in decision times between choice i and choice j. The sign of such change is uncertain since we do not know which lottery choice within a pair subjects find more difficult to discern. However, we suppose that longer decision times are associated with more difficult decisions.

Prediction 3 (decision times): Decision times change from choice i to choice j due to salience.

3.4 Implementation

At the beginning of a session, each subject was randomly assigned to one of three treatments: *Correlated Separate*, *Uncorrelated*, or *Correlated Joint*. Lotteries were presented in spinning wheels (see Figures 1, 2, and 3). The experiment starts with 5 practice rounds in which subjects spin wheels to understand the nature of the correlation between lotteries. Subjects then make 20 binary lottery choices without spinning the wheels. Both practice and non-practice lotteries were presented in random order.[8] Colors, the order of lotteries, and states were randomized at the subject-trial level to account for biases in subjects potentially finding a particular color more appealing than others, and the tendency to read from left-right and top-bottom. We changed the set of colors for different choice problems to reduce choice fatigue. At the end of the experiment, one of the twenty choices was randomly selected and the lottery outcome was resolved to determine a subject's payoff. An average session lasted about 20 minutes and subjects earned $25.37 including a $10 show-up fee.

A prize in a spinning wheel represents a state, and the outcome of the state depends on a binary lottery choice. We maintain marginal distributions of lotteries constant and change joint distributions for pairs of choices as explained in Section 3. Figure 1 illustrates a typical interface used in treatment *Correlated Separate*. We implement correlation of outcomes by making both wheels spin in tandem. Figure 2 illustrates a typical interface used in treatment *Uncorrelated*. We implement independence of outcomes by making only the selected wheel spin. Finally, Figure 3 illustrates a typical interface used in treatment *Correlated Joint*. This treatment presents lottery A and lottery B on the same wheel to make the correlation of outcomes more apparent.

[8] The complete set of choices including practice problems can be found in the Appendix.

Figure 1: *Separate. Wheels spin at the same rate (and stop at the same angle), with presentation being the only difference compared to treatment Correlated Joint. When wheels finish spinning, subjects receive a feedback message with their earnings. They can also see how much they earn in a practice round by observing the angle at which the selected wheel stops spinning. Subjects observe counterfactual earnings in this treatment too.*

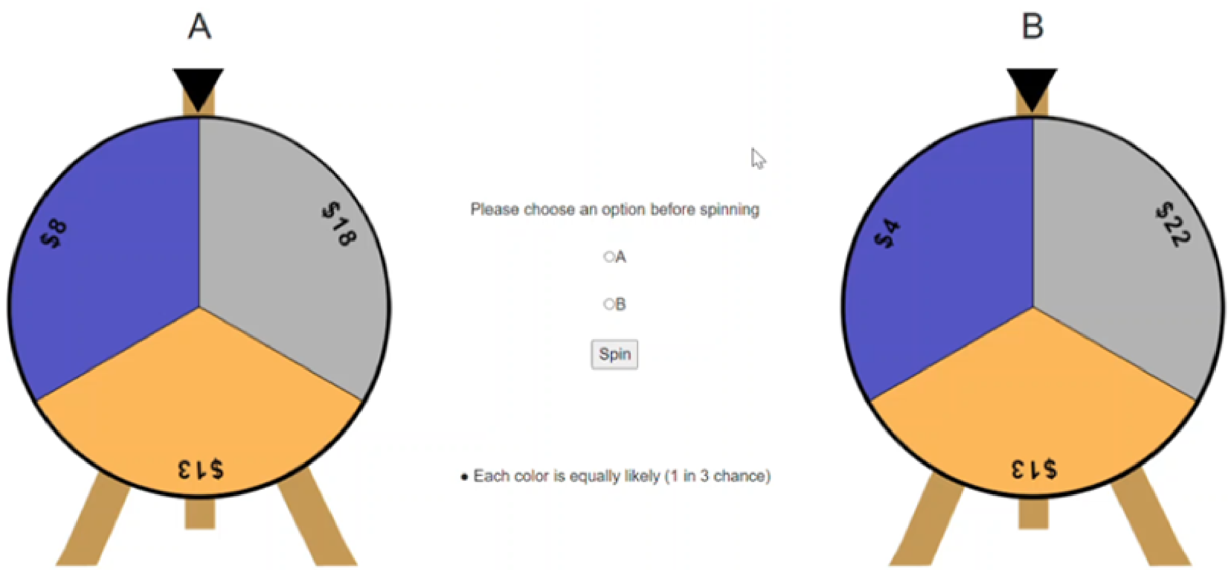


Figure 2: *Uncorrelated. Only the selected wheel spins. When the wheel finishes spinning, subjects receive a feedback message with their earnings. They can also see how much they earn in a practice round by observing the angle at which the wheel stops spinning. Subjects do not observe counterfactual earnings in this treatment (the non-chosen option does not spin).*

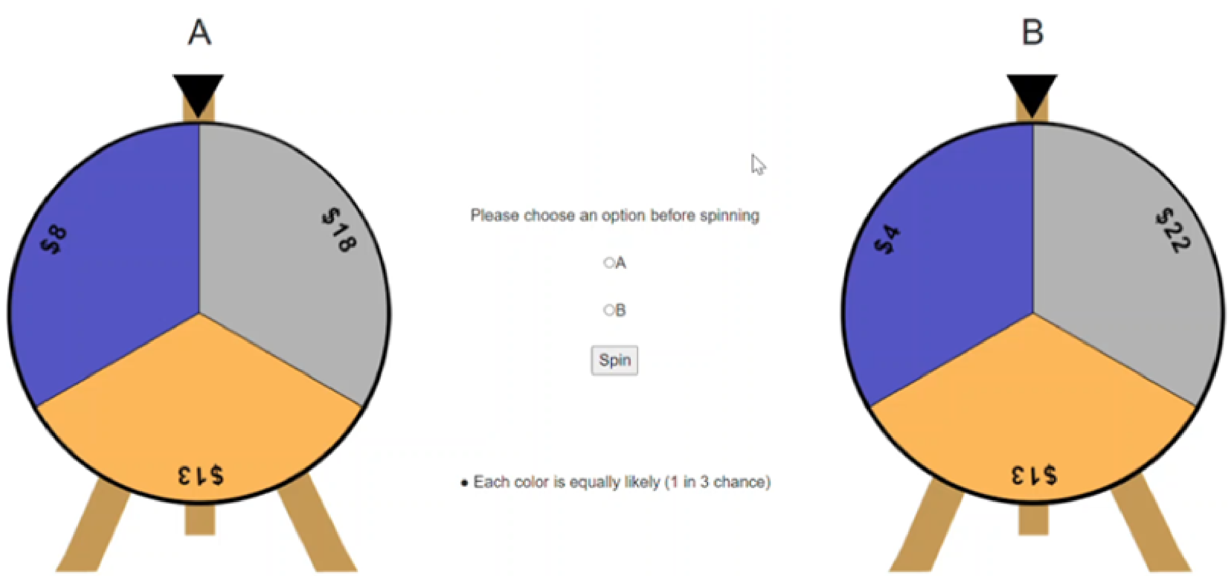
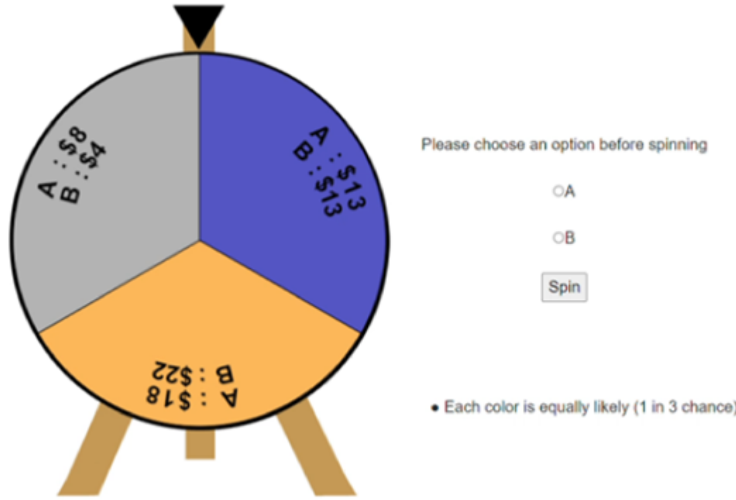


Figure 3: *Joint. When the wheel finishes spinning, subjects receive a feedback message with their earnings. They can also see how much they earn in a practice round by observing the angle at which the wheel stops spinning. They also observe counterfactual earnings.*



4 Results

This section studies choice reversals in decisions under risk. We describe the sample and basic choice patterns first. We analyze choice reversals second. We finish by discussing decision time patterns.

4.1 Sample description

A total of 280 Texas A&M undergraduate students participated in the experiment. Males comprised 41.4% of the sample and the average age of participants was around 21 years old. Data were collected over one year from October 2021 to October 2022. Columns (3) and (5) show differences between treatments *Correlated Joint* and *Uncorrelated*, and *Correlated Separate* and *Uncorrelated*, respectively. The proportion of males in treatment *Correlated Separate* was lower than in treatment *Uncorrelated* (two-sided t-test, $p = 0.063$). Other differences are not significant.

Table 3: Description of sample by treatment

Variable	(1) All	(2) Joint	(3) Diff.	(4) Separate	(5) Diff.	(6) Uncorrelated
male	0.414	0.475	-0.005	0.325	-0.154	0.479
	(0.493)	(0.501)	(0.086)	(0.470)	(0.083)	(0.505)
age	21.339	21.551	0.655	21.307	0.411	20.896
	(2.760)	(2.992)	(0.476)	(2.727)	(0.443)	(2.176)
N	280	118	166	114	162	48

4.2 Choice patterns across lottery types

As mentioned in Section 3, we test for correlation effects across a span of lotteries to account for heterogeneity in risk preferences. Figure 4 shows the proportion choosing lottery A for pairs in which the expected value of lottery A was larger or smaller than, or equal to the expected value of lottery B, and when lottery A was first-order stochastically dominated by lottery B. Table 4 presents the same results numerically. We obtain estimates using an OLS regression and cluster errors at the subject level to account for repeated measures. We observe that Lottery A is most likely to be chosen when its expected value exceeds that of Lottery B, and it is least likely to be chosen when it is FOSD by Lottery B. The proportion choosing lottery A when its expected value is smaller or equal to the expected value of lottery B is between these two proportions. All these differences are significant (see Table 4). We do not find a statistically significant difference in the proportion choosing lottery A when the expected value of lottery B is equal to or strictly larger than the expected value of lottery A. An exception to the last pattern is treatment *Correlated Separate* where the proportion of subjects choosing lottery A when the expected value of lottery B is larger than the expected value of lottery A is higher than in the mean-preserving spread choices.

All these patterns hold for each treatment separately. We conclude that our lottery choices can elicit systematic responses from subjects. That is, we reject the hypothesis that subjects were inattentive to incentives.

Figure 4: Probability of choosing lottery A by lottery type

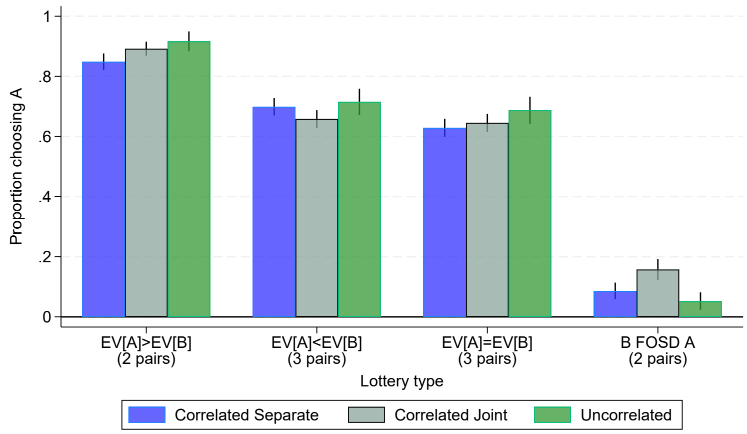


Table 4: Choice patterns

	Correlated Separate	Correlated Joint	Uncorrelated
(1) E[A]>[B]	0.321	0.298	0.338
	(0.044)	(0.042)	(0.085)
(2) E[A]<[B]	0.171	0.064	0.136
	(0.043)	(0.047)	(0.081)
(3) E[A]=E[B]	0.101	0.051	0.108
	(0.042)	(0.042)	(0.087)
(4) B FOSD A	-0.442	-0.437	-0.527
	(0.049)	(0.047)	(0.090)
Constant	0.528	0.594	0.579
	(0.044)	(0.042)	(0.086)
H0: (1)=(2)	29.03	69.76	25.64
	[0.000]	[0.000]	[0.000]
H0: (2)=(3)	4.44	0.15	0.52
	[0.037]	[0.701]	[0.476]
H0: (1)=(3)	72.40	372.565	44.13
	[0.000]	[0.000]	[0.000]
H0: (2)=(4)	272.07	86.19	134.53
	[0.000]	[0.000]	[0.000]
H0: (3)=(4)	221.78	169.69	137.21
	[0.000]	[0.000]	[0.000]

Errors clustered at the individual level. s.e. in parentheses, p-values in brackets.

4.3 Choice reversals

This section investigates choice reversals across lottery types and experimental treatments. To do this, we create a variable that equals 1 if a choice reversal is in the direction predicted by salience theory, equals 0 if there is no choice reversal, and equals -1 if a choice reversal is in the opposite direction from that predicted by salience theory. While salience theory makes a signed prediction, we use two-sided tests in the analysis to be conservative.[9] Figure 5 presents average and 90% confidence intervals of choice reversals by lottery type and experimental condition. Table 5 provides estimates of these effects.[10]

The first result is that choice reversals are not significant for groups of lotteries or overall in the *Uncorrelated* condition with an exception in stochastically dominated choices (see Table 4). While we cannot discard the possibility that color, or other features, affected FOSD choices, we intuit these results are due to subjects engaging in color comparison. As discussed in Section 3, salience theory predicts no choice reversals in treatment *Uncorrelated* since the state space is identical in choice i and choice j. We confirm that prediction.

Regarding choice reversals in the correlated conditions, we find partial evidence consistent with salience theory. In particular, we find choice reversals in the direction predicted by salience theory when the expected value of lottery A equals that of lottery B. This is significant in the *Correlated Joint* condition (p-value < 0.01), but not significant in the *Correlated Separate* condition (p-value > 0.10). We find evidence against salience theory when the expected value of lottery A exceeds that of lottery B in the *Correlated Separate* condition (p-value < 0.10), and when lottery A is FOSD by lottery B in the *Correlated Joint* condition (p-value < 0.01). We adjust p-values to account for multiple hypothesis testing (List, Shaikh, & Xu, 2019; Romano & Wolf, 2005).[11] After the adjustment, we observe that the only statistically significant differences that remain are those in the *Correlated Joint* condition.

[9] Alternative theories that assume correlation dependence of choices can predict violation of the opposite sign as salience. This occurs if the regret function is concave.

[10] We use OLS regression without a constant to calculate means and account for repeated measures. These estimates exploit the within-subject variation in our design. Between-subject conditions are not significant at conventional levels.

[11] We use the Stata *rwolf2* package for this purpose.

Figure 5: Choice reversals

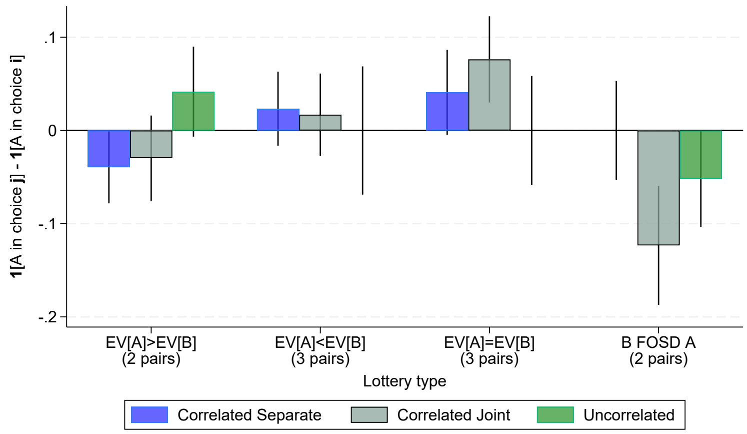


Table 5: Choice reversals

	All	E[A]>E[B]	E[A]<E[B]	E[A]=E[B]	B FOSD A
Correlated Separate	0.012	-0.039	0.023	0.041	0.000
	(0.015)	(0.023)	(0.026)	(0.030)	(0.032)
		[0.193]	[0.697]	[0.377]	[1.000]
Correlated Joint	0.007	-0.030	0.017	0.076	-0.123
	(0.015)	(0.028)	(0.029)	(0.027)	(0.039)
		[0.579]	[0.879]	[0.010]	[0.004]
Uncorrelated	0.000	0.042	0.000	0.000	-0.052
	(0.016)	(0.036)	(0.044)	(0.035)	(0.031)
		[0.526]	[1.000]	[1.000]	[0.193]
Obs	2602	560	840	840	362

Individual-level clustered standard errors in parentheses. *, **, *** denote significance at the 10%, 5% and 1% levels, respectively, prior to the multiple comparison adjustment. Romano-Wolf p-values adjusting for multiple comparisons in brackets.

As suggested in Section 3 we observe evidence consistent with salience theory in choices where subjects are close to indifferent between lottery A and lottery B. However, we also observe a pattern inconsistent with salience theory in choices when lottery A has a higher expected value than lottery B and in choices where lottery A is FOSD by lottery B. This last pattern is also in contradiction with a convex regret function. The evidence highlights the importance of calibration in testing for salience. Ex-ante, we expect either no choice reversal or choice reversals in the direction of salience theory. The data so far suggest the evidence in favor of salience is stronger when subjects are close to indifferent between lotteries and when the correlation of outcomes is made evident.

4.3.1 Decision times

This section investigates the relationship between choice reversals and decision times. We follow a long tradition in psychology and economics that uses decision time to assess the strength of preferences (e.g., Krajbich & Rangel, 2011, and the references therein). We then investigate if choice reversals could be classified as preference reversals.

We start by describing the main patterns on decision time. Figure 6 and Table 6 report the main patterns in decision times by lottery type and treatment condition. The first observation is that decision time is largest in the *Correlated Joint* condition, followed by *Correlated Separate* and *Uncorrelated*. This can be due to confusion or the fact that salience reduces the contrast between alternatives. However, we observe patterns across lotteries that hold across treatment conditions. Decision times on mean-preserving spread choices are significantly larger except in treatment *Correlated Separate*. This suggests that subjects find these choices harder to resolve regardless of the underlying correlation of lotteries. While subjects rarely choose dominated lotteries, decision times suggest they find it difficult to discern which lottery is better. Decision time patterns confirm that subjects responded differently to lottery types and experimental conditions. We observe that decision times are largest when we observe significant choice reversals in the *Correlated Joint* condition.

Figure 6: Time spent per choice and lottery type

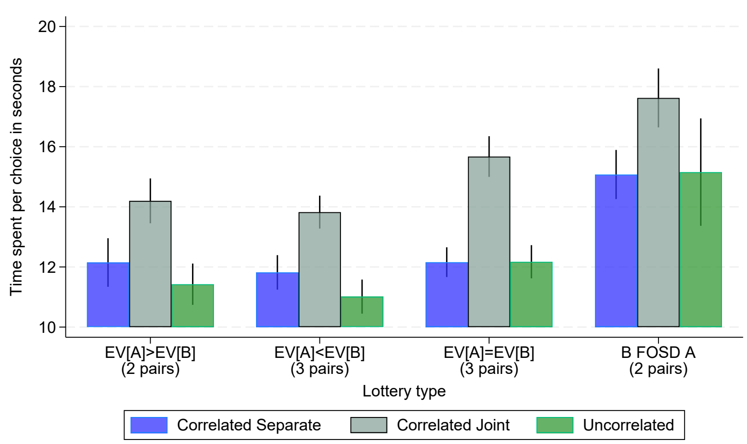


Table 6: Time use patterns

	Correlated Separate	Correlated Joint	Uncorrelated
(1) E[A]>[B]	1.238	1.882	0.401
	(0.706)	(0.957)	(1.214)
(2) E[A]<[B]	0.910	1.508	-0.012
	(0.673)	(0.996)	(1.333)
(3) E[A]=E[B]	1.250	3.357	1.147
	(0.702)	(0.856)	(1.196)
(4) B FOSD A	4.166	5.307	4.129
	(0.944)	(0.969)	(1.658)
Constant	10.910	12.317	11.026
	(0.934)	(0.947)	(1.399)
H0: (1)=(2)	0.44	0.64	1.04
	[0.511]	[0.426]	[0.312]
H0: (2)=(3)	0.72	11.99	6.07
	[0.399]	[0.001]	[0.018]
H0: (1)=(3)	0.00	8.88	8.79
	[0.982]	[0.004]	[0.005]
H0: (2)=(4)	29.18	29.95	13.02
	[0.000]	[0.000]	[0.001]
H0: (3)=(4)	31.54	9.53	7.76
	[0.000]	[0.003]	[0.008]

Errors clustered at the individual level. s.e. in parentheses, p-values in brackets.

A premise in salience theory, that we exploit in our experimental design, is that the correlation of outcomes affects the evaluation of lotteries. In particular, our design predicts choice reversals from choosing lottery B in choice i to lottery A in choice j. We do not know, ex-ante, if this occurs because the perceived expected utility of both lotteries is closer in choice i or choice j. If subjects become closer to indifference in choice j, we should expect they will take more time deciding j relative to choice i. If the opposite holds, we would expect to observe subjects taking more time in i.[12] Figure 7 and Table 7 explore this pattern. They both estimate within-subject variation on decision times between choice j and choice i across lottery types and treatment conditions.

As mentioned in Section 3, the contrast between lotteries due to salience differs across choice pairs. It is largest in dominance-ordered lotteries and second largest for mean-preserving spreads.

[12] We acknowledge that average behavior might be quite different from individual behavior. As we show later, these patterns do not reflect the behavior of a few subjects.

We observe a large, while insignificant, reversal in decision time that can be ordered by dominance in all conditions. We note that salience does not predict different treatments of lotteries in this case, so we cannot conclude that the observed pattern is due to salience. We are also cautious about this result because there are only 2 lottery pairs that can be dominance ordered.

Subjects spend around one and a half extra seconds in choice j when the expected value of lottery B is larger than or equal to that of lottery A. This pattern is observed only in the *Correlated Joint* condition. This pattern of behavior is important because it is consistent with the *Correlated Joint* condition increasing awareness of the correlation of outcomes. We say this because decision time reversals are within-subject measures, and therefore they eliminate any common feature affecting each lottery comparison. The results also suggest that decision time reversals are increasing in the contrast between lotteries due to salience (see equation (4)). We should remark that the pattern of decision time reversals already indicates that decision-making is affected by the correlation of outcomes. We are not aware of previous research reporting this pattern.

Figure 7: Decision time reversals

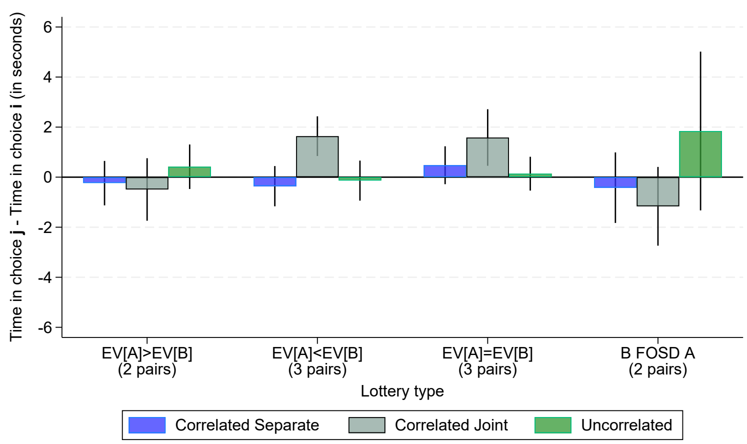


Table 7: DECISION TIME IN CHOICE j - DECISION TIME IN CHOICE i

	All	E[A]>E[B]	E[A]<E[B]	E[A]=E[B]	B FOSD A
Correlated Separate	-0.070	-0.239	-0.361	0.476	-0.420
	(0.246)	(0.484)	(0.490)	(0.366)	(0.854)
		[0.938]	[0.896]	[0.668]	[0.938]
Correlated Joint	0.784	-0.492	1.638	1.585	-1.164
	(0.342)	(0.664)	(0.510)	(0.550)	(0.924)
		[0.896]	[0.008]	[0.029]	[0.668]
Uncorrelated	0.395	0.417	-0.139	0.139	1.844
	(0.430)	(0.410)	(0.569)	(0.405)	(2.031)
		[0.832]	[0.938]	[0.938]	[0.861]
Obs	2596	558	839	838	361

Individual-level clustered standard errors in parentheses. *, **, *** denote significance at the 10%, 5% and 1% levels, respectively, prior to the multiple comparison adjustment. Romano-Wolf p-values adjusting for multiple comparisons in brackets.

Table 8 investigates if choice reversals are predicted by reversals in decision times. To do this we augment the regression model in Table 5 to include the change in decision time (in seconds). We observe that the magnitude and significance of the treatment effects on choice reversals are unchanged by the inclusion of this variable.

Table 8: DO DECISION TIME REVERSALS PREDICT CHOICE REVERSALS?

	All	E[A]>E[B]	E[A]<E[B]	E[A]=E[B]	B FOSD A
Correlated Separate	0.011	-0.039	0.022	0.038	-0.000
	(0.015)	(0.024)	(0.026)	(0.030)	(0.033)
		[0.274]	[0.866]	[0.585]	[1.000]
Correlated Joint	0.008	-0.028	0.024	0.076	-0.124
	(0.015)	(0.027)	(0.030)	(0.027)	(0.040)
		[0.741]	[0.866]	[0.012]	[0.006]
Uncorrelated	0.000	0.040	-0.001	0.000	-0.051
	(0.016)	(0.036)	(0.044)	(0.036)	(0.031)
		[0.673]	[1.000]	[1.000]	[0.274]
Change in Decision time	-0.000	0.003	-0.004	-0.000	-0.001
	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)
		[0.363]	[0.129]	[1.000]	[0.985]
Obs	2596	558	839	838	361

Individual-level clustered standard errors in parentheses. *, **, *** denote significance at the 10%, 5% and 1% levels, respectively, prior to the multiple comparison adjustment. Romano-Wolf p-values adjusting for multiple comparisons in brackets.

4.3.2 Are choice reversals preference reversals?

An important remaining question is whether the observed choice reversals can be considered preference reversals. The answer to this question has paramount implications for welfare analysis (e.g. Bernheim & Rangel, 2009). As we will show, our experimental design allows us to gain traction in this important issue.

Alós-Ferrer et al. (2021) derive conditions under which decision times can be used to determine the direction of preferences. In particular, they show that a revealed preference for lottery A over lottery B can be deduced if $F_B(t)$ q-FSD (q-first order dominates) $F_A(t)$ for $q = \frac{Pr(choice=A)}{Pr(choice=B)}$. This condition can be expressed as the following:

$$Pr(choice = A)F_A(t) - Pr(choice = B)F_B(t) \geq 0, \forall t \geq 0 \tag{5}$$

To give some intuition to this definition, consider the case in which lottery A and lottery B are chosen with probability one-half. In this case, equation (5) says that if lottery A is preferred to lottery B, it should be chosen more quickly. The first remark to make is that this statement applies to individual decision-making. We do not have enough choices per individual to be able to apply this framework at this level. However, we can exploit the long tradition in economics that uses random utility models to characterize the behavior of populations. We certainly do not expect individuals to have the same preferences or the same chronometric function. We, however, appeal to random assignment to balance individual differences across treatments and lotteries. We take the results that follow as thought experiments.

The second consideration refers to the empirical implementation of this approach. The statement above is based on exact probabilities and distribution functions. Since our data is finite, we estimate these probabilities and cumulative distributions. We use a nonparametric kernel density estimate.[13] We estimate a gap function, defined as:

$$\hat{D}(t) = Pr(\widehat{choice} = A)\hat{F}_A(t) - Pr(\widehat{choice} = B)\hat{F}_B(t) \tag{6}$$

where $Pr(\widehat{choice} = x)$ and $\hat{F}_x(t)$ for $x = A, B$ are sample analog probabilities and cumulative distributions. If $\hat{D}(t) \geq 0, \forall t \geq 0$, we can deduce that lottery A is revealed preferred to lottery B. If $\hat{D}(t) \leq 0, \forall t \geq 0$, we can deduce that lottery B is revealed preferred to lottery A. If the $\hat{D}(t)$ function crosses the X-axis for some value of t, we cannot deduce preferences without making

[13] We use the Stata *akdensity* package for this purpose.

distributional assumptions.

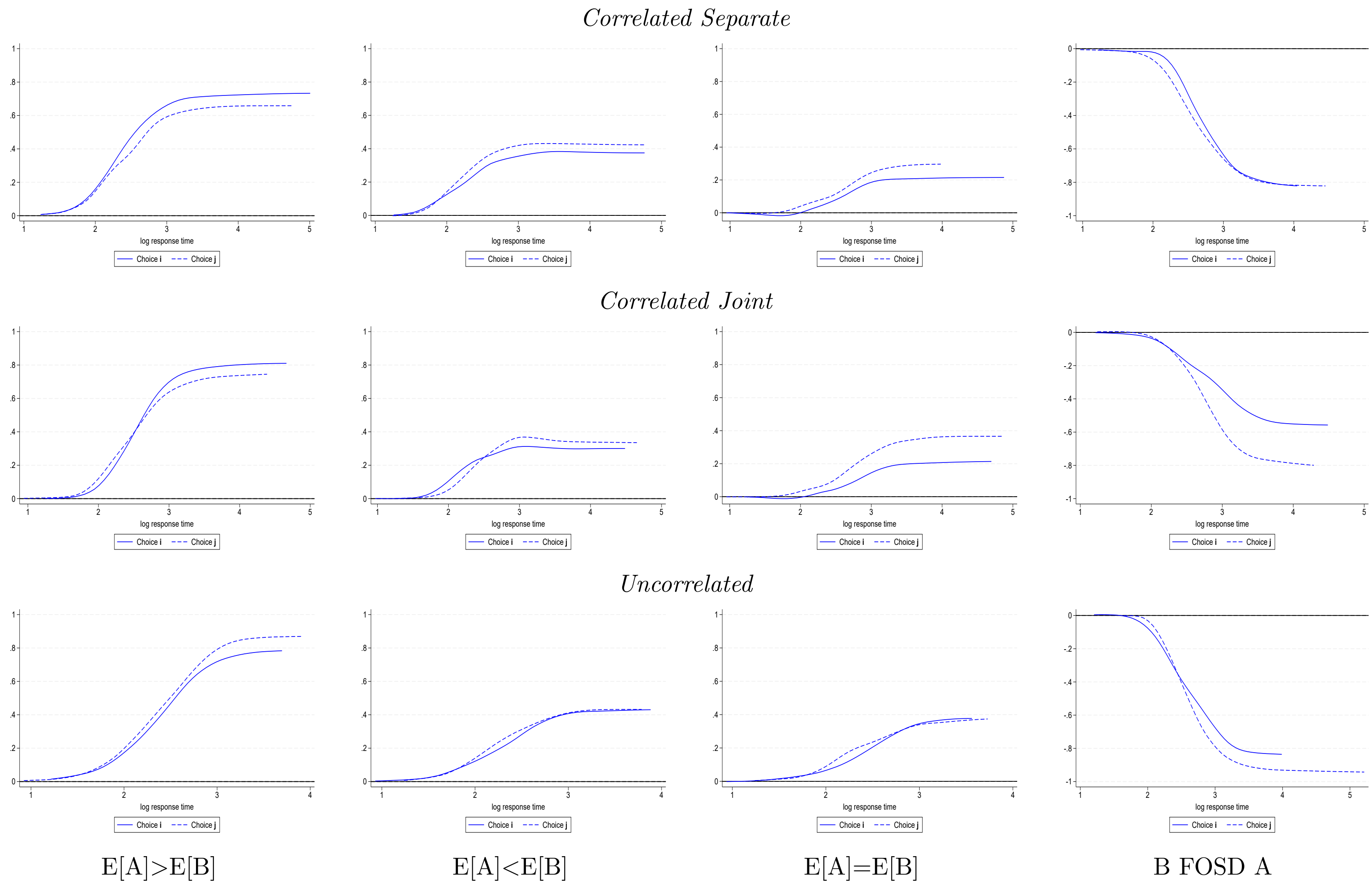
Figure 8 presents estimates of function $\hat{D}(t)$ by treatment, lottery type and choice i and j. Decision times are presented in log scales. Solid lines correspond to choice i, and dashed lines correspond to choice j. The patterns in the data are very clear: lottery A is revealed preferred to lottery B in all choices and treatments except for first-order stochastically dominated choices. In the latter case, lottery B is revealed preferred to lottery A. Violations of single-crossing are rare and small. They occur for the mean-preserving spreads when decision times are relatively faster. To test the qualitative robustness of the observed patterns in section 4.3, we apply response time techniques to the binary choice data. We divide the sample into choice problems i and j and, for each treatment and lottery type, make comparisons between the problem types to test the null hypothesis of first-order stochastic dominance of the latent distributions. Specifically, we draw upon a test for stochastic dominance proposed by Barrett and Donald (2003) and adapted by Liu and Netzer (2023) to examine whether $D_j(t)$ q-FSD $D_i(t)$ for all t across lottery types and treatments. While the test was originally developed to assess the validity of a given estimate, for our purposes, when the null hypothesis of first-order stochastic dominance is rejected, the idea is that the estimation results do not conform with salience-predicted choice reversals.[14] The evidence that lottery A is revealed preferred to lottery B with a differential intensity within pairs of a lottery type can be observed for mean-preserving spread choices in the *Correlated Joint* condition (second row, third column). We see that lottery A is more clearly found to be superior in choice j than in choice i. This is consistent with choice reversals being a result of a change in perceived expected utility in the direction of salience theory. The null hypothesis of first-order stochastic dominance of the latent distributions cannot be rejected ($p = 0.870$). The graphs also give us insight into the presence of preference reversals in the stochastic dominance lotteries. We see that lottery A is more clearly found inferior in choice j than in choice i in the *Correlated Joint* condition which contradicts predictions of salience theory and is further confirmed by the rejection of the null hypothesis of first-order stochastic dominance ($p = 0.003$). These tests show that significant coefficients of the observed choice reversals are qualitatively robust, further highlighting the use of response time techniques in assessing the validity of a given estimate.[15]

[14] The test is one-sided and we separately test $D_i(t)$ q-FSD $D_j(t)$ for all t. The validity of a given positive estimate from Table 5 is tested by the null $D_j(t)$ q-FSD $D_i(t)$ for all t, and the validity of a negative estimate is tested by the null that $D_i(t)$ q-FSD $D_j(t)$ for all t. We use the Stata *fosdtest* command developed by Liu and Netzer (2023) for this purpose.

[15] p-values from other comparisons that did not survive significance under conventional levels in Table 5 after accounting for multiple hypothesis testing can be found in the Appendix in Tables A1 and A2.

Overall, if we are willing to accept the existence of a representative agent, the patterns of decision times suggest that choice reversals are preference reversals.

Figure 8: Function $\hat{D}(t)$ by treatment, lottery type, and lottery choice



5 Conclusion

We conduct a non-parametric test of the salience theory of choice under risk by examining choice reversals as a function of the correlation between risky alternatives. Salience theory has clear predictions for the choice problems we study. Since neither risk attitudes nor the strength of salience are observed, we explore a wide range of payoffs and lottery types to avoid the possibility of false negatives. Similarly, we manipulate the framing of options to make the underlying correlation of risky alternatives evident. Choice reversals occur only when the correlation is made apparent and for lotteries with equal expected payoffs and lotteries that can be ordered by first-order stochastic dominance. The choice reversals we observe are consistent with salience theory in the first case but not in the second. These choices also reject either concave or convex regret theory. We exploit decision times to explore if choice reversals are consistent with preference reversals. We find decision time reversals consistent with preference reversals. This suggests that agents are sensitive to the correlation of outcomes but that correlation is not a salient feature of the decision problem. How subjects react to the correlation is not always predicted by existing theories.

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Appendix

Table A1: P-VALUES FROM FOSD TEST

	E[A]>E[B]	E[A]<E[B]	E[A]=E[B]	B FOSD A
Correlated Separate	0.219	0.641	0.550	0.411
Correlated Joint	0.278	0.258	0.870	0.003
Uncorrelated	0.911	0.726	0.772	0.241

Null hypothesis: $D_j(t)$ q-FSD $D_i(t)$ for all t.

Table A2: P-VALUES FROM FOSD TEST

	E[A]>E[B]	E[A]<E[B]	E[A]=E[B]	B FOSD A
Correlated Separate	0.637	0.228	0.118	0.918
Correlated Joint	0.404	0.074	0.013	0.870
Uncorrelated	0.413	0.555	0.626	0.665

Null hypothesis: $D_i(t)$ q-FSD $D_j(t)$ for all t.

EXPERIMENTAL MATERIALS

Instructions

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 we will come to assist you. Your earnings will depend on the decisions you make during the experiment. These earnings will be paid in addition to your $10 show-up payment.

In this experiment you will be asked to pick one of two options (Option A or Option B) for 20 choices. At the end of the experiment, 1 of the 20 choices will be randomly selected for payment. You will then be paid based on the outcome of that choice which will be resolved with a random drawing of a ball from a bingo cage. Therefore, it is in your best interest that you take every decision seriously.

First, you will be asked to make choices in 5 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 20 choices, of which 1 will be randomly selected for payment.

We will record your selections for all of the 20 choice problems. At the end of the experiment, a random number will be drawn (between 1 and 20, inclusive) to determine which of the 20 choices will be used for payment. Given your selection on this choice problem, the outcome is resolved by a randomly drawn ball from a bingo cage.

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

Now that you had the opportunity to learn how earnings are determined, you will be asked to make selections for 20 choices. We will record your selections for all of the 20 choices. At the end of the experiment, a random number will be drawn (between 1 and 20, inclusive) to determine the choice for which you will be paid. Given your selection on this choice problem, the outcome is resolved with a randomly drawn ball from a bingo cage. Since each choice could be selected for payment, it is in your best interest to take every decision seriously.

Choice Problems

Practice Choices (% chose A)

Choice 1							
State	Probability	A	B	Salience Rank	Joint	Separate	Uncorrelated
1	0.33	8	4	1	57% (N=118)	36% (N=114)	60% (N=48)
2	0.33	18	22	2			
3	0.33	13	13	3			

Choice 2							
State	Probability	A	B	Salience Rank	Joint	Separate	Uncorrelated
1	0.25	3	7	1	41% (N=118)	48% (N=114)	52% (N=48)
2	0.25	5	9	2			
3	0.25	19	15	3			
4	0.25	21	17	4			

Choice 3							
State	Probability	A	B	Salience Rank	Joint	Separate	Uncorrelated
1	0.5	2	9	1	39% (N=118)	43% (N=114)	29% (N=48)
2	0.5	21	14	2			

Choice 4							
State	Probability	A	B	Salience Rank	Joint	Separate	Uncorrelated
1	0.33	9	1	1	45% (N=118)	50% (N=114)	60% (N=48)
2	0.33	9	16	2			
3	0.33	16	17	3			

Choice 5							
State	Probability	A	B	Salience Rank	Joint	Separate	Uncorrelated
1	0.1	0	6	1	73% (N=118)	80% (N=114)	71% (N=48)
2	0.9	16	11	2			

Incentivized Choices (% chose A)

Choice 1							
State	Probability	A	B	Salience Rank	Joint	Separate	Uncorrelated
1	0.33	10	2	1			
2	0.33	9	14	2	91% (N=118)	89% (N=114)	92% (N=48)
3	0.33	13	11	3			

Choice 2							
State	Probability	A	B	Salience Rank	Joint	Separate	Uncorrelated
1	0.33	13	2	1			
2	0.33	9	14	2	88% (N=118)	88% (N=114)	94% (N=48)
3	0.33	10	11	3			

Choice 3							
State	Probability	A	B	Salience Rank	Joint	Separate	Uncorrelated
1	0.33	9	1	1			
2	0.33	10	18	2	91% (N=118)	84% (N=114)	88% (N=48)
3	0.33	14	11	3			

Choice 4							
State	Probability	A	B	Salience Rank	Joint	Separate	Uncorrelated
1	0.33	14	1	1			
2	0.33	9	18	2	87% (N=118)	78% (N=114)	94% (N=48)
3	0.33	10	11	3			

Choice 5							
State	Probability	A	B	Salience Rank	Joint	Separate	Uncorrelated
1	0.33	9	1	1			
2	0.33	10	18	2	69% (N=118)	70% (N=114)	71% (N=48)
3	0.33	15	17	3			

Choice 6							
State	Probability	A	B	Salience Rank	Joint	Separate	Uncorrelated
1	0.33	15	1	1	64% (N=118)	68% (N=114)	65% (N=48)
2	0.33	9	18	2			
3	0.33	10	17	3			

Choice 7							
State	Probability	A	B	Salience Rank	Joint	Separate	Uncorrelated
1	0.33	8	0	1	65% (N=118)	71% (N=114)	73% (N=48)
2	0.33	11	17	2			
3	0.33	16	22	3			

Choice 8							
State	Probability	A	B	Salience Rank	Joint	Separate	Uncorrelated
1	0.33	11	0	1	69% (N=118)	75% (N=114)	77% (N=48)
2	0.33	8	17	2			
3	0.33	16	22	3			

Choice 9							
State	Probability	A	B	Salience Rank	Joint	Separate	Uncorrelated
1	0.33	8	0	1	61% (N=118)	65% (N=114)	71% (N=48)
2	0.33	11	18	2			
3	0.33	17	24	3			

Choice 10							
State	Probability	A	B	Salience Rank	Joint	Separate	Uncorrelated
1	0.33	11	0	1	67% (N=118)	70% (N=114)	73% (N=48)
2	0.33	8	18	2			
3	0.33	17	24	3			

Choice 11							
State	Probability	A	B	Salience Rank	Joint	Separate	Uncorrelated
1	0.33	4	27	1	20% (N=118)	10% (N=114)	6% (N=48)
2	0.33	15	5	2			
3	0.33	26	16	3			

Choice 12							
State	Probability	A	B	Salience Rank	Joint	Separate	Uncorrelated
1	0.33	4	27	1	9% (N=118)	9% (N=114)	4% (N=48)
2	0.33	26	5	2			
3	0.33	15	16	3			

Choice 13							
State	Probability	A	B	Salience Rank	Joint	Separate	Uncorrelated
1	0.5	8	5	1	62% (N=118)	60% (N=114)	71% (N=48)
2	0.5	12	15	2			

Choice 14							
State	Probability	A	B	Salience Rank	Joint	Separate	Uncorrelated
1	0.5	12	5	1	71% (N=118)	66% (N=114)	79% (N=48)
2	0.5	8	15	2			

Choice 15							
State	Probability	A	B	Salience Rank	Joint	Separate	Uncorrelated
1	0.5	18	15	1	44% (N=118)	49% (N=114)	50% (N=48)
2	0.5	22	25	2			

Choice 16							
State	Probability	A	B	Salience Rank	Joint	Separate	Uncorrelated
1	0.5	22	15	1	55% (N=118)	50% (N=114)	50% (N=48)
2	0.5	18	25	2			

Choice 17							
State	Probability	A	B	Salience Rank	Joint	Separate	Uncorrelated
1	0.25	7	1	1	78% (N=118)	74% (N=114)	85% (N=48)
2	0.25	9	3	2			
3	0.25	11	17	3			
4	0.25	13	19	4			

Choice 18							
State	Probability	A	B	Salience Rank	Joint	Separate	Uncorrelated
1	0.25	11	1	1	80% (N=118)	79% (N=114)	77% (N=48)
2	0.25	13	3	2			
3	0.25	7	17	3			
4	0.25	9	19	4			

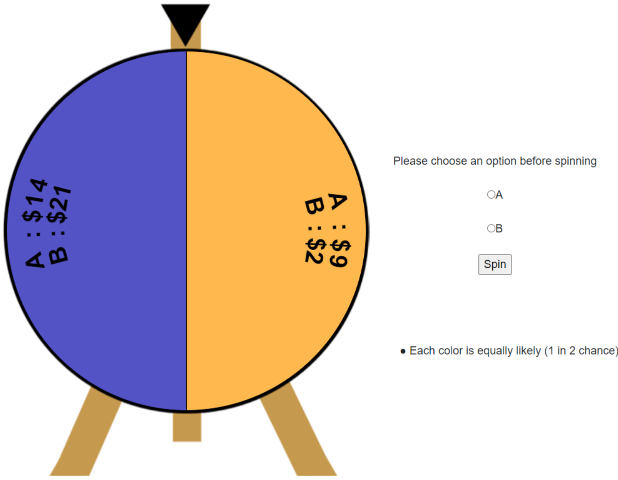
Choice 19							
State	Probability	A	B	Salience Rank	Joint	Separate	Uncorrelated
1	0.25	1	20	1	29% (N=28)	0% (N=25)	10% (N=29)
2	0.25	7	2	2			
3	0.25	13	8	3			
4	0.25	19	14	4			

Choice 20							
State	Probability	A	B	Salience Rank	Joint	Separate	Uncorrelated
1	0.25	1	20	1	11% (N=28)	8% (N=25)	0% (N=29)
2	0.25	19	2	2			
3	0.25	7	8	3			
4	0.25	13	14	4			

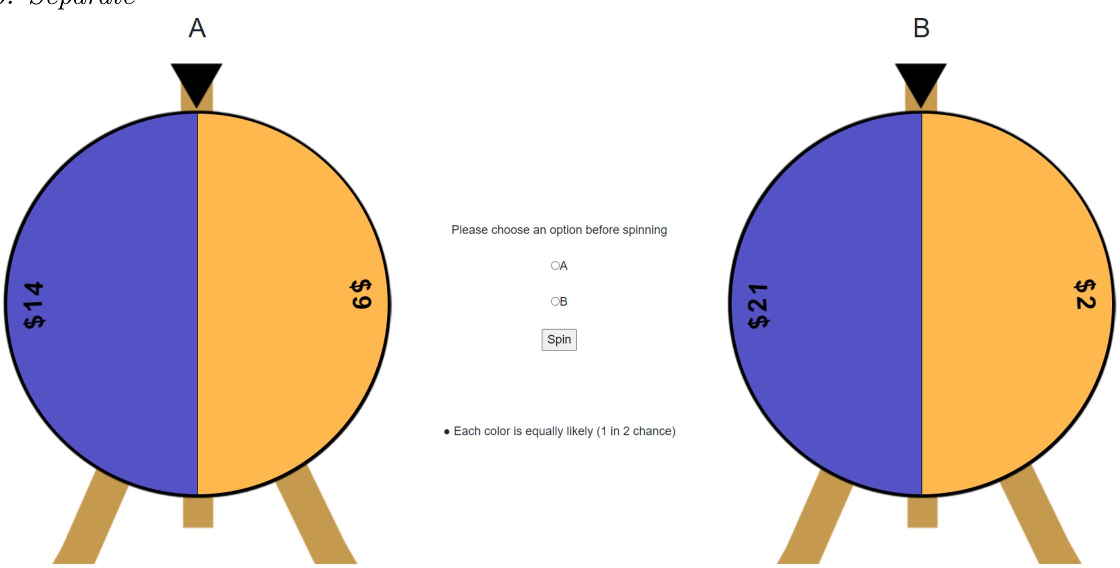
Lottery Presentations

50-50 Lotteries

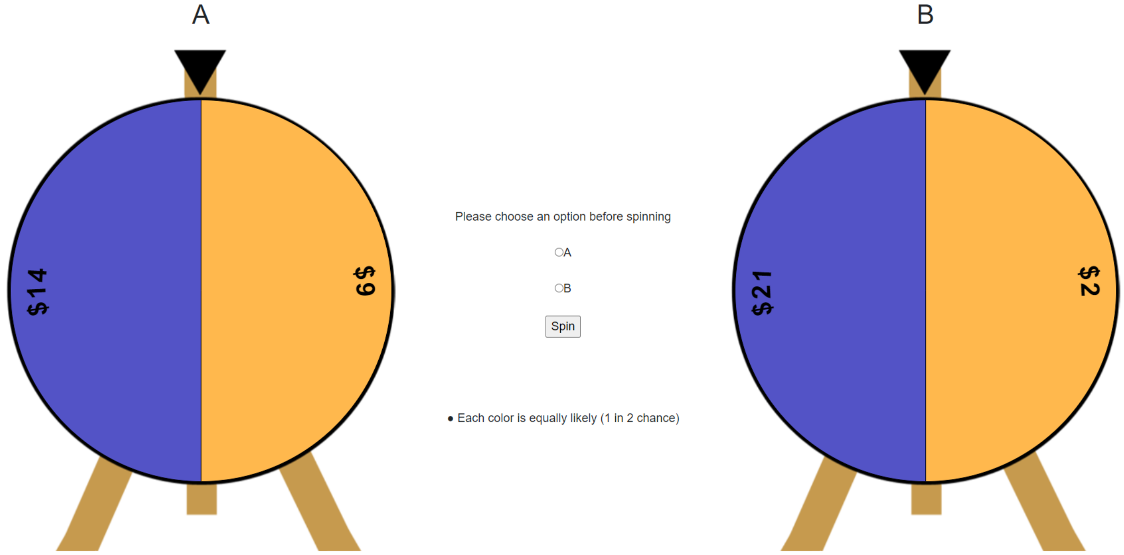
a. Joint



b. Separate

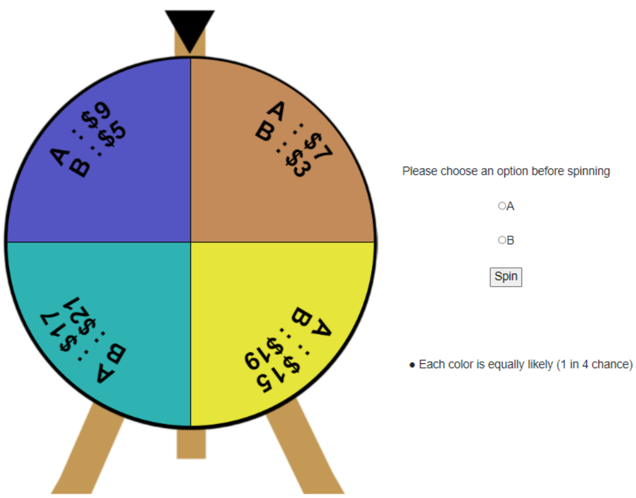


c. Uncorrelated

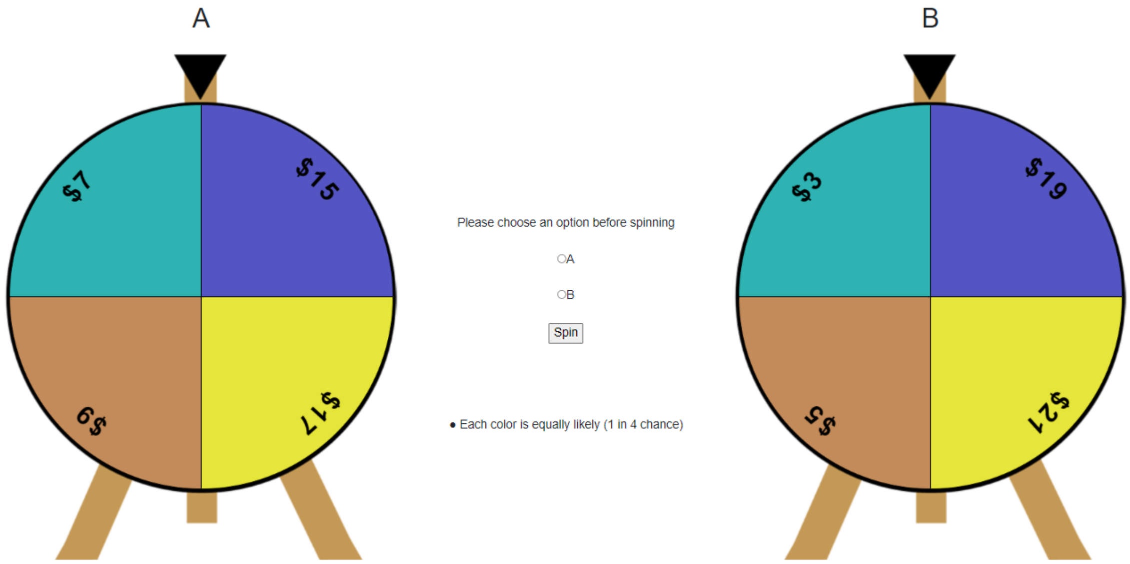


25-25-25-25 Lotteries

a. Joint



b. Separate



c. Uncorrelated