UNCOVERING CORRELATION SENSITIVITY IN DECISION MAKING UNDER RISK*

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Abstract

Allowing risk preferences to be sensitive to the correlation between lottery outcomes can resolve classical deviations from expected utility theory and provides a plausible explanation for phenomena in various real-world settings. However, evidence on correlation sensitivity is limited and mixed. In this paper, we first show that correlation-sensitive preferences in the general framework of Lanzani (2022) can be classified into three categories. We propose a novel experimental task that allows to classify experimental subjects according to this categorization. In a series of experiments, we find that aggregate choices display correlation sensitivity but in the opposite direction as often assumed in regret and salience theory. Individual level analysis suggests that the aggregate findings are driven by a minority who consistently exhibit this behavior even when it violates first-order stochastic dominance. Finally, we disentangle between correlation sensitivity due to deliberate within-state comparisons and incidental payoff comparisons due to the framing of decision problems, and find that both channels produce correlation sensitivity, with deliberate comparisons being somewhat more important.

Keywords: Choice under risk; Correlation effects; Experiment; Regret theory; Salience theory

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1 Introduction

In an influential class of risk preferences including regret theory and salience theory (Bell, 1982; Loomes and Sugden, 1982; Bordalo et al., 2012), the correlation between different risky prospects can significantly impact choices. Incorporating correlation sensitivity in preferences can help resolve several deviations from expected utility theory (EUT), including the Allais paradox (Allais, 1953), preference reversals, or simultaneous gambling and insurance. Moreover, it provides an explanation for skewness preferences (Dertwinkel-Kalt and Köster, 2020) and asset price puzzles (Bordalo et al., 2013a).

However, the key behavioral implications of correlation sensitivity remain somewhat elusive, and existing experimental evidence on the prevalence and nature of correlation sensitivity is inconclusive. In this paper, we consider the general class of correlation-sensitive preferences axiomatized by Lanzani (2022), which nests regret (Bell, 1982; Loomes and Sugden, 1982, 1987) and salience theory (Bordalo et al., 2013b). We show that there exist three types of correlation sensitivity. We then propose a simple experimental task that allows us to classify experimental subjects according to their type of correlation sensitivity. Finally, we provide experimental evidence on the prevalence and nature of correlation sensitivity, and probe its psychological foundations.

Our novel experimental task, the same marginal lotteries (SML) task illustrated in Table 1, captures the key features of correlation sensitivity. The marginal distribution of both lotteries is described by three distinct payoffs: h, m, and l, each of which occurs with equal probability. Whenever the row lottery yields the payoff h, m, or l, the column lottery yields, respectively, the payoff l, h, or m. Note that both lotteries share the same marginal distribution and are distinguishable only by the way payoffs are correlated. The row lottery yields a much higher outcome than the column lottery with probability 1/3 (h vs l), but a somewhat lower outcome with probability 2/3 (m vs h and l vs m). Evidently, a decision maker whose preferences are fully characterized by the marginal distribution of payoffs is indifferent between the two lotteries. A correlation-sensitive decision maker, however, has a strict preference for either the row or the column lottery.

Intuitively, the decision maker has to aggregate the differences between joint payoff realizations to form a preference. If she aggregates payoff differences linearly, we say that she satisfies constant sensitivity to payoff differences (CSPD). In this case, she is indifferent between the row and the

Table 1 The same marginal lotteries (SML) task

π^{sml}	$h(1/3)$	$m(1/3)$	$l(1/3)$
$h(1/3)$	0	1/3	0
$m(1/3)$	0	0	1/3
$l(1/3)$	1/3	0	0

column lottery. If the decision maker is increasingly sensitive to payoff differences (ISPD), large payoff differences have an outsized effect on preferences. The decision maker factors the high-contrast realization (h,l) more heavily than the two smaller differences of the realizations (m,h) and (l,m) combined. As a result, the decision maker has a strict preference for the row lottery. If the decision maker is decreasingly sensitive to payoff differences (DSPD), the reverse applies. Heuristically speaking, a decision maker characterized by ISPD chooses the lottery that yields the higher outcome for the payoff realization with the highest contrast, whereas a decision maker characterized by DSPD chooses the lottery that yields a higher payoff most of the time.

In the framework of Lanzani (2022), we show that preferences over the lotteries of the SML task allow us to classify people into the three mutually exclusive categories of preferences characterized by CSPD, ISPD, and DSPD. Lanzani provides a representation theorem for the class of correlation-sensitive preferences. He further shows that if transitivity is imposed, correlation-sensitive preferences collapse to EUT and become insensitive to the correlation structure. We slightly extend Lanzani's result to show that transitivity is equivalent to a simple and intuitive condition on the correlation-sensitive utility function. This condition can be understood as imposing CSPD, which implies that preferences are not correlation-sensitive, but are fully described by a relation over marginal distributions of payoffs. It follows that in Lanzani's framework, transitivity can be violated in two ways, and thus correlation sensitivity can take two directional forms: either ISPD or DSPD. We show that a decision maker satisfies CSPD if and only if she is indifferent between the row and the column lottery of the SML task. The decision maker strictly prefers the row lottery (the column lottery) if and only if she satisfies ISPD (DSPD). Therefore, we occasionally refer to the row as the ISPD lottery and the column as the DSPD lottery.

As Lanzani's framework nests regret and salience theory, our result shows that correlation sensitivity is the key behavioral property that distinguishes regret and salience theory from EUT. Both theories make assumptions that imply ISPD. In salience theory, joint realizations receive different decision weights according to their salience (Bordalo et al., 2012). The assumption that implies ISPD is that joint realizations with large payoff differences are the most salient and thus receive disproportionate decision weight. In regret theory, the decision maker's utility depends on a comparison of jointly realized payoffs. If the decision maker realizes that they could have received a higher payoff had they chosen differently, she experiences regret (Loomes and Sugden, 1982, 1987). The crucial assumption that yields ISPD is that the decision maker is increasingly sensitive to increments in regret.

The SML task serves as the basis for our experimental tests of correlation sensitivity. Since correlation sensitivity implies strict preferences for either the row or the column lottery, if a decision maker does not exhibit correlation sensitivity for the SML task, she will not exhibit correlation sensitivity in any other decision problem. Failure to detect correlation sensitivity thus provides strong evidence of correlation insensitivity. Intuitively, since the marginal distribution of both lotteries is the same, even correlation sensitivity of otherwise negligible importance should be apparent. On the flip side, if choices display correlation sensitivity, this might be caused by a weak preference that might not be evident in any other decision problem. To probe the strength of potential correlation sensitivity, we add a payoff premium to all payoffs of either the ISPD or the DSPD lottery, rendering one of the lotteries First-Order Stochastic Dominant (FOSD). We refer to these decision problems as FOSD tasks. A decision maker with CSPD has a strict preference for the lottery which is FOSD. Correlation-sensitive decision makers may violate FOSD in one direction, which comes at the cost of forgoing higher payoffs.

We further implement three between-subject treatments to investigate the psychological foundations of correlation sensitivity. ISPD is the key theoretical property in both regret and salience theory, but these theories rely on distinct psychological mechanisms. In regret theory (Bell, 1982; Loomes and Sugden, 1982), payoff comparisons are deliberate because the decision maker's true utility depends on a comparison of jointly realized payoffs. In salience theory (Bordalo et al., 2012), on the other hand, payoff comparisons impact the decision maker's perception of the choice at hand. As there is nothing about joint payoff realizations that the decision maker values intrinsically, payoff comparisons might be best described as incidental. Different authors have suggested that the framing of decision problems, rather than the joint realization of payoffs, might be the relevant criterion to determine the unit of payoff comparisons in salience theory (Dertwinkel-Kalt and Köster, 2015; Leland et al., 2019).

Our between-subject treatments build on the distinction between deliberate comparisons of jointly realized payoffs and incidental payoff comparisons due to the framing of the decision problem. In all treatments, the joint distribution of lotteries is described by reference to states of nature, which are determined by the turn of a wheel of fortune, and the lotteries yield different outcomes depending on the realized state of nature. We present the choice problems in tabular form. In the baseline treatment, each column describes the realizations of each lottery in a given state of the world. In this treatment, correlation sensitivity can arise from deliberate state-by-state comparisons of payoffs or incidental column-by-column comparisons of payoffs. Our remaining two treatments allow us to disentangle the two channels. In the column-effects treatment, payoffs are perfectly correlated across states, which means correlation sensitivity can only arise from column-by-column comparisons of payoffs. On the other hand, in the state-effects treatment, the payoffs displayed in each column are the same for both lotteries, while the joint distribution of payoffs remains consistent with the baseline treatment. Consequently, correlation effects observed in this treatment can only be attributed to deliberate state-by-state comparisons of payoffs across columns.

We further supplement the SML task in the baseline treatment with a within-subject treatment that varies whether subjects receive immediate outcome feedback after a given choice. We include this treatment to accommodate for the contingency that regret aversion is a prominent feature in decision making only if individuals anticipate immediate outcome feedback (Bell, 1983; Zeelenberg et al., 1996; Zeelenberg, 1999).

In one lab and two online experiments, comprising a total of 919 participants, we collected more than 18,000 observations. In the baseline treatment, the aggregate choices provide evidence for small but consistent effects that imply DSPD. We also document a precise null effect of immediate outcome feedback, suggesting that it does not interact with correlation sensitivity in a significant way. Using latent class analysis to identify categories of choice patterns, we find that most of our participants exhibit behavior consistent with CSPD. However, a minority of around 17% of the participants consistently exhibit behavior that satisfies DSPD, even if it violates FOSD. Importantly, the latent class analysis does not produce a corresponding category of participants whose behavior is characterized by ISPD. Therefore, both our aggregate and individual-level results strongly reject ISPD as the prevalent property governing preferences.

We find further evidence of DSPD in both the column-effects and the state-effects treatments. However, compared to the baseline treatment, the aggregate effect size is somewhat reduced, particularly in the column-effects treatment. Furthermore, when analyzing individual responses, we find that only 9% of participants in the column-effects treatment are assigned to the latent class characterized by strong DSPD. In contrast, the corresponding fraction in the state-effects treatment is 22%. This indicates that deliberate comparisons of jointly realized payoffs may play a somewhat more significant role in driving correlation sensitivity compared to incidental column-by-column comparisons of payoffs.

1.1 Related literature

We contribute to three strands of literature. First and foremost, we contribute to the experimental literature on correlation-sensitive preferences. Although models of correlation-sensitive preferences have drawn interest at least since the proposal of regret theory (Bell, 1982; Loomes and Sugden, 1982) and have recently seen a revival in salience theory (Bordalo et al., 2012), the experimental evidence for correlation sensitivity is inconclusive.

Three approaches to examining correlation sensitivity can be distinguished. The first approach builds on manipulations of the joint distribution of payoffs. A number of papers motivated by testing regret theory (Loomes and Sugden, 1987; Loomes, 1988a,b) and salience theory (Bordalo et al., 2012; Frydman and Mormann, 2018; Dertwinkel-Kalt and Köster, 2020; Bruhin et al.,

2022) used this approach and reported choice patterns that purportedly provided evidence for ISPD. However, Starmer and Sugden (1993) showed that the initial results attributed to correlation sensitivity were most likely caused by so called event-splitting effects, which are unintended changes in the choice display.[1] Once controlling for these simultaneous changes in the choice display, Starmer and Sugden (1993) found that the evidence for correlation sensitivity was considerably weakened and lost statistical significance. Humphrey (1995), and more recently Ostermair (2021) and Loewenfeld and Zheng (2023) also failed to find evidence for correlation sensitivity once changes in the choice display were controlled for. However the design of these studies does not allow to conclude that preferences satisfy CSPD. We will elaborate on this point in section 3.2. Therefore, their findings may be inconclusive. This view is echoed by (Starmer and Sugden, 1993, p.253), who find no statistically significant evidence for correlation sensitivity but argue that their "*data display a clear tendency towards a* [correlation] *effect, and it may be that such effects would be more apparent in other problem settings.*"

A second approach seeks to measure the correlation-sensitivity of preferences in a non-parametric way using the trade-off method (Wakker and Deneffe, 1996). Adopting this approach, both Bleichrodt et al. (2010) and Baillon et al. (2015) reported evidence suggesting the majority of their participants satisfied ISPD. However, Andersson et al. (2023) failed to replicate their findings with M-turk workers, who are supposedly more representative than university students. Moreover, these results are subject to severe limitations. The trade-off method involves a dynamically generated series of choices. The dynamic nature of the method creates a critical issue, namely a lack of incentive compatibility, which could produce behavior equivalent to ISPD.[2]

The third approach relies on testing for preference cycles as prescribed by regret theory (Loomes et al., 1991; Baillon et al., 2015). As pointed out above, in Lanzani's framework, decision makers violate transitivity if and only if they are correlation-sensitive.[3] Therefore, tests for preference cycles predicted by ISPD constitute a test of correlation insensitivity. Initial studies seemed to find

[1] In these studies, subjects were confronted with a choice between two different lotteries under two different joint distributions. Correlation sensitivity implies that subjects might shift their choices in response to the change in the joint distribution. However, simultaneous to changing the correlation structure, the number of states displayed to subjects was changed as well, in a way that has been shown to produce behavioral patterns similar to those implied by ISPD (Starmer and Sugden, 1993; Ostermair, 2021; Loewenfeld and Zheng, 2023).

[2] The trade-off method consists of eliciting a series of values x_j that make the decision maker indifferent between a lottery $(x_j, p; g, 1-p)$ and another lottery $(x_{j-1}, p; G, 1-p)$, with g, G, x_0, and p being chosen by the experimenter. In the first step, g, G, and x_0 are used to elicit x_1. The second step then consists of using g, G, and x_1 to elicit x_2, and so on up to x_5 in Bleichrodt et al. (2010). If subjects anticipate the structure of the method, it provides an incentive to report higher values of x_1, x_2, etc., as would correspond to their actual preferences.

[3] Although we do not test for violations of transitivity directly in the sense of showing evidence for cycling preferences, strict preferences for one of the lotteries of the SML task and cycling preferences are equivalent in the framework of Lanzani (2022). Indeed, we show that the SML task is a "reduced form" test for the cycle $A \succ B \succ C \succ A$ as it cuts out the middle part and directly tests for $A \succ A$. It should be stressed here that the concept of transitivity commonly used in the decision literature is defined for A, B, C denoting marginal distributions. While this facilitates comparisons to EUT and other models of risk taking, this concept of transitivity is conceptually odd from the perspective of correlation-sensitive preferences. For a correlation-sensitive decision maker, the row and the column lottery of the SML task are clearly distinct from one another.

support for such cycling preferences (Loomes et al., 1989, 1991). However, subsequent studies claimed that the preference cycles previously observed were likely the result of decision noise rather than intransitive preferences (Sopher and Gigliotti, 1993; Regenwetter et al., 2011). Motivated by this development, Baillon et al. (2015) employed a two-step procedure. In the first step, they employed the trade-off method to measure subjects' correlation-sensitive preferences. In the second step, subjects were confronted with choice-triples tailored to their preferences, such that systematic violations of transitivity should be triggered. However, this was not observed, despite simulation exercises suggesting statistical power near 100%. These findings suggests that the trade-off method might not provide reliable estimates of correlation sensitivity.[4]

With the SML task, we advance the investigation of correlation sensitivity by providing a novel diagnostic tool. From an experimental viewpoint, the simplicity of the SML task is its main strength as it avoids methodological shortcomings. It is incentive compatible, and the results can be interpreted in a straightforward way, while undesirable and confounding features of the choice display are naturally avoided (see section 3.2 for details). The SML task is capable of detecting correlation sensitivity, even if it were of negligible importance, which is a theoretical advantage. While previous studies have been somewhat inconclusive, this property of the SML task enables us to firmly reject that behavior satisfies ISPD both at the aggregate and the individual level. Furthermore, in a large sample of participants, we document for the first time small but persistent effects implying DSPD at the aggregate level, which is driven by a minority of participants who consistently display behavior satisfying DSPD. These results are in sharp contrast with the predictions of regret and salience theory and existing findings in the literature. We attribute our ability to document DSPD to a mix of high statistical power and our improved experimental task.

We also contribute to the experimental literature on correlation sensitivity by investigating its psychological foundations. To the best of our knowledge, we are the first to do so. Our results suggest that both incidental payoff comparisons due to the framing of choice problems, as well as deliberate state-by-state comparisons of payoffs play their part in producing correlation sensitivity, although the latter channel might be somewhat more important.

Finally, we contribute to the broader literature on regret and salience theory. A number of experimental studies have tested the implications of regret (Somasundaram and Diecidue, 2017) and salience theory (Dertwinkel-Kalt et al., 2017; Königsheim et al., 2019; Alós-Ferrer and Ritschel, 2022), but without testing for correlation sensitivity. A large literature has developed regret theory theoretically (Bell, 1982; Loomes and Sugden, 1982; Bell, 1983; Loomes and Sugden, 1987; Quiggin, 1990, 1994; Sarver, 2008; Diecidue and Somasundaram, 2017; Gollier, 2020). Applied theoretical work has explored the implications of regret theory for insurance demand (Braun and

[4] We are thankful to Aurélien Baillon for pointing this out.

Muermann, 2004; Wong, 2012), portfolio choice (Michenaud and Solnik, 2008; Qin, 2015), asset pricing (Gollier and Salanié, 2006), and health prevention (Zheng, 2021). Salience theory (Bordalo et al., 2012) has been shown to provide a potential foundation for skewness preferences (Dertwinkel-Kalt and Köster, 2020) and has been applied to the study of asset pricing, both theoretically (Bordalo et al., 2013a) and empirically (Cosemans and Frehen, 2021), as well as the newsvendor problem (Dertwinkel-Kalt and Köster, 2017).

The popularity of these two theories is due to their intuitively plausible explanations for many perplexing choice phenomena observed in various settings, ranging from experimental labs to insurance and asset markets. We contribute to this literature by testing the ISPD property, which is the key theoretical property that sets apart regret and salience theory from other prominent decision-making theories under risk. Our rejection of ISPD at the aggregate and individual level suggests that the mechanisms postulated in regret and salience theory are unlikely to be the cause of deviations from EUT, such as the Allais paradox or simultaneous gambling and insurance, as well as behavioral tendencies like the commonly observed preference for right-skewed risks. One might argue that much of the ability of regret and salience theory to explain these behavioral anomalies is due to its capability to endogenize the probability weighting of cumulative prospect theory (Tversky and Kahneman, 1992). The recent literature on behavioral inattention and Bayesian updating provides promising avenues for understanding these behaviors without violating transitivity (Gabaix, 2014; Enke and Graeber, 2021).

The remainder of this paper is organized as follows. Section 2 provides a formal discussion of correlation-sensitive preferences. We then introduce our novel experimental task in section 3. Section 4 details the experimental procedures, and section 5 presents the main experimental results. We discuss our results in section 6. Section 7 concludes.

2 Correlation-sensitive preferences

In the framework of Lanzani (2022), choices between two lotteries are described by a nonempty set of payoffs X and a finite measure of the joint probability distribution $\pi \in \Delta(X \times X)$. To avoid technicalities we impose $X \subseteq \mathbb{R}$. Consider Table 2. The decision maker decides between the row and the column lottery so as to be paid accordingly to the realized row or column outcome. The payoff pair (x_i, y_j) realizes with a probability of π_{ij}. For a decision maker who is not correlation-sensitive, preferences are fully described by a binary ranking over the marginal distribution of the row lottery $\pi_1 \in \Delta(X)$ (light gray area in Table 2) and that of the column lottery $\pi_2 \in \Delta(X)$ (gray area in Table 2). Formally, the marginal distribution of the row lottery is given by $\pi_1(x) = \sum_{y \in Y} \pi(x,y) = (p_1, ..., p_m)$ and that of the column lottery by $\pi_2(y) = \sum_{x \in X} \pi(x,y) = (q_1, ..., q_n)$.

Table 2 Binary choices in the tabular form

π	$y_1(p_1)$	...	$y_m(p_m)$
$x_1(q_1)$	π_{11}	...	π_{1m}
...	...	...	...
$x_n(q_n)$	π_{n1}	...	π_{nm}

To allow for correlation sensitivity, Lanzani defines the decision maker's preferences over the joint distribution of outcomes. Binary preferences are modeled as a preference set $\Pi \subseteq \Delta(X \times X)$. The decision maker is said to have a preference for the row lottery for a given joint distribution π if $\pi \in \Pi$. Define $\overline{\pi}$ to be the conjugate distribution of π, that is, $\forall(x,y) \in X \times X$, $\overline{\pi}(x,y) = \pi(y,x)$. Intuitively, the conjugate distribution is the distribution that obtains when switching the row and the column lottery. Then, a decision maker has a preference for the column lottery if $\overline{\pi} \in \Pi$.

The relation $\pi \in \Pi$ is analogous to the familiar weak preference relation $\succeq$, and $\pi, \overline{\pi} \in \Pi$ corresponds to indifference. Note that the classical preference relation $\succeq$ also induces a preference set. However, it is defined over $\Delta(X) \times \Delta(X)$ whereas Π is defined over $\Delta(X \times X)$. Given the notion of weak preferences, a notion of strict preferences, in the language of preference sets, can be introduced. Given a preference set Π, the subset of strict preferences $\hat{\Pi}$ is defined as $\hat{\Pi} = \{\pi \in \Pi : \overline{\pi} \notin \Pi\}$. That is, for $\pi \in \hat{\Pi}$ the decision maker strictly prefers to be paid according to the row rather than the column lottery.

Lanzani (2022) imposes three axioms on the preference set Π that are necessary and sufficient to obtain a representation theorem for correlation-sensitive preferences. The three axioms are completeness, strong independence, and continuity, and are natural analogues to the corresponding axioms in the v.N.M axiomatization of EUT.[5] Consider a skew-symmetric function $\phi : X \times X \to \mathbb{R}$, that is, $\phi(x,y) = -\phi(y,x)$, $\forall(x,y) \in \mathbb{R} \times \mathbb{R}$. A preference set Π satisfies Lanzani's three axioms if and only if there exists a skew-symmetric function ϕ such that, for any $\pi \in \Delta(X \times X)$

$$\pi \in \Pi \iff \sum_{x,y} \phi(x,y)\pi(x,y) \geq 0 \tag{1}$$

As Lanzani points out, the binary preference relation induced by preferences defined over the marginal distributions of payoffs is a possibly incomplete subset of the relation defined over the joint distribution of payoffs. In other words, preferences defined over the joint distribution are more general than preferences defined over the marginal distribution of payoffs. As such, it might

[5] Whereas completeness and archimedean continuity can be seen as a translation of the corresponding axioms in the v.N.M. axiomatization of EUT into the language of preference sets, the strong independence axiom implies considerably less structure than the corresponding standard independence axiom of EUT. The standard independence axiom implies that common consequences, understood as payoffs that are yielded by the marginal distribution of both lotteries, do not impact choice and can be edited out. The strong independence axiom implies that payoffs yielded by both the row and the column lottery can be edited out if they realize jointly.

not be surprising that Lanzani's framework can accommodate EUT preferences.[6]

However, the generality of correlation-sensitive preferences comes at a cost of added complexity. Whether this added complexity is necessary, that is whether risk preferences are indeed meaningfully correlation-sensitive, is a crucial question. As it is part of our motivation to provide evidence on this question, we introduce a formal definition of correlation-sensitive preferences, whose counterpart are naturally correlation-insensitive.

Definition of correlation-sensitive preferences. *Let the set of payoffs $X = \mathbb{R}$. A preference relation is correlation-sensitive if and only if* $\exists \pi,\ \pi' \in \Delta(X \times X) : \pi_1 = \pi'_2,\ \pi_2 = \pi'_1,\ \pi \in \hat{\Pi}$ *and* $\pi' \in \hat{\Pi}$.

Intuitively, preferences are correlation-sensitive if and only if there exists a pair of row and column marginals such that the row lottery is strictly preferred under one joint distribution π, but the column lottery is strictly preferred under a different joint distribution π'. In other words, correlation-sensitive preferences cannot be fully described by a binary relation over marginal distributions.

Lanzani (2022) introduces a fourth axiom, transitivity, which is essentially a translation of the classic transitivity axiom into the language of preference sets. In words, the transitivity states that if a marginal distribution π_1 is preferred to another marginal distribution χ_1 under a joint distribution π, and the marginal distribution χ_1 is preferred to another marginal distribution χ_2 under a joint distribution χ, then the marginal distribution π_1 must be preferred to the marginal distribution χ_2 under a joint distribution ρ.[7]

In his Proposition 1, Lanzani (2022) shows that if transitivity is imposed, the preference relation is fully characterized by an EUT representation. Below, we restate Lanzani's proposition, and slightly extend it by showing that transitivity is equivalent to correlation insensitivity, as well as to a simple and intuitive condition on the function ϕ. This characterization of correlation insensitivity will greatly help in clarifying the directional effect of correlation sensitivity and in deriving our experimental tests of correlation sensitivity.

Proposition 1. *If Π admits a correlation-sensitive preference representation as given in the expression (1), the following statements are equivalent:*

1. *Π satisfies transitivity.*
2. *Π is fully characterized by EUT (and thus correlation-insensitive).*
3. *$\forall h, m, l \in \mathbb{R}$ such that $h > m > l$, $\phi(h,l) = \phi(h,m) + \phi(m,l)$*

[6] A preference set admits an EUT representation if there exists $u : X \to \mathbb{R}$ such that $\pi \in \Pi \iff \sum_{x,y}(u(x) - u(y))\pi(x,y) \geq 0$. In other words, $\phi(x,y) = u(x) - u(y)$.

[7] Formally, the transitivity axiom can be stated as follows: $\forall\ \pi, \chi, \rho \in \Delta(X \times X)$, if $\pi_2 = \chi_1$, $\rho_1 = \pi_1$, and $\rho_2 = \chi_2$, then $(\pi \in \Pi, \chi \in \Pi) \Rightarrow \rho \in \Pi$.

Proof. see Appendix A. □

2.1 Classification of correlation-sensitive preferences

This restated and extended version of Lanzani's proposition is meaningful for several reasons. First, it highlights that preferences are correlation-sensitive, and transitivity is violated if and only if $\phi(h,l) \neq \phi(h,m) + \phi(m,l)$. This allows to distinguish broadly between three mutually exclusive categories of preferences. The first category is correlation insensitivity. Decision makers falling into this category satisfy Constantly Sensitivity to Payoff differences (CSPD). such decision makers are indifferent between one large payoff difference and two smaller differences that add up to the same size (see Proposition 1). For the other two categories of preferences, correlation sensitivity goes in two opposite directions. If $\phi(h,l) > \phi(h,m) + \phi(m,l)$, decision makers prefer one large payoff difference to two smaller differences that add up to the same size. We will say that decision makers in this category are Increasingly Sensitive to Payoff Differences (ISPD). For the reverse direction, we will say that decision makers are Decreasingly Sensitive to Payoff Differences (DSPD). This forms the third category. We summarize the classification of correlation-sensitive preferences below.

Classification of correlation-sensitive preferences. *Suppose that a decision maker's preference relation admits a correlation-sensitive preference representation as given in the expression* (1). *Then,*
(1) the decision maker is CSPD (or correlation-insensitive) if $\phi(h,l) = \phi(h,m) + \phi(m,l)$*;*
(2) the decision maker is ISPD if $\phi(h,l) > \phi(h,m) + \phi(m,l)$*;*
(3) the decision maker is DSPD if $\phi(h,l) < \phi(h,m) + \phi(m,l)$*.*

The condition on the preference functional connects naturally to the literature on regret and salience theory. In their generalization of original regret theory (Loomes and Sugden, 1982), Loomes and Sugden (1987) impose the condition $\phi(h,l) > \phi(h,m) + \phi(m,l)$, which is usually referred to as regret aversion or convexity in the regret theory literature. As Herweg and Müller (2021) demonstrate, from a mathematical perspective, salience theory is a special case of generalized regret theory. Thus, both salience and and regret regret theory imply ISPD. Proposition 1 highlights the fact that correlation-sensitivity is the defining feature of both salience and regret theory. When preferences satisfy CSPD, they are correlation-insensitive and collapse to an EU representation.

Finally, it is worth mentioning that in the context of binary choices, the recently proposed attention theory by Chew et al. (2023) incorporates correlation sensitivity. Particularly, when the attention function exhibits skew symmetry, attention theory aligns with regret theory and salience theory. While our experiments primarily focus on characterizing correlation sensitivity within the framework of Lanzani (2022), they also serve as a test for correlation sensitivity induced by attention theory.

3 An experimental test of correlation sensitivity

3.1 The same marginal lotteries (SML) task

Consider the choice tasks displayed in Table 3. Panel (3i) presents our main experimental task, the SML task. As the name suggests, subjects choose between two lotteries that have the same marginal distribution. The lotteries can be distinguished only based on the joint distribution π^{sml}. In panels (3ii) and (3iii), a payoff premium (i.e., $\varepsilon > 0$) is added to all possible payoffs of either the row or the column lottery, which makes the corresponding lottery first-order stochastic dominant. We refer to these choice problems as the FOSD tasks, which are denoted as π^r and π^c depending on whether the row or column lottery is dominant. The following corollary trivially follows from Proposition 1.

Corollary 1. *If Π admits a correlation-sensitive representation as given in the expression (1), the following holds for all $h, m, l \in \mathbb{R}$ such that $h > m > l$.*

1. $\phi(h,l) > \phi(h,m) + \phi(m,l) \iff \pi^{sml} \in \hat{\Pi}$;
2. $\phi(h,l) < \phi(h,m) + \phi(m,l) \iff \overline{\pi}^{sml} \in \hat{\Pi}$;
3. $\phi(h,l) = \phi(h,m) + \phi(m,l) \iff \pi^{sml} \in \Pi$ *and* $\overline{\pi}^{sml} \in \Pi \iff \pi^r \in \hat{\Pi}$ *and* $\overline{\pi}^c \in \hat{\Pi}$, $\forall \varepsilon > 0$.

The corollary states that any correlation-sensitive decision maker has a strict preference for either the row or the column lottery of π^{sml}. That is, in an experimental setting, any decision

Table 3 Tests of correlation sensitivity

π^{sml}	$h(1/3)$	$m(1/3)$	$l(1/3)$
$h(1/3)$	0	0	1/3
$m(1/3)$	1/3	0	0
$l(1/3)$	0	1/3	0

(i) The SML task

π^r	$h(1/3)$	$m(1/3)$	$l(1/3)$
$h+\varepsilon(1/3)$	0	0	1/3
$m+\varepsilon(1/3)$	1/3	0	0
$l+\varepsilon(1/3)$	0	1/3	0

(ii) The raw lottery being FOSD

π^c	$h+\varepsilon(1/3)$	$m+\varepsilon(1/3)$	$l+\varepsilon(1/3)$
$h(1/3)$	0	0	1/3
$m(1/3)$	1/3	0	0
$l(1/3)$	0	1/3	0

(iii) The column lottery being FOSD

maker satisfying ISPD must express a preference for the row lottery. By contrast, a decision maker satisfying DSPD must express a preference for the column lottery. We will therefore refer to the row lottery as the ISPD lottery, and to the column lottery as the DSPD lottery. The SML task provides a stringent test of correlation-sensitive preferences in the following sense. Should a decision maker fail to express a preference for the ISPD (DSPD) lottery, it can be concluded that the decision maker will not display increasing ISPD (DSPD) for any choice task.

A correlation insensitive decision maker is indifferent between the row and the column lottery of π^{sml}. If experimental subjects are forced to choose either the row or the column lottery, indifference implies that they choose either option with 50% probability. Subjects satisfying ISPD (DSPD), on the other hand will, safe for decision error, choose the row (the column) lottery. Therefore, a single choice of a single subject cannot be used to infer correlation insensitivity. However, averaging over choices, either across different subjects or across different choices within the same subjects, allows to cleanly distinguish between the three categories of preferences we introduced previously.

To gauge the strength of correlation sensitivity, we further consider the FOSD tasks. Correlation insensitivity implies a strict preference for the dominant lotteries under the joint distributions π^r as well as π^c. The SML task should reveal correlation sensitivity even if it is only of second-order importance in the sense of lexicographic preferences. For the FOSD tasks, however, experimental subjects have to violate FOSD in order to express their correlation-sensitive preferences.

The SML task also is a test of transitivity. Because correlation sensitivity is equivalent to intransitivity, proposition 1 in conjunction with corollary 3.1 imply that a strict preference for the row or the column lottery is equivalent to violating transitivity in Lanzani's framework. However, the SML task provides a test of transitivity in a more general sense. As Lemma A used in the proof of Proposition 1 shows, one needs only impose the completeness axiom, and neither strong independence, nor Archimedean continuity, for a strict preference for the row or the column lottery of the SML task to constitute a violation of transitivity. Note however, when only completeness is imposed, correlation insensitivity is no longer equivalent to transitivity, meaning that transitivity can be violated in ways unrelated to correlation sensitivity. The SML task therefore allows to unambiguously distinguish between transitive and intransitive preferences only within Lanzani's framework, but not in the more general case in which only completeness is imposed.

3.2 A comparison to past studies

In this section, we compare the SML task to previous experimental tasks used to test for correlation sensitivity. The approach closest the SML task is testing for correlation sensitivity by manipulating the joint distribution for choices between lotteries with different marginal distributions (Starmer and Sugden, 1993; Humphrey, 1995; Ostermair, 2021; Loewenfeld and Zheng, 2023). If no evidence of correlation sensitivity is observed in these studies, it does not necessarily imply that subjects are not correlation-sensitive. To clarify this point, consider the example task of Starmer and Sugden (1993) illustrated in Table 4 below. Subjects have to choose between the row and the column lotteries. The marginal distribution of the row lottery is relatively riskier but has a higher expected value. Note that the choice on the right hand side of the table is the same in terms of the marginal distributions of the lotteries. However, the joint distributions differ, with the lotteries on the left-hand panel being more negatively correlated than on the right-hand panel.

Consequently, observing a subject express a preference for the raw lottery under the joint distribution π and a preference for the column lottery under the joint distribution π' implies that her preferences are characterized by ISPD. The reverse choice pattern implies DSPD. However, these choice patterns are not implied by increasing or decreasing sensitivity to payoff differences. Formally, $\pi \in \Pi$ and $\overline{\pi}' \in \Pi \Rightarrow \phi(h,l) \geq \phi(h,m) + \phi(m,l)$, and $\pi' \in \Pi$ and $\overline{\pi} \in \Pi \Rightarrow \phi(h,l) \leq \phi(h,m) + \phi(m,l)$, but the reverse direction ($\Leftarrow$) does not hold. Thus, failing to observe these patterns cannot be taken to imply that preferences are correlation-insensitive.

Confronting subjects with this kind of tasks, Starmer and Sugden (1993) find no evidence for correlation-sensitive preferences. As the authors themselves conclude, the implications of these results are unclear as it is possible that correlation sensitivity would be more prevalent in another setting (Starmer and Sugden, 1993, p.253). Intuitively, correlation-sensitive preferences do not necessarily need to manifest in the setting of Starmer and Sugden (1993) if preferences over the marginal distributions of the lotteries are strong enough. For instance, since the row lottery in Table 4 yields a higher expected payoff, a given subject might choose it under both correlation structures, even if the very same subject would display correlation sensitivity in another setting. The SML task does away with such ambiguities. Intuitively, since choices are between two lotteries with the same marginal distribution, preferences over marginal distributions cannot play any role. This forces decision makers to reveal their correlation sensitivity.

A second set of studies uses choice triples to test for violations of transitivity as implied by ISPD (Loomes et al., 1991; Baillon et al., 2015). Consider the example displayed in Table 5. Subjects choose between the three marginal distributions $A = (8, 0.6; 0, 0.4)$, $B = (18, 0.3; 0, 0.7)$,

Table 4 An example task from Starmer and Sugden (1993)

π	7(55%)	0(45%)
11(45%)	0%	45%
0(55%)	55%	0%

(i) Negative correlation structure

π'	7(55%)	0(45%)
11(45%)	45%	0%
0(55%)	10%	45%

(ii) Positive correlation structure

Table 5 An example task from Loomes et al. (1991)

π^A	8(60%)	0(40%)
18(30%)	30%	0%
0(70%)	30%	40%

(i) Lottery A vs lottery B

π^B	18(30%)	0(70%)
4(100%)	30%	70%

(ii) Lottery B vs lottery C

π^C	4(100%)
8(60%)	60%
0(40%)	40%

(iii) Lottery A vs lottery C

and $C = (4,1)$. The cycle $A \succ B$, $B \succ C$, and $C \succ A$ is consonant with ISPD, whereas the reverse cycle $B \succ A, C \succ B, A \succ C$ is consistent with DSPD. In the absence of decision noise, observing an ISPD (DSPD) conform cycle implies ISPD (DSPD) of preferences. However, following a similar argument as above, not observing such cycles does not imply CSPD. Decision noise, which might affect all three choices required by experimental subjects, further complicates inference about the transitivity of preferences in non-trivial ways (Sopher and Gigliotti, 1993; Regenwetter et al., 2011; Loomes, 2005; Baillon et al., 2015). As the SML task consists of a single choice, it avoids such issues.

Apart from these theoretical properties, the SML task has a number of additional advantages from an experimental viewpoint. First, all joint payoff realizations have equal probability, which renders the task easy to understand. Second, our task naturally controls for event-splitting effects that are present in a number of studies on correlation sensitivity (e.g., Loomes, 1988b; Frydman and Mormann, 2018; Bruhin et al., 2022). Third, we avoid displaying duplicated states to experimental subjects, which is common in studies testing for correlation sensitivity while controlling for event-splitting effects (e.g., Loomes et al., 1991; Starmer and Sugden, 1993; Humphrey, 1995; Ostermair, 2021; Loewenfeld and Zheng, 2023). We also avoid “null states" or other states that should be edited out. While it might be argued that these features are undesirable since they could have unexpected effects on behavior, they are present in many of the choice tasks that have been used to test for correlation-sensitive preferences (Loomes, 1988b; Starmer and Sugden, 1993; Humphrey, 1995; Dertwinkel-Kalt and Köster, 2020; Ostermair, 2021; Loewenfeld and Zheng, 2023).

3.3 Probing the psychological foundations of correlation sensitivity

Although regret and salience theory both induce ISPD, they build on distinct psychological mechanisms. In both regret and salience theory, decision makers compare payoffs within states of nature, although for different reasons. In regret theory, within-state comparisons of payoffs are deliberate as they impact the decision maker's utility. In salience theory, within-state comparisons of payoffs can be seen as incidental. They impact the decision maker's perception of the choice task. However, there is nothing about within-state difference of payoffs that the decision maker intrinsically values. This has led to the suggestion that payoff comparisons need not necessarily be determined by which payoffs realize jointly but by how decision problems are framed when presented to decision makers (Dertwinkel-Kalt and Köster, 2015; Leland et al., 2019). This approach seems broadly consistent with the description of salience as "a property of states of nature that depends on the lottery payoffs that occur in each state, as they are presented to the decision maker" (Bordalo et al., 2012, p.1256), and the recurring allusions to salience-driven framing effects throughout the paper.

We use this distinction to experimentally differentiate between correlation sensitivity that arises from intentional comparisons of jointly realizing payoffs and correlation sensitivity that arises from payoff comparisons due to the visual presentation of choice problems. We implement a set of three between-subjects treatments as illustrated in Table 6. In all three treatments, subjects face a binary choice similar to our SML task in panel (3i) of Table 3. Following the experimental literature, we describe the joint distribution of lotteries by referring to the underlying states of nature. That is, the payoff generated by the lotteries depends on the realization of state of nature, represented by different fields of a wheel of fortune. In panel (6i), which represents the baseline treatment, each column describes the realizations of both lotteries in a given state of the world. In this treatment, correlation-sensitivity can arise because subjects deliberately compare payoffs state-by-state, but it could also arise if subjects incidentally compare payoffs column-by-column. Evidently, it is not possible to distinguish between the two. This display follows previous studies on correlation sensitivity (Starmer and Sugden, 1993; Humphrey, 1995; Ostermair, 2021; Loewenfeld and Zheng, 2023).

The remaining two treatments allow to distinguish between correlation sensitivity arising from state-by-state and column-by-column comparisons of payoffs. Consider the display in the column-effects treatment, illustrated in panel (6ii). Note that the two lotteries are perfectly correlated. To a decision maker whose correlation sensitivity is caused by deliberate state-by-state comparisons of payoffs, they are equivalent. However, note that the column-by-column comparison of payoffs is equivalent to that in the baseline treatment. Thus, any correlation sensitivity arising in this treatment can be only attributed to incidental payoff comparisons that arise from presenting payoffs column-by-column. Finally, consider the state-effects treatment illustrated in panel (6iii). The payoffs displayed in each column are the same for both lotteries, whereas the joint distribution of payoffs is as in the baseline treatment. Therefore, correlation sensitivity arising in the state-effects treatment cannot be caused by incidental column-by-column comparisons of payoffs, but it can only arise from state-by-state comparisons of payoffs. Arguably, such state-by-state comparisons

Table 6 Between-subjects treatments for differentiating the distinct mechanisms underlying correlation sensitivity

Lotteries	Payoffs & States of nature		
A	h if s_1	m if s_2	l if s_3
B	l if s_1	h if s_2	m if s_3

(i) Baseline treatment

Lotteries	Payoffs & States of nature		
A	h if s_1	m if s_2	l if s_3
B	l if s_3	h if s_1	m if s_2

(ii) Column-effects treatment

Lotteries	Payoffs & States of nature		
A	h if s_1	m if s_2	l if s_3
B	h if s_2	m if s_3	l if s_1

(iii) State-effects treatment

Table notes: all states are equally likely. Payoffs $h, m, l \in \mathbb{R}$ satisfy the relationship that $h > m > l$.

now require a deliberate effort on behalf of the experimental subjects.

Within the baseline treatment, we further implement a within-subject treatment that varies the timing of outcome feedback. An argument often put forward in the psychology literature is that in order for people to minimize ex-post regret, they have to anticipate immediate outcome feedback (Bell, 1983; Zeelenberg et al., 1996; Zeelenberg, 1999; Somasundaram and Diecidue, 2017). While the timing of outcome feedback is not part of regret theory (Loomes and Sugden, 1982, 1987), we explore the possibility that immediate feedback is important for correlation sensitivity to emerge by providing immediate feedback on some, but not all tasks.[8] In the experiment, participants make a number of choices, one of which is randomly selected to be payoff relevant. When participants receive immediate outcome feedback, they are informed only about the outcome of their choice, but not whether the task was selected for payoff. Note that, when participants do not obtain immediate outcome feedback, they still receive feedback for the payoff relevant task at the end of the experiment. Therefore, while any feedback effects we observe will be ascribed to anticipated regret, it should not be inferred that correlation sensitivity in the absence of immediate feedback cannot be driven by anticipated regret.

[8] Our feedback manipulation is similar to that of Somasundaram and Diecidue (2017), but we are, to the best of our knowledge, the first to test for feedback effects on correlation sensitivity.

3.4 Main experimental hypotheses

Testing properties of deterministic models on invariably noisy choice data necessitates imposing assumptions about the nature of noise and probabilistic choice (Loomes and Sugden, 1995; Luce, 1995; Baillon et al., 2015). We impose the minimal assumption that, if individuals are indifferent, they choose at random, and that their probability of choosing a given lottery is (weakly) increasing in their utility of doing so. This implies that correlation-insensitive individuals choose either lottery of the SML task with 50% probability. This random choice benchmark constitutes our null. As regret and salience theory are the main theories implying correlation sensitivity, we derive our alternative hypothesis assuming that preferences are characterized by ISPD, which implies that the ISPD lottery is chosen at a frequency higher than 50%. This motivates Hypothesis 1(a).

Second, if immediate feedback is necessary for correlation sensitivity driven by regret aversion to arise, we might expect the preference for the ISPD lottery to be more pronounced when subjects receive immediate feedback, as opposed to when feedback is only provided at the end of the experiment. This motivates Hypothesis 1(b).

Further, observing choice frequencies different from 50% in the column-effects treatment will provide evidence of correlation sensitivity driven by column-by-column comparisons, whereas observing choice frequencies different from 50% in the states-effects treatment will provide evidence of correlation sensitivity caused by state-by-state comparisons. In the first two of three experiments only the baseline treatment was employed. After having observed choice frequencies lower than 50% in these experiments, we hypothesized, based on introspection, that the observed correlation sensitivity is driven by column-by-column comparisons. This motivates our Hypothesis 1(c) and (d).

Finally, we gauge the strength of correlation sensitivity. If preferences are correlation-insensitive, subjects will, safe for decision noise, choose the dominant lottery in both panels (3ii) and (3iii) of Table 3. This implies an overall choice frequency of the row lottery of 50%. Pooling choices for both cases, we can again test for correlation-sensitive preferences by testing whether the ISPD lottery is chosen at an overall frequency higher than 50%.[9] We summarize our experimental hypotheses below.

Hypothesis 1. *Correlation-sensitivity at the aggregate level.*

(a) The ISPD lottery will be chosen at a frequency higher than 50%.

(b) The above effect will be larger when subjects receive immediate outcome feedback.

[9] An alternative way of testing for correlation-sensitive preferences, that is more in the spirit of Starmer and Sugden (1993), would be to test whether violations of first-order stochastic dominance occur more often when ISPD favors the dominated lottery than when it favors the dominant one.

(c) *The ISPD lottery will be chosen at a frequency significantly lower than 50% in the column-effects treatment.*

(d) *The ISPD lottery will not be chosen at a frequency significantly different from 50% in the state-effects treatment.*

(e) *Correlation sensitivity will persist even if one lottery is first-order stochastic dominant.*

4 Experimental procedures

We conducted 3 preregistered experiments.[10] Table 7 provides a summary of the experiments. The first experiment was conducted in March 2021 at Renmin University of China in Beijing.[11] In June 2022 and December 2022, we conducted two additional online experiments. After excluding subjects who violated a pre-defined attention check, we remain with 289 valid responses from the lab experiment, 145 from the first and 467 from the second online experiment, 158 of which are from the baseline, 159 from the column-effects, and 150 from the state-effects treatment.[12] All participants in the lab experiment were students, whereas only between 17% and 27% of the participants in the online experiments stated to be students, with the majority of the remaining participants being part- or full-time employed. Participants in the lab experiment were around 20 years old on average, while the average age in the online experiments was around 30. 59% of the participants in the lab and the first online experiment were female, whereas around 50% participants of the second online experiment were female in each of the treatments. See Table B.1 in Appendix B for more summary statistics.

The lab and the first online experiment included SML tasks in the baseline display as well as the immediate feedback treatment. The second online experiment included SML tasks as well

[10] We pre-registered with the AEA social science registry under the IDs AEARCTR-0007239, AEARCTR-0009573, and AEARCTR-0010279. In our results section, we follow the structure of our pre-analysis plan, but supply additional analysis and deviate from our pre-analysis plan in one instance in which the data requires such a deviation. This approach is in line with the arguments made in recent articles that the pre-analysis plan should guide the data analysis but that research papers should not be just a “populated pre-analysis plan" (Banerjee et al., 2020; Janzen and Michler, 2020).

[11] Students who were preregistered in a platform called *Yanzhong Lab* (https://www.yanzhonglab.com) received a message regarding our experiment in their WeChat account. They could choose which session they would attend and then come to the lab at their preferred time slot.

[12] In all experiments, we included two choice tasks for which one option dominates the other state- and column-wise. In the analysis we exclude subjects who chose the dominated option for these tasks at least once. We exclude 7 participants of the lab experiment, 11 participants of the first, and a total of 173 subject of the second online experiment, among which 59 were in the baseline treatment, 53 in the column-effects treatment, and 61 in the state-effects treatment. The differences in rates of exclusion are likely due to differences in the samples. People who were excluded are younger on average, less educated, more likely to be a student, and less likely to be married. However, none of these variables is found to be correlated with correlation sensitivity. Including excluded participants in the analysis does not change results qualitatively, but reduces effects. Especially in the second online experiment, the choices of excluded participants seem to be quasi-random. For instance, pooling all three treatments, excluded subjects violated FOSD with 45% frequency overall, with no detectable pattern, whereas non-excluded subjects violate FOSD with an overall frequency 19%, some of which seems to be caused by systematic correlation sensitivity. We take this to suggest that our attention check was successful in filtering out bots or human participants who clicked through the experiment randomly.

Table 7 Summary of the experiments

	Lab	Online 1	Online 2	Online 2	Online 2
Treatment	Baseline	Baseline	Baseline	State	Column
Sample	Students	General	General	General	General
Date	2021.03	2022.06	2022.12	2022.12	2022.12
Tasks	SML	SML	SML	SML	SML
	Event-splitting[a]	FOSD	FOSD	FOSD	FOSD
	Feedback	Feedback	-	-	-
	Attention	Attention	Attention	Attention	Attention
Valid subjects	289	145	158	159	150
Excluded subjects	7	11	59	53	61

[a] Results from this part are reported in a companion paper (Loewenfeld and Zheng, 2023).

FOSD tasks, and consisted of the baseline, column-effects, and state-effects treatment that were described in Table 6, but we dropped the immediate feedback treatment.

In the lab experiment, participants completed a total of 35 choice tasks. Among these, 10 choices were between two lotteries with the same marginal distribution.[13] We employed 2 sets of SML tasks (see Table 8). Each set consists of three choice tasks with three states and two choice tasks with four states, all equiprobable. For one set of SML tasks, subjects did not receive immediate feedback. These choices were presented to subjects in random order among the other 25 choice tasks. The five choices for which subjects received immediate feedback were always encountered at the end of the experiment. After having decided on the choices for which no feedback was provided, subjects were informed that they would make five more decisions for which they would now receive immediate feedback on their choice. Subjects were then exposed to these choice tasks in random order. We chose this particular order so as to avoid potential effects of past feedback on choice tasks for which subjects did not receive feedback. We counterbalanced whether subjects received feedback for set 1 or 2.

The main motivation for the first online experiment was to test for correlation-sensitive preferences using a more general population.[14] The experiment was similar in design to the lab experiment, but it only included SML tasks. In addition, we included four FOSD tasks and one state-wise dominant lottery as an attention check, which, for ease of exposition, we describe in

[13] The remaining choice tasks were part of a related study and are described in Loewenfeld and Zheng (2023).
[14] Renmin University of China is generally considered as one of the Chinese top universities and its students are highly trained in mathematics, which might reduce the scope to document correlation-sensitive preferences.

Table 8 Parameters for the SML tasks in the lab and first online experiment

Set 1				
Task	a	b	c	d
1	73	64	20	-
2	120	33	0	-
3	101	53	0	-
4	149	50	16	0
5	120	60	20	0

Set 2				
Task	a	b	c	d
1	110	33	9	-
2	101	41	15	-
3	86	50	3	-
4	143	32	26	7
5	94	81	37	13

Table notes: the three-states lotteries always have the following three possible states: $(x^A, x^B) \in \{(c,a),(b,c),(a,b)\}$. The four-state lotteries always have the following four possible states: $(x^A, x^B) \in \{(d,a),(c,d),(b,c),(a,b)\}$. All states are equally likely.

Appendix C.[15] Subjects in the first online experiment made a total of 19 choices.

The goals of the second online experiment were to disentangle between correlation sensitivity caused by state-by-state and column-by-column comparisons, and to gauge the strength of correlation sensitivity by including FOSD tasks. We implemented all three between-subject treatments discussed above. Each subject encountered all 9 SML tasks with parameters displayed in Table 9. We slightly changed the set of parameter values in order to include 3 choice tasks with 6 states.[16] The parameters of the three- and four-state choice tasks used in the second online experiment are shared among all experiments, which ensures comparability. We obtain pairs of first-order stochastic dominant and dominated lotteries by adding a premium of 1, 3, or 9 (approximately 2%, 6%, and 18% of the lotteries' expected value) to either the DSPD or the ISPD lottery, as illustrated in Table 3. Each subject further encountered each of the 9 lotteries with one of the three premiums. That is, they encountered each lottery with a premium of 1, 3, or 9.[17] Premiums are varied between subjects such that the same number of subjects encounter a given parameter set for a given premium. As an attention check, we also included two choices for which one lottery dominates the other state- and column-wise. See examples in Appendix E. Subjects made a total

[15] Overall choice patterns are similar to those observed in the second online experiment. For ease of exposition and because we systematically vary premiums in the second online experiment, we focus the discussion on FOSD tasks from this experiment. Results are qualitatively similar. We also varied the choice display of the FOSD tasks systematically in a way that increases the complexity of the choice tasks to account for the possibility that effects as prescribed by salience theory might only become apparent when choices are sufficiently complex. We describe this in detail in Appendix D.

[16] The inclusion of six-state choice tasks was motivated by an argument that correlation effects as prescribed in salience theory might not be apparent in three-state choice tasks because it is too obvious that both lotteries have the same marginal distribution.

[17] The premium of 1 is chosen because it is the smallest possible premium while sticking to integer values. We then increase the premiums by a factor of three.

Table 9 Parameters for the SML tasks in the second online experiment

Task	a	b	c	d	e	f
1	73	64	20	-	-	-
2	101	53	0	-	-	-
3	110	22	9	-	-	-
4	149	50	16	0	-	-
5	120	60	20	0	-	-
6	94	81	37	13	-	-
7	93	75	57	39	21	3
8	135	72	50	37	24	8
9	115	75	61	39	27	14

Table notes: the joint distribution of the choice tasks is always given as follows. For the three-state lotteries: $\{(a,c),1/3;(b,a),1/3;(c,b),1/3\}$. The four-state lotteries always have the following four possible states: $\{(a,d),1/4;(b,a),1/4;(c,b),1/4;(d,c),1/4\}$. The six-state lotteries always have the following four possible states: $\{(a,f),(b,a),(c,b),(d,c),(e,d),(f,e)\}$. All states are equally likely.

of 29 $(3\times 9+2)$ lottery choices.

In all experiments, participants read that for each choice task, there were two options with payoffs that depend on the turn of a personal wheel of fortune.[18] In all treatments, choice problems were displayed to subjects as shown in Figure 1a. In the baseline treatment of the lab and first online experiment, the wheel of fortune was described as having 99 equally likely fields. The implementation of the column-effects and the state-effects treatment necessitated a slightly different display. To avoid overloading choice presentation, we decided to implement the state space through a wheel of fortune with up to six equiprobable fields of different colors. We color-coded the fields to improve state-by-state comparability. See Figure 1b-1d for examples. The implementation of the baseline treatment ensures comparability between the different experiments. Before they were allowed to start real choice tasks, subjects had to answer a set of comprehension questions correctly. In case a subject gave a wrong answer, they received feedback intended to help them understand the task at hand.

During the experiment, payoffs were displayed in an experimental currency that was translated into Yuan at a rate of 0.5 in the lab and at a rate of 0.4 in the online experiments. To avoid any unwanted effects of the way in which choices are presented, we randomized the order in which states appear. Lotteries were referred to in neutral language, as “Option A" and “Option B". We also randomized which lottery was labelled option A and B. All of this randomization was done at the subject level. After the choice tasks, subjects were prompted to answer a short questionnaire. Upon finishing the experiment, subjects received their payment. Participants in the lab study received a show-up fee of 10 Yuan and had one randomly selected choice paid out. Participants in the online experiments received a participation fee of 9 Yuan and had a 1/3 chance of having

[18] By referring to a *personal* wheel of fortune, we address the concern that correlation structure might impact subjects' choices because of other-regarding preferences.

Figure 1 The display of choice problems in different treatments and experiments

	Fields 1-33 (33.3%)	Fields 34-66 (33.3%)	Fields 67-99 (33.3%)
○ Option A	101	53	0
○ Option B	0	101	53

(a) Lab and 1st online experiment: Baseline

○ Option A	**101** if **Red**	**53** if **Blue**	**0** if **Green**
○ Option B	**0** if **Red**	**101** if **Blue**	**53** if **Green**

(b) 2nd online experiment: Baseline

○ Option A	**101** if **Red**	**53** if **Blue**	**0** if **Green**
○ Option B	**0** if **Green**	**101** if **Red**	**53** if **Blue**

(c) 2nd online experiment: Column-effects

○ Option A	**101** if **Red**	**53** if **Blue**	**0** if **Green**
○ Option B	**101** if **Blue**	**53** if **Green**	**0** if **Red**

(d) 2nd online experiment: State-effects

one of their choices paid out. Subjects received an average payoff of around 41 Yuan in the lab experiment, 17 Yuan in the first and 16 Yuan in the second online experiment. The lab experiment lasted around 30 minutes, and the two online experiments took between 10 and 15 minutes. All experiments were programmed with oTree (Chen et al., 2016).

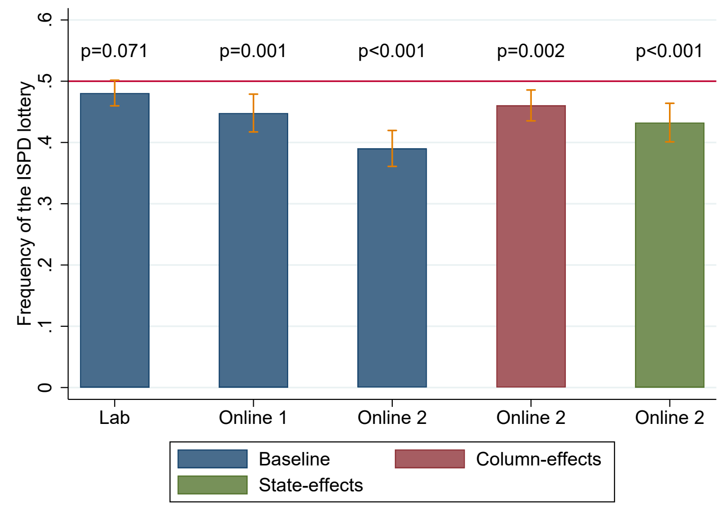
5 Results

5.1 Correlation sensitivity at the aggregate level

We begin by testing for correlation sensitivity. At this stage, we combine data from choices with and without immediate feedback. We analyze data from SML tasks from all three experiments for the baseline treatment, resulting in a sample of 5762 choices made by 592 participants. Participants in the lab experiment chose the ISPD lottery with a frequency of 48.1%, while participants in the first online experiment chose it with a frequency of 45.1%, and subjects in the second online experiment chose it with a frequency of 39.0% (see Figure 2). Running logistic regressions again, we find that the choice frequency differed only marginally from the 50% random-choice benchmark for the lab experiment ($p = 0.08$), but significantly in the first and second online experiments ($p = 0.003$ and $p < 0.001$, respectively). Correlation sensitivity appears to be insignificant for the lab experiment participants, slightly stronger for the first online experiment, and even stronger for the second online experiment. As we discuss in more detail in Appendix C, these disparities may be due to a combination of differences in the subject pool, changes in the choice display, as well as the number of states of the choice tasks. Notably, correlation sensitivity seems to be particularly evident for choice tasks with six states. Overall, the results provide strong evidence against Hypothesis 1(a). In contrast to the predictions of regret and salience theory, the aggregate choices suggest a modest preference for the DSPD lottery.

In the next step, we test for the impact of immediate feedback. We find that choices were not

Figure 2 Choice frequencies of the ISPD lottery

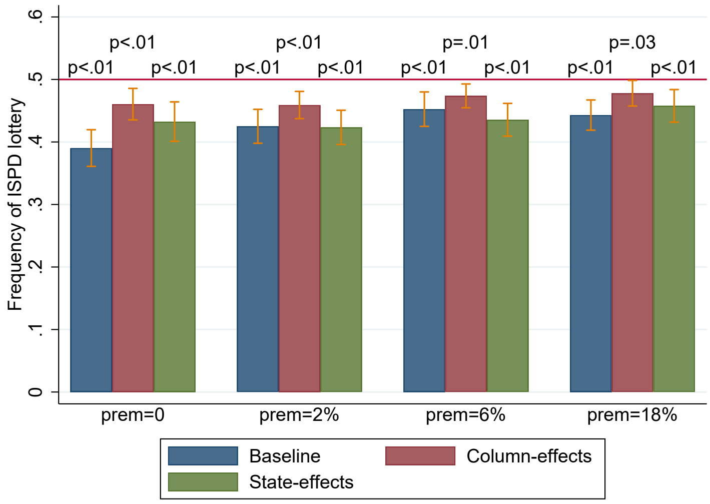


significantly influenced by immediate feedback in both the lab and the first online experiment. In the lab experiment, 47.8% of choices were for the ISPD lottery when subjects received immediate feedback, while 48.4% were without feedback. Similarly, in the online experiment, subjects chose the ISPD lottery at a frequency of 44.8% with immediate feedback and at a frequency of 45.4% without it. Running logistic regressions with a dummy variable for ISPD lottery choice as the dependent variable and a dummy variable indicating whether immediate feedback was provided as the explanatory variable, we find that feedback did not significantly impact choices in either the lab ($p = 0.73$) or the online experiment ($p = 0.83$), or when we pool the two ($p = 0.68$).[19] To assess the precision of these null results, we calculate 95% confidence intervals for the effect of feedback on choice frequencies. The confidence intervals for the immediate feedback effect are [-0.046, 0.032] for the lab experiment, [-0.046, 0.032] for the online experiment, and [-0.037, 0.024] for the pooled sample. This suggests that the null result on feedback effects is precisely estimated and not the result of noisy data. Therefore, we reject Hypothesis 1(b). In Appendix B, we explore heterogeneity in feedback effects and find that participants reporting a higher tendency to feel regret in a hypothetical investment scenario (Guiso, 2015) chose the ISPD lottery less often under immediate feedback than without feedback. We interpret this finding as suggestive evidence that anticipated feedback might play an important role only for individuals with a high propensity to experience regret.

We next turn to the column-effects and state-effects treatments to shed some light on the drivers of correlation-sensitivity. In the column-effects treatment, participants chose the ISPD lottery with a frequency of 46.1%, while in the state-effects treatment, they chose it with a frequency

[19] Regressions results can be found in Table B.2. Unless otherwise noted, p-values are obtained from Wald Chi-Square test with standard errors clustered at the subject level. We also obtained similar results using pre-registered non-parametric Wilcoxon signed-rank tests (p-values of 0.58, 0.22, and 0.20 for the lab, online, and pooled samples, respectively).

Figure 3 Choice frequencies of the ISPD lottery by levels of premium



of 43.3% (see Figure 2). Using logistic regressions with standard errors clustered at the subject level (see Table B.2), we find that the choice frequency of the ISDP lottery is significantly below 50% in both treatments ($p = 0.002$ in the column-effects treatment and $p < 0.001$ in the state-effects treatment). The logistic regressions also suggest that the difference in choice frequencies of 7.1 percentage points (ppt) between the baseline treatment and the column-effects treatment is statistically significant ($p < 0.001$). The difference of 4.1 ppt between the baseline and the state-effects treatment is marginally significant at $p = 0.054$, and the 2.8 ppt difference between the column-effects and the state-effects treatment is not statistically significant ($p = 0.17$, based on a Chi-squared test).

We do not reject Hypothesis 1(c) but reject Hypothesis 1(d). If anything, state-by-state comparisons seem to be somewhat more important, although the difference between the state-effects and the column-effects treatment is not statistically significant. The findings suggest that correlation sensitivity in the baseline treatment arises from both deliberate state-by-state comparisons of payoffs, as well as incidental column-by-column comparisons of payoffs. Importantly, results from both treatments again imply modest aggregate correlation sensitivity in line with DSPD.

The results so far provide very consistent evidence for DSPD. However, since the effects were observed with same marginal lotteries, these could, in principle, be of second-order importance only. To test the robustness of the observed correlation sensitivity, we now turn to the FOSD tasks. Figure (3) displays the choice frequencies of the ISPD lottery as a function of the payoff premium. As can be seen, the choice frequencies are always significantly smaller than 50% at the 5% level in all three treatments, even for the highest level of premium, but seem to be moving closer to 50% as the premium is increased. To test for the impact of the size of the premium on choice behavior

Table 10 Logistic regressions on SML tasks

Variables	(1) Baseline ISDP	(2) Column-effects ISDP	(3) State-effects ISDP
p2	0.144**	-0.006	-0.038
	(0.070)	(0.062)	(0.063)
p6	0.256***	0.053	0.012
	(0.071)	(0.060)	(0.064)
p18	0.217***	0.070	0.102
	(0.073)	(0.064)	(0.065)
Constant	-0.446***	-0.158***	-0.271***
	(0.063)	(0.052)	(0.066)
Observations	4,266	4,293	4,050
Individuals	158	159	150

Table notes: the notations for significance levels are as follows: * for p≤0.1; ** for p≤0.05; *** for p≤0.01.

more formally, we run the following logistic regressions separately for each treatment.

$$ISDP_{i,t} = c + \beta_1 p2_{i,t} + \beta_2 p6_{i,t} + \beta_3 p18_{i,t} + \varepsilon_{i,t}, \tag{2}$$

where $p2_{i,t}$, $p6_{i,t}$, and $p18_{i,t}$, with i being the index of subjects and t being the index of treatments, are dummy variables that indicate the levels of premium 2%, 6%, and 18% respectively. Zero premium is the omitted category. Table 10 reports the regression results. Higher premiums significantly reduce DSPD only in the baseline treatment, but not in the other two treatments.

Another way to look at the effects of correlation sensitivity is to consider its impact on rates of violations of first-order stochastic dominance. Pooling all levels of the payoff premium, subjects in the baseline treatment violate first-order stochastic dominance at a rate of 15.2% when the DSPD lottery is dominant. The rate of FOSD violations is increased by 78% to 27.1% when it is the ISPD lottery that is dominant. In the column-effects treatment, the rate of FOSD violations is 9.5% when the DSPD lottery is dominant. This rate is increased by 62% to 15.4% when it is the ISPD lottery that is first-order stochastic dominant. In the state-effects treatment, subjects violate FOSD at a rate of 12.9% when the DSPD lottery is dominant, but at a 95% higher rate of 25.1% when the ISPD lottery is dominant. For all comparisons, the increase in the rate of FOSD violations is statistically significant ($p < 0.001$, logistic regression with standard errors clustered at the subject level).

Overall, the results from FOSD tasks provide further evidence of a DSPD effect of modest size. FOSD is much more predictive of aggregate choice patterns than the joint distribution of lotteries. However, our results also suggest that correlation sensitivity is responsible for a sizable fraction of the FOSD violations we observe. This suggests that correlation sensitivity is not only of second-order importance but can exert a significant influence over participants' choices. We do not reject Hypothesis 1(e).

We summarize our findings on correlation sensitivity at the aggregate level below.

Result 1. *On SML tasks and treatment effects:*

(a) *In the baseline treatment, we find that subjects chose the ISPD lottery at a frequency of 48.1% in the lab experiment, 45.1% in the first online experiment, and 39.0% in the second online experiment. The choice frequencies differ from the 50% random choice benchmark marginally in the lab experiment (p = 0.08) and significantly in both online experiments ($p < 0.002$). We reject Hypothesis 1(a).*

(b) *Estimating the effect of immediate feedback on choices, we find a precisely null effect. We reject Hypothesis 1(b).*

(c) *The ISPD lottery is chosen at a frequency of 46.1% in the column-effects treatment, which is significantly different from 50% at $p = 0.002$. We do not reject Hypothesis 1(c).*

(d) *The ISPD lottery is chosen at a frequency of 43.3% in the state-effects treatment, which is significantly different from 50% at $p < 0.001$. We reject Hypothesis 1(d).*

(e) *In all three treatments, we find evidence for DSPD even when one lottery in a pair is first-order stochastic dominant. Pooling all levels of the payoff premium, we find that the ISDP lottery is chosen at a frequency of 44.0% in the baseline treatment, 47.0% in the column-effects treatment, and 43.9% in the state-effects treatment (all with $p < 0.001$). We do not reject Hypothesis 1(e).*

5.2 Correlation sensitivity at the individual level

After discussing correlation sensitivity at the aggregate level, we now turn to analyzing individual heterogeneity. This analysis is exploratory in nature. In the first step, we non-parametrically test whether some individuals consistently display greater correlation sensitivity than others. We conduct the following exercise by focusing on the SML tasks of all experiments and treatments, pooling choices with and without immediate feedback. For each individual, we randomly divide the tasks into two sets.[20] We then calculate the choice frequency of the ISPD lottery for each of

[20] For the lab and the first online experiment, we divide the choice tasks into two sets of 5. For the second online experiment, we divide the choice tasks into one set of 5 and one set of 4.

the two sets and compute their Spearman's rank-order correlation coefficient. We use a bootstrap approach and repeat this procedure 10,000 times, which allows us to obtain confidence intervals for the correlation coefficients and also helps us avoid arbitrary choices. The idea behind this exercise is the following. If correlation sensitivity is uniformly distributed among our sample, we should observe correlation coefficients of zero. If, however, some individuals consistently express more correlation sensitivity than others, we should observe positive correlation coefficients.

Figure 4 shows the results of this exercise. As shown, the bootstrapped correlation coefficient is around 0.2 and does not include zero in all experiments and treatments, except for the column-effects treatment of the second online experiment. For this treatment, the confidence interval of the correlation coefficient is centered around zero. These results suggest that correlation sensitivity induced by incidental column-by-column comparisons of payoffs affects all participants in a similar way. However, there seems to be some heterogeneity in correlation sensitivity due to deliberate state-by-state comparisons of payoffs.

We further explore individual heterogeneity using latent class analysis based on structural equation models. For this purpose, we focus on our second online experiment, since the inclusion of FOSD tasks allows for a richer analysis. We divide choice tasks into the three different categories displayed in Table 3: SML tasks, FOSD tasks where the ISPD lottery is dominant, and FOSD tasks where the DSPD lottery is dominant. For each category, we sum all choices a subject made for the ISPD lottery and specify that the resulting variables are distributed according to a binomial distribution with 9 trials. We estimate latent class models pooling all observations from the different treatments.[21] We estimate latent class models with up to seven classes. For models with

Figure 4 Bootstrapped correlation coefficients

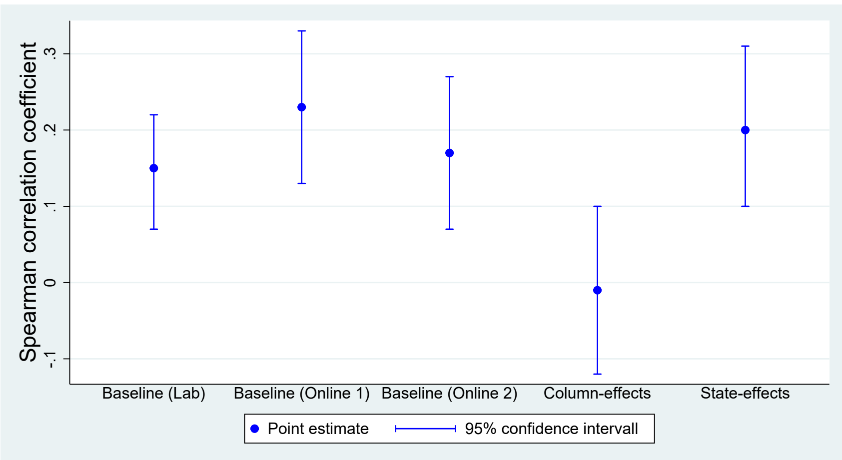


Figure notes: we display Spearman's rank-order correlation coefficients, bootstrapped with 10,000 repetitions, with empirical confidence intervals.

[21] As we are able to recover the frequency of each class for each treatment, this approach allows for the possibility that different latent classes emerge in the different treatments while avoiding potential issues of unstable classes that could arise from small samples. This approach also enhances interpretability of our results.

Table 11 Latent-class analysis

	By tasks	% ISPD (SD)	95% CI	By treatments	% Subjects	Averaged
Class 1	Same marginal	0.484 (0.012)	[0.461 - 0.507]	Baseline	0.335	0.494
	ISPD-FOSD	0.987 (0.005)	[0.977 - 0.998]	Column	0.640	
	DSPD-FOSD	0.023 (0.005)	[0.014 - 0.032]	State	0.505	
Class 2	Same marginal	0.227 (0.024)	[0.180 - 0.273]	Baseline	0.191	0.167
	ISPD-FOSD	0.334 (0.029)	[0.276 - 0.391]	Column	0.094	
	DSPD-FOSD	0.229 (0.024)	[0.181 - 0.277]	State	0.216	
Class 3	Same marginal	0.405 (0.029)	[0.348 - 0.462]	Baseline	0.318	0.207
	ISPD-FOSD	0.774 (0.042)	[0.691 - 0.857]	Column	0.156	
	DSPD-FOSD	0.082 (0.017)	[0.049 - 0.114]	State	0.147	
Class 4	Same marginal	0.507 (0.033)	[0.442 - 0.572]	Baseline	0.156	0.132
	ISPD-FOSD	0.537 (0.033)	[0.472 - 0.601]	Column	0.110	
	DSPD-FOSD	0.445 (0.032)	[0.383 - 0.507]	State	0.131	

more classes, convergence fails. Among the estimated models, we select the one with the lowest Bayesian information criterion (BIC) value, which is a model with four classes. Considering posterior probabilities, i.e., the probability of class membership for each individual, we find that the medium participant is assigned to one class with 95% probability and only about 20% of the participants are assigned to one class with less than 75% probability. This suggests that most subjects can be assigned to one of the classes with high probability.

Table 11 reports the results from the latent class analysis. The behavior of individuals in Class 1 is nearly perfectly characterized by correlation insensitivity. Individuals in this class choose the ISDP lottery with a frequency that does not differ significantly from the 50% random-choice benchmark for the SML tasks and respect FOSD almost perfectly. That is, the ISPD lottery is chosen practically always when it is dominant and practically never when it is dominated.

Classes 2 and 3 display correlation sensitivity, both consistent with DSPD. Individuals in class 2 display strong DSPD. They choose the DSPD lottery at a frequency of 77% for the SML tasks, at a frequency of 67% when it is first-order stochastic dominated, and at a frequency of 77% when it is first-order stochastic dominant. Individuals in this category seem to be relatively unaffected by FOSD and seem to implement their correlation sensitivity somewhat imperfectly, especially compared to individuals in class 1 who satisfy CSPD near perfectly. The behavior of individuals in class 3 might be best characterized as weak DSPD. Overall, choice behavior in this class is similar to that in class 1 but is somewhat skewed towards the DSPD lottery. The DSPD lottery is chosen at a frequency of 59% for the SML tasks, 23% when it is first-order stochastic dominated, and 92% when it is first-order stochastic dominant. We posit that choices in class 2 can be interpreted as expressing deliberate correlation sensitivity, whereas choice behavior in class 3 could be interpreted as stemming from individuals who are generally correlation insensitive, but whose choices are somewhat biased towards DSPD.

Finally, the fourth class seems to capture random behavior. For all three types of choice tasks, choice frequencies do not differ significantly from 50%. What is striking is the absence of any class of individuals who display behavior consistent with ISPD. This suggests that ISPD is not only rejected as the property governing aggregate behavior, but that virtually none of our participants display behavior that is characterized by ISPD.[22]

Averaging over all three treatments, 49% of the participants are assigned to the correlation-insensitive class 1, while 17% and 21% are assigned to classes 2 and 3 that capture strong and weak DSPD respectively, and 13% are assigned to the random-choice class 4. This suggests that although correlation insensitivity is the predominant category, a sizable fraction of the participants are characterized by DSPD.

Comparing the fractions of participants assigned to the four classes across treatments reveals interesting differences. In all treatments, a similar fraction of 11%-16% of participants are assigned to the random-choice class 4. It is reassuring that these fractions do not differ greatly between treatments. The fraction of subjects assigned to the correlation-insensitive class 1 is only 34% in the baseline treatment, 51% in the state-effects treatment, and reaches 64% in the column-effects treatment. This pattern mirrors our aggregate results, which show that subjects display the highest correlation sensitivity in the baseline treatment, followed by the state-effects and column-effects treatments.

Similar fractions of participants in the baseline and state-effects treatments are assigned to the strongly correlation-sensitive class 2, namely 19% and 22% respectively, while only about 9% of participants in the column-effects treatment are assigned to this class. This suggests that strong and consistent DSPD may be primarily driven by deliberate state-by-state comparisons of payoffs. This finding is also consistent with our analysis above, which failed to find evidence for consistent correlation sensitivity at the individual level in the column-effects treatment (see Figure 4). Finally, about 32% of participants in the baseline treatment are assigned to the moderate-DSPD class 3, whereas the corresponding fractions in the column-effects and state-effects treatments are 16% and 15%. The high prevalence of this class in the baseline treatment may be explained by the fact that both column-by-column and state-by-state comparisons of payoffs are aligned in this treatment. This might make it more challenging to discern that both lotteries share the same marginal distribution or that one lottery is dominant.

[22] When estimating a model with 7 latent classes, a class characterized by moderate ISPD emerges. Subjects in this class choose the ISPD lottery at frequency of 67% for the SML tasks, 83% when the ISDP lottery is first-order stochastic dominant, and 58% when it is first-order stochastic dominated. A negligible fraction of 1.4% of the participants are assigned to this class.

6 Discussion

Our results provide consistent evidence of modest DSPD on the aggregate. The latent-class analysis suggests that this aggregate effect might be driven by a minority of subjects who display strong DSPD, even if it means violating FOSD. Importantly, the analysis does not produce an equivalent class of participants displaying strong ISPD. These findings are in contrast with previous studies that are based on manipulations of the joint distribution and tend to report null results (Starmer and Sugden, 1993; Humphrey, 1995; Ostermair, 2021; Dertwinkel-Kalt and Köster, 2021; Loewenfeld and Zheng, 2023), or studies using the trade-off method that report evidence for ISPD (Bleichrodt et al., 2010; Baillon et al., 2015). Our ability to uncover evidence for DSPD might be attributed to several factors. The SML task improves on previous tests by being more suitable to correlation-sensitive preferences in a theoretical sense and avoids some features that seem undesirable to an experimenter, such as lack of incentive compatibility or duplicated states.

As our findings clearly reject the hypothesis that behavior is characterized by ISPD, both at the aggregate and individual levels, our results strongly reject both regret and salience theory. We would like to reiterate that it is ISPD that allows the theories to rationalize classical behavioral anomalies, such as the Allais paradox or simultaneous gambling and insurance, as well as the commonly observed preference for right-skewed risks. Broadly speaking, DSPD produces the opposite of the commonly observed patterns, such as preferences for negative skewness and an aversion to long-shot lotteries.

As the observed correlation sensitivity contradicts regret and salience theory, it is important to investigate its drivers. Our three between-subject treatments suggest that both incidental payoff comparisons resulting from the framing of choices and deliberate state-by-state comparisons contribute to the observed correlation sensitivity. The latter suggests that some subjects may have genuine preferences that are impacted by the correlation of payoffs across states. Otherwise, it is difficult to understand why subjects would compare payoffs state-by-state across different columns. While regret and salience theory postulate an increase in sensitivity to within-state differences, one could also argue that decreasing sensitivity to payoff differences has strong intuitive appeal. In EUT, for instance, decreasing sensitivity to increments of wealth is commonly assumed to explain risk aversion. In prospect theory, decreasing sensitivity to incremental losses is used to explain risk aversion in the gain domain and risk-seeking in the loss domain, as well as probability weighting (Tversky and Kahneman, 1992). Our results suggest that decreasing sensitivity is also the predominant pattern governing within-state comparisons.

We believe that our null effect of immediate outcome feedback does not provide good evidence against the possibility that correlation sensitivity is, at least to some degree, driven by an aversion to regret. Since subjects receive outcome feedback on the payoff relevant lottery in any case at the end of the experiment, it is possible that simply changing the timing of the feedback was not sufficient to alter subjects anticipation of regret. We would also like to highlight that our null finding for immediate feedback effects is compatible with studies that document feedback effects (e.g., Zeelenberg et al., 1996; Zeelenberg, 1999). In these studies choices can usually be used to manipulate the outcome feedback one obtains, which is not possible in our setting. Moreover, ISPD is not necessary to rationalize such feedback effects. All one has to assume is that people feel less regret in the absence of feedback on the forgone outcome, as modelled by Bell (1983), for instance. Applied research on regret has often modeled regret in this vein (see, e.g., Filiz-Ozbay and Ozbay, 2007; Engelbrecht-Wiggans and Katok, 2008; Strack and Viefers, 2021; Zheng, 2021).

Given the increase in complexity that arises from intransitive preferences, should (applied) economists allow for correlation sensitivity in their models? Although we find some evidence for correlation sensitivity, we take our results to suggest that, in most applications, the steep price economists have to pay in added complexity when allowing for correlation sensitivity might not be worth it. We arrive at this conclusion for mainly two reasons. First, correlation-sensitive preferences satisfying DSPD induce, broadly speaking, the opposite of the commonly observed patterns such as skewness seeking. Second, although we do observe evidence for DSPD, the overall effect size on the aggregate is rather small. Considering the baseline treatment of the second online experiment, which is the treatment for which we observe the strongest correlation sensitivity, we find an overall choice frequency of 39% for the ISPD lottery in the SML tasks. Using Cohen's g as a rough measure of effect size, this constitutes a small effect.[23] It can be argued that the ability of correlation-sensitive preferences to rationalize commonly observed behavioral patterns results largely from its capability to endogenize the probability weighting of cumulative prospect theory (Tversky and Kahneman, 1992). The recent literature on behavioral inattention and Bayesian updating (Gabaix, 2014; Enke and Graeber, 2021) may provide a way forward without violating transitivity.

Finally, we would like to stress that our study examines correlation-sensitivity in the important but specific setting in which choices are made in a static setting. Comparisons of joint payoff realizations might induce behavior to be more strongly correlation-sensitive in other settings. For instance, Loewenfeld (2023) studies a setting of delegated risk-taking in which principals can reward agents ex-post. He shows that a tendency of principals to condition bonus payments on an ex-post comparison of the realized outcomes can render bonus payments, and therefore agents' incentives to choose between different actions, strongly correlation-sensitive. In a similar vein, studies in the cognitive psychology literature show that an ex-post comparison of the realized

[23] If p is the choice frequency, Cohen's g is calculated as $g = |0.5 - p| \cdot g < 0.05$ is categorized as negligible, $g \in [0.05, 0.15)$ as small, $g \in [0.15, 0.25)$ as medium, and $g > 0.25$ as large.

and forgone outcome can lead to subjects experiencing regret, which can influence future choices (Camille et al., 2004; Coricelli et al., 2007). It seems conceivable that this mechanism might induce correlation-sensitive behavior in settings in which decision makers have to learn from their choices (Hertwig et al., 2004; Hart and Mas-Colell, 2000; Hart, 2005). The theoretical literature on correlation-sensitive preferences (Loomes and Sugden, 1982, 1987; Bordalo et al., 2012; Lanzani, 2022) will provide valuable guidance in tackling this important issue.

7 Conclusion

In this paper, we proposed a theory-tailored experimental task, namely the SML task, to test for correlation-sensitive preferences in risk-taking (Lanzani, 2022). To assess the strength of these preferences and understand their drivers, we further introduced different treatments built on the SML task. In a series of experiments with over 900 participants, we found that aggregate choices displayed modest evidence for decreasing sensitivity to differences in jointly realized payoffs (i.e., DSPD), which contrasts with what regret and salience theory have advocated. Not only could the documented correlation-sensitive preferences survive in face of first-order stochastic dominance, but they were also robust to the absence of immediate outcome feedback. Additionally, we found that both column-by-column and state-by-state payoff comparisons seemed to impact decision-making, but the latter played a more critical role, suggesting that correlation sensitivity arises mainly due to deliberate considerations such as regret avoidance rather than incidental biases such as salience. Finally, our latent-class analysis discovered that only a relatively small sample of subjects contributed to the documented evidence for correlation sensitivity.

References

Allais, M. (1953). Le comportement de l'homme rationnel devant le risque: critique des postulats et axiomes de l'école Américaine. *Econometrica 21*(4), 503–546.

Alós-Ferrer, C. and A. Ritschel (2022). Attention and salience in preference reversals. *Experimental Economics*, 1–28.

Andersson, H., H. Sholtz, and J. Zheng (2023). Measuring regret theory in the health and financial domain. *Working Paper*.

Baillon, A., H. Bleichrodt, and A. Cillo (2015). A tailor-made test of intransitive choice. *Operations Research 63*(1), 198–211.

Banerjee, A., E. Duflo, A. Finkelstein, L. F. Katz, B. A. Olken, and A. Sautmann (2020). In praise of moderation: Suggestions for the scope and use of pre-analysis plans for RCTs in economics. *NBER Working Paper*.

Bell, D. E. (1982). Regret in decision making under uncertainty. *Operations Research 30*(5), 961–981.

Bell, D. E. (1983). Risk premiums for decision regret. *Management Science 29*(10), 1156–1166.

Bleichrodt, H., A. Cillo, and E. Diecidue (2010). A quantitative measurement of regret theory. *Management Science 56*(1), 161–175.

Bordalo, P., N. Gennaioli, and A. Shleifer (2012). Salience theory of choice under risk. *Quarterly Journal of Economics 127*(3), 1243–1285.

Bordalo, P., N. Gennaioli, and A. Shleifer (2013a). Salience and asset prices. *American Economic Review 103*(3), 623–28.

Bordalo, P., N. Gennaioli, and A. Shleifer (2013b). Salience and consumer choice. *Journal of Political Economy 121*(5), 803–843.

Braun, M. and A. Muermann (2004). The impact of regret on the demand for insurance. *Journal of Risk and Insurance 71*(4), 737–767.

Bruhin, A., M. Manai, and L. Santos-Pinto (2022). Risk and rationality: the relative importance of probability weighting and choice set dependence. *Journal of Risk and Uncertainty 65*(2), 139–184.

Camille, N., G. Coricelli, J. Sallet, P. Pradat-Diehl, J.-R. Duhamel, and A. Sirigu (2004). The involvement of the orbitofrontal cortex in the experience of regret. *Science 304*(5674), 1167–1170.

Chen, D. L., M. Schonger, and C. Wickens (2016). oTree: An open-source platform for laboratory, online, and field experiments. *Journal of Behavioral and Experimental Finance 9*(C), 88–97.

Chew, S. H., W. Wang, and S. Zhong (2023). Attention theory. *Working Paper*.

Cokely, E. T., M. Galesic, E. Schulz, S. Ghazal, and R. Garcia-Retamero (2012). Measuring risk literacy: The berlin numeracy test. *Judgment and Decision Making 7*(1), 25–47.

Coricelli, G., R. J. Dolan, and A. Sirigu (2007). Brain, emotion and decision making: the paradigmatic example of regret. *Trends in cognitive sciences 11*(6), 258–265.

Cosemans, M. and R. Frehen (2021). Salience theory and stock prices: Empirical evidence. *Journal of Financial Economics 140*(2), 460–483.

Dertwinkel-Kalt, M., K. Köhler, M. R. Lange, and T. Wenzel (2017). Demand shifts due to salience effects: Experimental evidence. *Journal of the European Economic Association 15*(3), 626–653.

Dertwinkel-Kalt, M. and M. Köster (2015). Violations of first-order stochastic dominance as salience effects. *Journal of Behavioral and Experimental Economics 59*(2015), 42–46.

Dertwinkel-Kalt, M. and M. Köster (2017). Salient compromises in the newsvendor game. *Journal of Economic Behavior & Organization 141*, 301–315.

Dertwinkel-Kalt, M. and M. Köster (2020). Salience and skewness preferences. *Journal of the European Economic Association 18*(5), 2057–2107.

Dertwinkel-Kalt, M. and M. Köster (2021). Replication: Salience and skewness preferences.

Diecidue, E. and J. Somasundaram (2017). Regret theory: A new foundation. *Journal of Economic Theory 172*, 88–119.

Engelbrecht-Wiggans, R. and E. Katok (2008). Regret and feedback information in first-price sealed-bid auctions. *Management Science 54*(4), 808–819.

Enke, B. and T. Graeber (2021). Cognitive uncertainty.

Filiz-Ozbay, E. and E. Y. Ozbay (2007). Auctions with anticipated regret: Theory and experiment. *American Economic Review 97*(4), 1407–1418.

Frederick, S. (2005). Cognitive reflection and decision making. *Journal of Economic Perspectives 19*(4), 25–42.

Frydman, C. and M. M. Mormann (2018). The role of salience in choice under risk: An experimental investigation. *Working Paper*.

Gabaix, X. (2014). A sparsity-based model of bounded rationality. *The Quarterly Journal of Economics 129*(4), 1661–1710.

Gollier, C. (2020). Aversion to risk of regret and preference for positively skewed risks. *Economic Theory 70*(4), 913–941.

Gollier, C. and B. Salanié (2006). Individual decisions under risk, risk sharing and asset prices with regret. *Working Paper*.

Guiso, L. (2015). A test of narrow framing and its origin. *Italian Economic Journal 1*(1), 61–100.

Hart, S. (2005). Adaptive heuristics. *Econometrica 73*(5), 1401–1430.

Hart, S. and A. Mas-Colell (2000). A simple adaptive procedure leading to correlated equilibrium. *Econometrica 68*(5), 1127–1150.

Hertwig, R., G. Barron, E. U. Weber, and I. Erev (2004). Decisions from experience and the effect of rare events in risky choice. *Psychological science 15*(8), 534–539.

Herweg, F. and D. Müller (2021). A comparison of regret theory and salience theory for decisions under risk. *Journal of Economic Theory 193*(2021), 105226.

Humphrey, S. J. (1995). Regret aversion or event-splitting effects? more evidence under risk and uncertainty. *Journal of Risk and Uncertainty 11*(3), 263–274.

Janzen, S. A. and J. D. Michler (2020). Ulysses' pact or Ulysses' raft: Using pre-analysis plans in experimental and non-experimental research. *Applied Economic Perspectives and Policy*.

Königsheim, C., M. Lukas, and M. Nöth (2019). Salience theory: Calibration and heterogeneity in probability distortion. *Journal of Economic Behavior & Organization 157*(JAN), 477–495.

Lanzani, G. (2022). Correlation made simple: Applications to salience and regret theory. *Quarterly Journal of Economics 137*(2), 959–987.

Leland, J. W., M. Schneider, and N. T. Wilcox (2019). Minimal frames and transparent frames for risk, time, and uncertainty. *Management Science 65*(9), 4318–4335.

Loewenfeld, M. (2023). Outcome bias and risk taking in a principal agent setting. *Working Paper*.

Loewenfeld, M. and J. Zheng (2023). Salience or event-splitting? an experimental investigation of correlation sensitivity in risk-taking. *Working Paper*.

Loomes, G. (1988a). Further evidence of the impact of regret and disappointment in choice under uncertainty. *Economica 55*(217), 47–62.

Loomes, G. (1988b). When actions speak louder than prospects. *American Economic Review*, 463–470.

Loomes, G. (2005). Modelling the stochastic component of behaviour in experiments: Some issues for the interpretation of data. *Experimental Economics 8*, 301–323.

Loomes, G., C. Starmer, and R. Sugden (1989). Preference reversal: information-processing effect or rational non-transitive choice? *The Economic Journal 99*(395), 140–151.

Loomes, G., C. Starmer, and R. Sugden (1991). Observing violations of transitivity by experimental methods. *Econometrica*, 425–439.

Loomes, G. and R. Sugden (1982). Regret theory: An alternative theory of rational choice under uncertainty. *The Economic Journal 92*(368), 805–824.

Loomes, G. and R. Sugden (1987). Some implications of a more general form of regret theory. *Journal of Economic Theory 41*(2), 270–287.

Loomes, G. and R. Sugden (1995). Incorporating a stochastic element into decision theories. *European Economic Review 39*(3-4), 641–648.

Luce, R. D. (1995). Four tensions concerning mathematical modeling in psychology. *Annual Review of Psychology 46*(1), 1–27.

Michenaud, S. and B. Solnik (2008). Applying regret theory to investment choices: Currency hedging decisions. *Journal of International Money and Finance 27*(5), 677–694.

Ostermair, C. (2021). Investigating the empirical validity of salience theory: The role of display format effects. *Available at SSRN 3903649*.

Qin, J. (2015). A model of regret, investor behavior, and market turbulence. *Journal of Economic Theory 160*, 150–174.

Quiggin, J. (1990). Stochastic dominance in regret theory. *Review of Economic Studies 57*(3), 503–511.

Quiggin, J. (1994). Regret theory with general choice sets. *Journal of Risk and Uncertainty 8*(2), 153–165.

Regenwetter, M., J. Dana, and C. P. Davis-Stober (2011). Transitivity of preferences. *Psychological Review 118*(1), 42.

Romano, J. P. and M. Wolf (2005). Stepwise multiple testing as formalized data snooping. *Econometrica 73*(4), 1237–1282.

Romano, J. P. and M. Wolf (2016). Efficient computation of adjusted p-values for resampling-based stepdown multiple testing. *Statistics & Probability Letters 113*, 38–40.

Sarver, T. (2008). Anticipating regret: Why fewer options may be better. *Econometrica 76*(2), 263–305.

Schwartz, B., A. Ward, J. Monterosso, S. Lyubomirsky, K. White, and D. R. Lehman (2002). Maximizing versus satisficing: Happiness is a matter of choice. *Journal of Personality and Social Psychology 83*(5), 1178.

Schwartz, L. M., S. Woloshin, W. C. Black, and H. G. Welch (1997). The role of numeracy in understanding the benefit of screening mammography. *Annals of Internal Medicine 127*(11), 966–972.

Somasundaram, J. and E. Diecidue (2017). Regret theory and risk attitudes. *Journal of Risk and Uncertainty 55*(2-3), 147–175.

Sopher, B. and G. Gigliotti (1993). Intransitive cycles: Rational choice or random error? an answer based on estimation of error rates with experimental data. *Theory and Decision 35*, 311–336.

Starmer, C. and R. Sugden (1993). Testing for juxtaposition and event-splitting effects. *Journal of Risk and Uncertainty 6*(3), 235–254.

Strack, P. and P. Viefers (2021). Too proud to stop: Regret in dynamic decisions. *Journal of the European Economic Association 19*(1), 165–199.

Tversky, A. and D. Kahneman (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty 5*(4), 297–323.

Wakker, P. and D. Deneffe (1996). Eliciting von neumann-morgenstern utilities when probabilities are distorted or unknown. *Management Science 42*(8), 1131–1150.

Wong, K. P. (2012). Production and insurance under regret aversion. *Economic Modeling 29*(4), 1154–1160.

Zeelenberg, M. (1999). Anticipated regret, expected feedback and behavioral decision making. *Journal of Behavioral Decision Making 12*(2), 93–106.

Zeelenberg, M., J. Beattie, J. Van der Pligt, and N. K. De Vries (1996). Consequences of regret aversion: Effects of expected feedback on risky decision making. *Organizational Behavior and Human Decision Processes 65*(2), 148–158.

Zheng, J. (2021). Willingness to pay for reductions in health risks under anticipated regret. *Journal of Health Economics 78*(2021), 102476.

Appendix A: Proof of Proposition 1

Step 1 and 2 of the proof follow that of Lanzani (2022) closely. However, we replace the condition of modularity of the ϕ function with the CSPD property.

Step 1: (3) $\implies$ (2). Take any $h,m,l \in X$. Without loss of generality, suppose $h \geq m \geq l$, and define $u : X \to \mathbb{R}$ such that $u(z) = \phi(z,l)$. According to the statement (3) and by definition of $u(\cdot)$, we have

$$\phi(h,l) = \phi(h,m) + \phi(m,l) \iff \phi(h,m) = \phi(h,l) - \phi(m,l) = u(h) - u(m).$$

This proves that $\phi(h,m) = u(h) - u(m)$ whenever $h \geq m$. Whenever $m > h$, skew-symmetry of $\phi(\cdot)$ implies $\phi(h,m) = -\phi(m,h) = -(u(m) - u(h)) = u(h) - u(m)$. This proves that $\phi(h,m) = u(h) - u(m)$ holds for any $m,h \in X$.

Thus, $\pi \in \Pi$ if and only if

$$\sum_{(x,y)\in X\times X} \phi(x,y)\pi(x,y) \geq 0 \iff \sum_{(x,y)\in X\times X} [u(x) - u(y)]\pi(x,y) \geq 0 \iff$$
$$\sum_{x\in X} \pi_1(x)u(x) \geq \sum_{x\in X} \pi_2(x)u(x).$$

Step 2: (2) $\implies$ (3). If Π admits an expected utility representation, then

$$\pi \in \Pi \iff \sum_{(x,y)\in X\times X} (u(x) - u(y))\pi(x,y)$$

Defining $\phi(z,w) = u(z) - u(w)$, (3) is satisfied for any $h,m,l \in X$, that is

$$\phi(h,l) = \phi(h,m) + \phi(m,l) \iff u(h) - u(l) = u(h) - u(m) + u(m) - u(l)$$

Step 3: (2) $\implies$ (1) is a well known result.

To proof (1) $\implies$ (3), we first proof the following lemma, which clarifies that a strict preference for one of the lotteries of the SML task constitutes a violation of transitivity in a quite general framework where only the completeness axiom is imposed.

Lemma 1. When the completeness axiom is satisfied, the following statements are equivalent.

(a) $\pi, \overline{\pi} \in \Pi$ for any $\pi \in \Delta(X \times X)$ such that $\pi_1 = \pi_2$

(1) π satisfies transitivity .

The lemma states that when completeness is satisfied, transitivity is equivalent indifference between any row and column lottery with the same marginal distribution. The completeness axiom states that for all $\pi \in \Delta(X \times X)$, $\pi \notin \Pi \implies \overline{\pi} \in \Pi$.

Step i: We proof $(1) \implies (a)$ by contrapositive, that is not $(a) \implies$ no t(1). Not (a) implies that there exists π with $\pi_1 = \pi_2$ such that $\pi \in \hat{\Pi}$. Consider also the joint distribution χ with $\chi_1 = \chi_2 = \pi_1$ such that $\chi = \overline{\chi}$. Completeness implies $\chi, \overline{\chi} \in \Pi$. Finally, define the joint distribution $\rho = \overline{\pi}$. Preferences over the three joint distributions π, χ, and ρ violate transitivity.

For the reader's convenience, we restate here the transitivity axiom. Transitivity means that $\forall\ \pi, \chi, \rho \in \Delta(X \times X)$, if $\pi_2 = \chi_1$, $\rho_1 = \pi_1$, and $\rho_2 = \chi_2$, then $(\pi \in \Pi, \chi \in \Pi) \Rightarrow \rho \in \Pi$. In the example, $\pi_1 = \pi_2 = \rho_1 = \rho_2 = \xi_1 = \xi_2$, and $(\pi \in \Pi, \chi \in \Pi)$. But, by construction, $\rho \notin \Pi$. This concludes step (i).

Step ii: We also proof $(a) \implies (1)$ by contrapositive, that is not $(1) \implies$ not (a). Consider the three joint distributions π, χ, and ρ defined above and suppose transitivity does not hold, that is $(\pi \in \Pi, \chi \in \Pi)$, but $\rho \notin \Pi$. This implies $\pi \in \Pi$, but $\overline{\pi} = \rho \notin \Pi$, although $\pi_1 = \pi_2$. This concludes the proof of the lemma.

Step 4: $(1) \implies (3)$. We prove this by contrapositive, that is showing that not $(3) \implies$ not (1). Consider $\pi = ((h,l), 1/3; (m,h), 1/3; (l,m), 1/3)$, where $h > m > l$. Note that $\pi_1 = \pi_2$. Imposing $\phi(h,l) > \phi(h,m) + \phi(m,l)$ or $\phi(h,l) < \phi(h,m) + \phi(m,l)$ implies $\pi \in \hat{\Pi}$ or $\overline{\pi} \in \hat{\Pi}$ respectively. By Lemma 1, this violates transitivity.

This concludes the proof proposition 1.

It is worth pointing out that the only way to violate transitivity in Lanzani's framework is to have preferences such that $\phi(h,l) \neq \phi(h,m) + \phi(m,l)$. Lemma 1 shows that such preferences constitute a violation of transitivity in a much more general framework that imposes only the completeness axiom. Note that in this more general framework, $\phi(h,l) \neq \phi(h,m) + \phi(m,l)$ is no longer the only of violating transitivity.

Appendix B: Supplementary tables and figures

Table B.1 Summary statistics of participants' characteristics

	Lab	Online 1	Online 2	Online 2	Online 2
Treatment	Baseline	Baseline	Baseline	State	Column
Male	0.41	0.41	0.51	0.51	0.48
	(0.49)	(0.49)	(0.50)	(0.50)	(0.50)
Age	19.79	28.70	29.40	31.40	30.52
	(1.53)	(7.49)	(7.70)	(8.70)	(8.30)
Student	1.00	0.27	0.27	0.21	0.17
	(0.00)	(0.45)	(0.44)	(0.41)	(0.37)
Married	0.00	0.41	0.51	0.55	0.60
	(0.00)	(0.49)	(0.50)	0.50)	(0.49)
Highest degree	2.03	2.04	2.28	2.36	2.24
	(0.31)	(0.56)	(0.70)	(0.77)	(0.71)
Total included	289	145	158	159	150
Total excluded	7	11	59	53	61

Table notes: standard errors are in parentheses. Highest degree: 1=high school, 2=undergrad 3=master, 4=PhD, 0=none of the above.

Table B.2 Logistic regressions on the SML tasks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sample	Lab	Online	Pooled	Lab	Online	Pooled	Pooled
Variables	Dependent variable: Choice of the ISPD lottery						
Feedback	-0.028	-0.022	-0.026				
	(0.080)	(0.102)	(0.063)				
Online						-0.120	
						(0.079)	
Constant	-0.062	-0.185**	-0.103**	-0.076*	-0.196***	-0.076*	-0.116***
	(0.057)	(0.083)	(0.047)	(0.043)	(0.067)	(0.043)	(0.037)
Observations	2,890	1,450	4,340	2,890	1,450	4,340	4,340
Individuals	289	145	434	289	145	434	434

Table notes: the dependent variable is a dummy that is equal to 1 if a subject chose the ISPD lottery, and 0 otherwise. The variable "Feedback" is equal to 1 if immediate feedback was received and 0 otherwise. The variable "Online" is equal to 1 if an observation comes from the online experiment and 0 otherwise. The notations for significance levels are as follows: * for p≤0.1; ** for p≤0.05; *** for p≤0.01.

Heterogeneity in response to immediate feedback

To explore heterogeneity in feedback effects, we conduct a latent class analysis, similar to that presented in section 5.2. For each subject, we compute the frequency of choosing the ISPD lottery, separately for choices with and without immediate feedback. We specify that the resulting variables are distributed according to a binomial distribution with five trials. We estimate models with up to five classes, but convergence fails for models with six or more classes. Both the Bayesian and the Akaike information criteria select the model with two classes. The first class of individuals chooses the ISPD lottery at a frequency of 0.60 without immediate feedback and at a frequency of 0.30 with immediate feedback. However, this difference is not statistically significant ($p = 0.30$). Approximately 7% of subjects are allocated to this class, characterized by strong DSPD. The remaining 93% are assigned to a class that chooses the ISPD lottery at a frequency of 50% both with and without immediate feedback. In summary, the latent class analysis does not provide any evidence for heterogeneity in feedback effects.

We further explore correlations between survey measures and feedback effects. To do this, we compute, for each individual, the frequency of choosing the ISPD lottery, separately for choices with and without immediate feedback, and calculate the difference. The resulting variable $\Delta(ISPD)$ ranges between -1 and 1. It is positive if a subject chose the ISPD lottery more often when receiving immediate feedback, and negative otherwise.

In column (1) of Table B.3, we pool observations from the lab and the first online experiment and perform an OLS regression with $\Delta(ISPD)$ as the dependent variable. We include a number of demographic variables as explanatory variables, such as dummies indicating whether a participant is married, a student, or male. Additionally, we include variables indicating their participation in the lab experiment, age, and education level (1=high school, 2=undergraduate, 3=master, 4=PhD, 0=none of the other levels).

For the lab experiment, we conduct an additional OLS regression with several survey measures, including individuals' CRT score (Frederick (2005), see Figure E.10), their tendency to experience general regret (Schwartz et al. (2002), see Figure E.11), investment regret (Guiso (2015), see Figure E.13), and their score on a numeracy test (Schwartz et al. (1997); Cokely et al. (2012), see Figure E.14). The CRT and numeracy scores are calculated based on the number of correct answers. Both regret scores are calculated as the average response and are coded such that a higher score implies a higher tendency to experience regret. These results are reported in column 2.

We apply the Romano-Wolf step-wise procedure (Romano and Wolf, 2005, 2016) to correct p-values for multiple hypotheses testing. After the correction, two explanatory variables remain statistically significant at the 5% level. These are the dummy variable indicating whether a participant is a student and the subjects' self-reported tendency to experience investment regret. In response to immediate feedback, students chose the ISPD lottery approximately 23 percentage points more often. For a standard deviation increase in the reported tendency to experience investment regret ($sd = 0.92$), participants chose the ISPD lottery roughly 6.2 percentage points less often under immediate feedback.

Table B.3 OLS regressions exploring correlates of feedback effects

Variables	(1) $\Delta(ISPD)$	(2)	$\Delta(ISPD)$
married	0.121	CRT score	-0.004
	(0.071)		(0.035)
	[0.451]		[0.981]
student	0.227**	general regret	0.054
	(0.069)		(0.029)
	[0.017]		[0.405]
male	0.011	investment regret	-0.067**
	(0.032)		(0.023)
	[0.981]		[0.042]
age	0.002	numeracy score	-0.018
	(0.005)		(0.018)
	[0.981]		[0.84]
education level	-0.012		
	(0.028)		
	[0.981]		
lab	0.129		
	(0.056)		
	[0.187]		
Constant	-0.158	Constant	0.091
	(0.138)		(0.125)
Observations	434	Observations	289
R-squared	0.024	R-squared	0.035

Table notes: the dependent variable is the difference between the frequency of choosing the ISPD lottery with and without feedback. The notations for significance levels are as follows: * for $p \leq 0.1$; ** for $p \leq 0.05$; *** for $p \leq 0.01$. Significance levels are indicated with respect to p-values that were corrected for multiple hypotheses testing following the Romano-Wolf procedure (Romano and Wolf, 2005, 2016). The corrected p-values are reported in brackets.

Correlates of correlation sensitivity

In the survey, we asked participants to rate on Likert scales to what extent they compared lotteries column-by-column, state-by-state, row-by-row, and whether they calculated the expected values. We explore whether the subjects' reports are consistent with the latent classes they are assigned to. To simplify the analysis, we code two variables that average the responses to modes of comparisons that might be more conducive to correlation sensitivity and modes that might be more conducive to correlation insensitivity. Comparing lotteries row-by-row and calculating expected values might be associated with correlation insensitivity. In the baseline treatment, column-by-column comparisons and state-by-state comparisons should induce correlation sensitivity. In the column-effects treatment, only column-by-column comparisons might be associated with correlation sensitivity, whereas state-by-state comparisons might be associated with correlation insensitivity. The reverse might hold true in the state-effects treatment.

We regress, for each of the four latent classes, the posterior probability on the two indexes measuring modes of comparison that might be conducive to correlation sensitivity or insensitivity (see Table B.4). We compute p-values controlling for the family-wise error rate (Romano and Wolf, 2005, 2016). We find subjects self-reports are broadly consistent with their probability of being assigned to the different classes. The probability of being assigned to the correlation-insensitive class 1 significantly decreased with comparison modes that were conducive to correlation sensitivity, whereas the probabilities of being assigned to the correlation-sensitive classes 2 and 3 increased with these modes of comparison. We did not find any correlation between the modes of comparison that might be conducive to correlation insensitivity and class assignment in any of the three classes. Finally, none of the coefficients reached significance in the random-choice class 4.

We also explore correlations between correlation sensitivity at the individual-level and survey repose variables. To do so, we calculate for each subject the fraction with which the ISPD lottery was chosen for the SML tasks, and regress this variable on demographics and other survey variables (see Table B.5). Throughout, we pool as much observations possible, in order to increase power. We again compute p-values controlling for the family-wise error rate (Romano and Wolf, 2005, 2016). None of the considered variables reaches statistical significance at the 5% level.

Table B.4 Self-reported mode of lottery comparison and class assignment

Variables	(1) p_1 "insensitive"	(2) p_2 "strong DSPD"	(3) p_3 "modest DSPD"	(4) p_4 "random choice"
Sensitive mode	-0.052***	0.016***	0.026***	0.010
	(0.008)	(0.005)	(0.005)	(0.005)
	[0.003]	[0.010]	[0.003]	[0.136]
Insensitive mode	0.014	0.003	-0.008	-0.010
	(0.014)	(0.010)	(0.011)	(0.010)
	[0.684]	[0.748]	[0.711]	[0.684]
Constant	0.755***	0.031	0.085	0.129
	(0.102)	(0.068)	(0.066)	(0.078)
Observations	467	467	467	467
R-squared	0.060	0.014	0.031	0.006

Table notes: the notations for significance levels are as follows: * for p≤0.1; ** for p≤0.05; *** for p≤0.01. Significance levels are indicated with respect to p-values that were corrected for multiple hypotheses testing following the Romano-Wolf procedure (Romano and Wolf, 2005, 2016). The corrected p-values are reported in brackets. Robust standard errors are reported in parentheses. The variable "Sensitive mode" is calculated as follows. Baseline: $(column_i + state_i)/2$. Column-effects: $column_i$. State-effects: $state_i$. The variable "Insensitive mode" is calculated as follows. Baseline: $(rows_i + EV_i)/2$. Column-effects: $(rows_i + EV_i + state_i)/3$. State-effects: $(rows_i + EV_i + column_i)/3$, where $rows_i$, EV_i, $column_i$, and $state_i$ are the extent to which subjects state they compared lottery row-by-row, by calculating the expected payoff, by comparing payoffs column-by-column, or state-by-state, each on a Likert scale from 1-9.

Table B.5 Self-reported mode of lottery comparison and class assignment

Variables	(1) ISPD	(2) ISPD	(3) ISPD
Age	-0.001		
	(0.001)		
	[0.864]		
Male	0.007		
	(0.012)		
	[0.910]		
Education level	0.015		
	(0.010)		
	[0.711]		
Student	0.031		
	(0.017)		
	[0.468]		
CRT score		0.021	0.015
		(0.019)	(0.014)
		[0.864]	[0.864]
Numeracy		-0.002	
		(0.009)	
		[0.967]	
General regret		0.012	
		(0.015)	
		[0.887]	
Investment regret		-0.018	
		(0.012)	
		[0.771]	
WTR		0.000	
		(0.005)	
		[0.967]	
Constant	0.426***	0.465***	0.446***
	(0.036)	(0.078)	(0.025)
Observations	919	296	452
R-squared	0.033	0.010	0.002

Table notes: the notations for significance levels are as follows: * for p≤0.1; ** for p≤0.05; *** for p≤0.01. Significance levels are indicated with respect to p-values that were corrected for multiple hypotheses testing following the Romano-Wolf procedure (Romano and Wolf, 2005, 2016). The corrected p-values are reported in brackets. Robust standard errors are reported in parentheses.

Appendix C: Differences between experiments

Considering the choice frequencies in the baseline treatment for the different experiments reveals differences in correlation sensitivity across treatments. In the following, we focus on the six same marginal lotteries of three- and six-state choice tasks that were common among the three experiments (see tasks 1-6 in Table 9). Subjects chose the ISPD lottery at a frequency of 47.8% in the lab experiment, at a frequency of 45.8% in the first online experiment, and at a frequency of 41.4% in the second online experiment. Running logistic regressions, we find that the choice frequency does not differ significantly between the lab and the first online experiment ($p = 0.396$), but does differ significantly between the lab and the second online experiment $p = 0.004$ and marginally between the first and second online experiment $p = 0.08$. This suggests that the choice display we used in the second online experiment might be somewhat more conducive to trigger correlation sensitivity.

To further explore the causes of differences in behavior between the different treatments, we run a logistic regression with a dummy indicating whether a subject chose the ISPD lottery for a given choice task, and number of demographics and task characteristics as explanatory variables. Demographic variables include age, education level (1=high school, 2=undergraduate, 3=master, 4=Phd, 0=none of the other levels), and dummies indicating whether a subject is male and a student. We further include dummies indicating whether a subject took part in the first online experiment, one dummy for each of the three treatments of the second online experiment, and dummies indicating the number of states.

Results can be found in Table C.1. We apply the Romano-Wolf step-wise procedure (Romano and Wolf, 2005, 2016) to correct p-values for multiple hypotheses testing. After the correction, two variables remain statistically significant at the 5% level. These are the dummy indicating the baseline treatment of the second online experiment and the dummy indicating that a choice task had six states, both of which enter negatively and are highly significant (corrected $p < 0.01$). The omitted category is choices in the lab study with three states. The estimates suggest that both the choice display in the second online experiment and a high number of states might lead to stronger correlation sensitivity.

Table C.1 Logistic regressions on the SML tasks

Variables	(1) ISPD
age	-0.004
	(0.004)
	[0.428]
male	0.041
	(0.049)
	[0.671]
education level	0.077*
	(0.043)
	[0.060]
student	0.040
	(0.084)
	[0.709]
online 1	-0.063
	(0.097)
	[0.671]
online 2 - baseline	-0.269***
	(0.095)
	[0.002]
online 2 - column	0.023
	(0.092)
	[0.709]
online 2 - state	-0.081
	(0.102)
	[0.671]
four states	-0.083*
	(0.046)
	[0.060]
six states	-0.171***
	(0.070)
	[0.007]
Constant	-0.168
	(0.156)
Observations	8,723

Table notes: the notations for significance levels are as follows: * for $p \leq 0.1$; ** for $p \leq 0.05$; *** for $p \leq 0.01$. Significance levels are indicated with respect to p-values that were corrected for multiple hypotheses testing following the Romano-Wolf procedure (Romano and Wolf, 2005, 2016). The corrected p-values are reported in brackets. Standard errors, clustered at the subject level, are in parentheses.

Appendix D: Exploration of potential drivers of correlation sensitivity

Parameters for the FOSD tasks in the first online experiment can be found in Table D.1. We obtain these pairs of choice tasks by adding an additional payoff to each payoff of lottery A or B in two SML tasks. We further include one choice between a state-wise dominant and a dominated lottery as an attention check.

As we only implemented these choices in the online experiment, we have choices for four pairs of choice tasks as illustrated in Table 3 for 145 subjects. Pooling observations from all lottery pairs, participants chose the ISPD lottery at a frequency of 18.0% when it was first-order stochastic dominated but at a frequency of 68.4% when it was dominant. Clearly, participants expressed a strong preference for first-order stochastic dominance. Importantly, when pooling all choices regardless of which lottery was dominant, participants chose the ISPD lottery at a frequency of about 43.2%, which is again significantly lower than the random-choice benchmark of 50% ($p < 0.001$). Thus, the observed correlation-sensitivity in lottery choices persists even when one lottery is first-order stochastic dominant. This suggests that the observed effects are not of second-order importance only.[24] Moreover, the overall choice frequency of the ISPD lottery is significantly lower than 50% for both the three states and the six states tasks ($p = 0.005$ and $p < 0.001$ respectively, logistic regression with standard errors clustered at the subject level.) For further discussion on the role of the number of states, see Appendix C.

To address the potential concern that meaningful correlation sensitivity might arise only when choices are sufficiently complex we included lottery choices with three and six states and further manipulated the choice display to explore whether task complexity is linked to correlation

Table D.1 Parameters for choice tasks involving FOSD

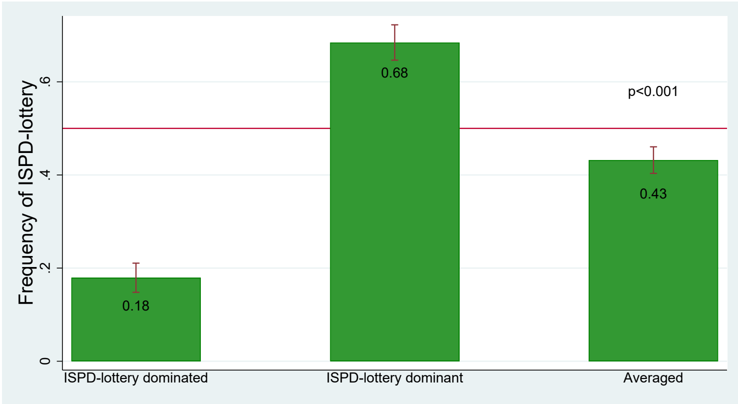
Set 1						
Pair	a	b	c	d	e	f
1	71	63	22	-	-	-
2	93	75	57	39	21	3

Set 2						
Pair	a	b	c	d	e	f
1	94	45	4	-	-	-
2	94	88	83	15	10	4

Table notes: the three-state lotteries always have the following three possible states: $(x^A, x^B) \in \{(c,a),(b,c),(a,b)\}$. The four state lotteries always have the following four possible states: $(x^A, x^B) \in \{(f,a),(e,f),(d,e),(c,d),(b,c),(a,b)\}$. All states are equally likely. We added 4 to each state of either lottery to make it first-order stochastic dominant.

[24] Another way of seeing these results is that first-order stochastic dominance is violated at a frequency of 18% when the ISPD lottery is dominated, but at a frequency of 31.6% when the ISPD lottery is dominant.

Figure D.1 Choice frequencies of the ISPD lottery



sensitivity. Task complexity might be linked to correlation sensitivity if correlation sensitivity is caused by the salience channel or heuristics in decision making.[25] We employ the following within-subject treatment. We present subjects the choice tasks either in the minimal state space (i.e., 3 displayed states for the 3 states and 6 displayed states for the 6 states choice task), or we split each state into two, which results in a presentation with double the number of states as in the minimal state space (i.e., 6 displayed states for the 3 states and 12 displayed states for the 6 states choice task). The states are split such that each initial state is split in the same way. For instance, if state 1 of a 3-states choice task that occurs with probability 1/3 is split into two states that occur with probability 1/9 and 2/9, state 2 and 3 are split in the same way. For an illustration of this, consider Figure D.2. Half of the subjects received set 1 in Table D.1 non-split, and set 2 split, and the other group received set 2 non-split and set 1 split.

We find that the split display significantly increases violations of FOSD by about 7% ($p = 0.001$, logistic regression with standard errors clustered at the subject level). We take this as evidence that this manipulation succeeded in making the choice tasks more complex. If correlation sensitivity in choices is increased by complexity, we should expect stronger correlation sensitivity when subjects faced choices in the split display. This is however not the case. Overall, the ISPD lottery was chosen at a frequency of 43.6% when choices were displayed in the minimal state

Figure D.2 Examples of the minimal state display and the split display

Please choose between option A and B

	Fields 1-20 (33.3%)	Fields 21-40 (33.3%)	Fields 41-60 (33.3%)
○ Option A	67	59	18
○ Option B	22	71	63

(a) Minimal state display

Please choose between option A and B

	Fields 1-16 (26.7%)	Fields 17-32 (26.7%)	Fields 33-36 (6.7%)	Fields 37-52 (26.7%)	Fields 53-56 (6.7%)	Fields 57-60 (6.7%)
○ Option A	63	71	71	22	63	22
○ Option B	67	18	18	59	67	59

(b) Split state display

[25] For instance, subjects might count which lottery yields the higher payoff in most states and then choose this lottery.

display and a frequency of 42.8% when choices were displayed in the split display. This difference is not statistically significant ($p = 0.68$, Wald Chi-Square test, standard errors clustered at the subject level).[26]

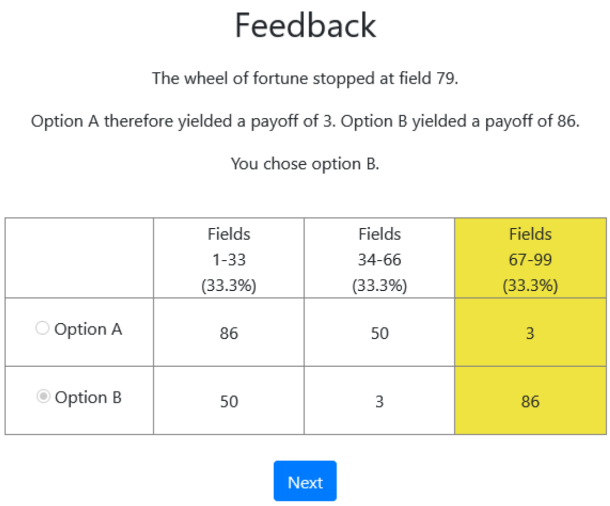
[26] We obtain similar results when summing, for each subject, the number of choices for the ISDP lottery and running a non-parametric Wilcoxon signed-rank test ($p = 0.66$).

Appendix E: Screenshots of the experiments

The experiments were conducted in Chinese. The following screenshots are translations into English. The instructions and the display of the choice tasks were very similar in the different experiments. The online experiments included an abbreviated version of the questionnaire shown here, which included only the Cognitive Reflection Test (Frederick, 2005) and demographic questions. The demographic survey used in the first online experiment was slightly different from that used in the lab experiment.

Appendix E.1: The lab and first online experiment

Figure E.1 Example of feedback on choices' outcomes



Feedback

The wheel of fortune stopped at field 79.

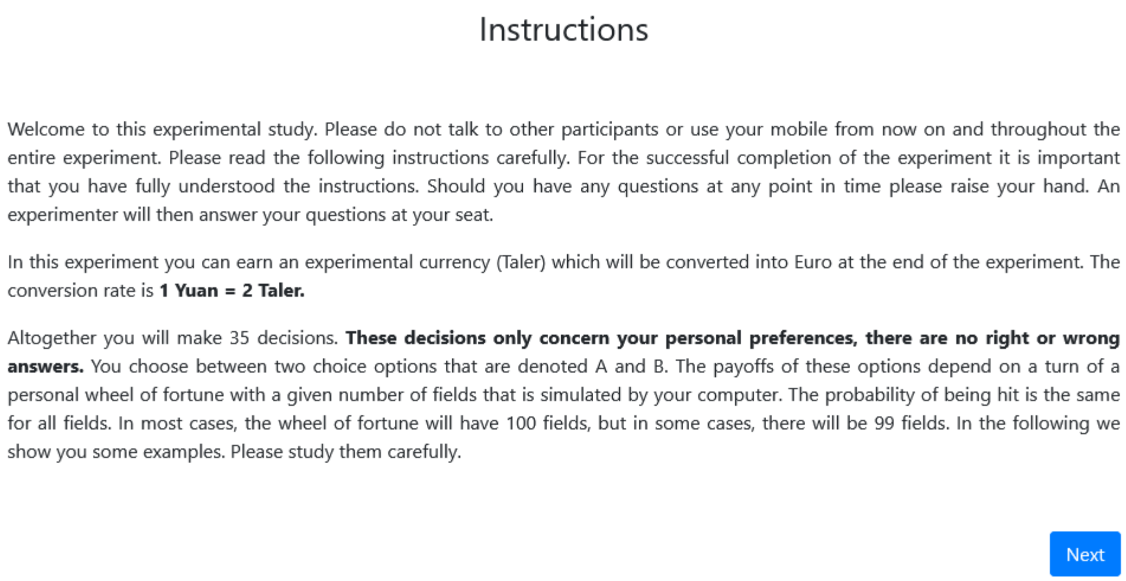
Option A therefore yielded a payoff of 3. Option B yielded a payoff of 86.

You chose option B.

	Fields 1-33 (33.3%)	Fields 34-66 (33.3%)	Fields 67-99 (33.3%)
Option A	86	50	3
Option B	50	3	86

Next

Figure E.2 Introduction (1/4)



Instructions

Welcome to this experimental study. Please do not talk to other participants or use your mobile from now on and throughout the entire experiment. Please read the following instructions carefully. For the successful completion of the experiment it is important that you have fully understood the instructions. Should you have any questions at any point in time please raise your hand. An experimenter will then answer your questions at your seat.

In this experiment you can earn an experimental currency (Taler) which will be converted into Euro at the end of the experiment. The conversion rate is **1 Yuan = 2 Taler.**

Altogether you will make 35 decisions. **These decisions only concern your personal preferences, there are no right or wrong answers.** You choose between two choice options that are denoted A and B. The payoffs of these options depend on a turn of a personal wheel of fortune with a given number of fields that is simulated by your computer. The probability of being hit is the same for all fields. In most cases, the wheel of fortune will have 100 fields, but in some cases, there will be 99 fields. In the following we show you some examples. Please study them carefully.

Next

Figure E.3 Introduction (2/4)

Instructions

Example task:

	Fields 1-35 (35%)	Fields 36-60 (25%)	Fields 61-100 (40%)
○ Option A	20	40	70
○ Option B	30	70	50

If the wheel of fortune stops on fields 1-35 (that corresponds to a 35% probability) with Option A you will receive exactly 20 Taler and with Option B exactly 30 Taler. If the wheel of fortune stops on fields 36-60 (that corresponds to a 25% probability) with Option A you will receive exactly 40 Taler and with Option B exactly 70 Taler. If the wheel of fortune stops on fields 61-100 (that corresponds to a 40% probability) with Option A you will receive exactly 70 Taler and with Option B exactly 50 Taler.

Payoffs:
At the end of the experiment the computer will choose one of your 35 choice tasks randomly. This choice task is payoff relevant. Your payoff will be determined through the simulation of the turn of a wheel of fortune. Assume, for instance, the choice task given in Example 1 is payoff relevant and the wheel of fortune stops on field 93. If you have chosen option A you will receive 70 Taler. If you have chosen Option B you will receive 50 Taler.

Your payoff will be paid in cash at the end of the experiment.

Please look carefully at each of the 35 choice tasks. Between tasks the payoff probabilities and the corresponding payoffs change.

Back

Next

Figure E.4 Introduction (3/4)

Comprehension Test

Before beginning with the experiment, please answer the following comprehension questions.

	Fields 1-15 (15%)	Fields 16-95 (80%)	Fields 96-100 (5%)
○ Option A	20	30	150
○ Option B	70	40	50

Suppose you chose option A. What will your outcome be?

○ 70 with 15% probability, 40 with 80% probability, 50 with 5% probability.

○ 20 with 15% probability, 30 with 80% probability, 150 with 5% probability.

○ 20 with 30% probability, 30 with 30% probability, 150 with 40% probability.

Suppose the wheel of fortune stops at the field 36. Which of the following is correct?

○ Option A yields a payoff of 30 and option B yields a payoff of 40.

○ Option A yields a payoff of 20 and option B yields a payoff of 70.

○ Option A yields a payoff of 150 and option B yields a payoff of 150.

Which of the following is true?

○ If the wheel of fortune stops at field 97, Option A yields a payoff of 30.

○ No matter which option I choose, I will always get the same payoff.

○ Option B yields a payoff of 70 with 15% probability.

Back

Next

Figure E.5 Introduction (4/4)

Please fix the errors in the form.

- You answered at least one of the questions wrong. Please read the hints below and make sure you understand the task well.

Comprehension Test

Before beginning with the experiment, please answer the following comprehension questions.

	Fields 1-15 (15%)	Fields 16-95 (80%)	Fields 96-100 (5%)
○ Option A	20	30	150
○ Option B	70	40	50

Suppose you chose option A. What will your outcome be?

○ 70 with 15% probability, 40 with 80% probability, 50 with 5% probability.

◉ 20 with 15% probability, 30 with 80% probability, 150 with 5% probability.

○ 20 with 30% probability, 30 with 30% probability, 150 with 40% probability.

You answered this question correctly. If you chose option A, you will obtain 20 with 15% probability, 30 with 80% probability, 150 with 5% probability.

Suppose the wheel of fortune stops at the field 36. Which of the following is correct?

○ Option A yields a payoff of 30 and option B yields a payoff of 40.

○ Option A yields a payoff of 20 and option B yields a payoff of 70.

○ Option A yields a payoff of 150 and option B yields a payoff of 150.

You gave a wrong answer to this question. Remember that the outcome of both options depends on a turn of a wheel of fortune.
Option A yields a payoff of 20 if the wheel of fortune stops on fields 1-15, it yields 30 if the wheel of fortune stops on fields 16-95, and 150 if the wheel of fortune stops on fields 96-100.
Option B yields a payoff of 70 if the wheel of fortune stops on fields 1-15, it yields 40 if the wheel of fortune stops on fields 16-95, and 50 if the wheel of fortune stops on fields 96-100.

Which of the following is true?

○ If the wheel of fortune stops at field 97, Option A yields a payoff of 30.

○ No matter which option I choose, I will always get the same payoff.

○ Option B yields a payoff of 70 with 15% probability.

You gave a wrong answer to this question. Remember that your outcome will depend on the option you choose. The outcome of both options depends on a turn of a wheel of fortune.
Option A yields a payoff of 20 if the wheel of fortune stops on fields 1-15, it yields 30 if the wheel of fortune stops on fields 16-95, and 150 if the wheel of fortune stops on fields 96-100.
Option B yields a payoff of 70 if the wheel of fortune stops on fields 1-15, it yields 40 if the wheel of fortune stops on fields 16-95, and 50 if the wheel of fortune stops on fields 96-100.
Each field of the wheel of fortune is equality likely to occur.

Back Next

Figure E.6 Example of a choice task

Decision 3/35

Please choose between options A and B.

	Fields 1-10 (10.0%)	Fields 11-20 (10.0%)	Fields 21-100 (80.0%)
○ Option A	216	96	96
○ Option B	120	0	120

Next

Figure E.7 Example of a state-wise dominant task

Decision Tasks (16/35)

Please choose between options A and B:

	Fields 1-33 (33.3%)	Fields 34-66 (33.3%)	Fields 67-99 (33.3%)
○ Option A	71	48	12
○ option B	76	53	17

Next step

Figure E.8 Announcement of feedback for the last five choice tasks

Instructions 2

There are five decisions left for you to make. These five decision will be similar to the ones you have seen so far. However, from now on, **you will receive immediate feedback about the outcome of your decision.**

After each decision, we will inform you immediately which field the wheel of fortune has hit. We will also inform you which outcome your chosen option as well the alternative option yielded. Remember that all choice tasks are equally likely to be selected to determine your final earnings from the experiment. Therefore, please consider your next five decisions carefully.

Next

Figure E.9 Survey on how participants made their decisions

How did you make your decisions?

You just made several decisions similar to the one displayed below. Below you will find some questions about how you made your decisions. There are no right or wrong answers. We would simply like to better understand how you made your decisions.

	Fields 1-35 (35%)	Fields 36-60 (25%)	Fields 61-100 (40%)
◉ Option A	20	40	70
○ Option B	30	70	50

In the above table, columns are vertically aligned cells. For instance, the yellow cells form a column.
Rows are horizontally aligned cells. For instance, the blue cells in the table above form a row.

Please indicate below to which extend the following statements apply to you.

When deciding between two options,

I compared the payoffs of the two options column by column. (1 means “Does not apply not at all”, and 9 means “Applies completely”).

○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9

I compared options row by row. (I looked at the two options individually.) (1 means “Does not apply not at all”, and 9 means “Applies completely”).

○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9

I considered the probabilities of the different payoffs. (1 means “Does not apply not at all”, and 9 means “Applies completely”).

○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9

I calculated the expected value of each option. (1 means “Does not apply not at all”, and 9 means “Applies completely”).

○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9

Are there any other aspects that influenced your decision? You can also leave any comments regarding the experiments here.

Next

Figure E.10 Survey (1/6)

Survey (1/6)

Q1. A bat and a ball cost 1.10 AUD in total. The bat costs 1.00 AUD more than the ball. How many cents does the ball cost?

Q2. If it takes 5 machines 5 minutes to make 5 widgets, how many minutes would it take 100 machines to make 100 widgets?

Q3. In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how many days would it take for the patch to cover half of the lake?

Q4. Have you ever seen or answered the previous set of questions?

○ Yes

○ No

Next

Figure E.11 Survey (2/6)

Survey (2/6)

Q5. Whenever I make a choice, I am curious about what would have happened if I had chosen differently (1 means "completely disagree", and 5 means "completely agree").

○ 1 ○ 2 ○ 3 ○ 4 ○ 5

Q6. Whenever I make a choice, I try to get information about how the other alternatives turned out (1 means "completely disagree", and 5 means "completely agree").

○ 1 ○ 2 ○ 3 ○ 4 ○ 5

Q7. If I make a choice and it turns out well, I still feel like something of a failure if I find out that another choice would have turned out better (1 means "completely disagree", and 5 means "completely agree").

○ 1 ○ 2 ○ 3 ○ 4 ○ 5

Q8. When I think about how I am doing in life, I often assess opportunities I have passed up. (1 means "completely disagree", and 5 means "completely agree").

○ 1 ○ 2 ○ 3 ○ 4 ○ 5

Q9. Once I make a decision, I do not look back (1 means "completely disagree", and 5 means "completely agree").

○ 1 ○ 2 ○ 3 ○ 4 ○ 5

Next

Figure E.12 Survey (3/6)

Survey (3/6)

Q10. How do you see yourself: are you a person who is generally willing to take risks or do you try to avoid taking risks (0 means "completely unwilling to take risks", and 10 means "very willing to take risks") ?

○ 0 ○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9 ○ 10

Next

Figure E.13 Survey (4/6)

Survey (4/6)

Could you please tell me how you would react if you found yourself in the following situation? Two years ago a friend who is knowledgeable about finance recommended that you undertake an investment which, on the basis of the information available to him then, had good chances of success.

Q11. You chose not to make the investment. Meanwhile, the value of the investment has more than doubled and had you made it, you could have made a big gain. In such circumstances, today you would (1 means "Deeply regret for not having made the investment", and 5 means "Feel no regret") :

○ 1 ○ 2 ○ 3 ○ 4 ○ 5

Q12. Now think of another situation. You invested a significant amount in the investment that was recommended. Meanwhile, market conditions have deteriorated and your investment has lost half of its value. In such circumstances, today you would (1 means "Deeply regret for having made the investment", and 5 means "Feel no regret") :

○ 1 ○ 2 ○ 3 ○ 4 ○ 5

Next

Figure E.14 Survey (5/6)

Survey (5/6)

Q13. Imagine that we throw a fair coin 1000 times. How many times do you think the coin will show tails?

Q14. In a small American lottery the chance of winning 10 $ is 1%. What is your best guess about how many people will win the 10 dollar prize if 1000 people each by a single ticket?

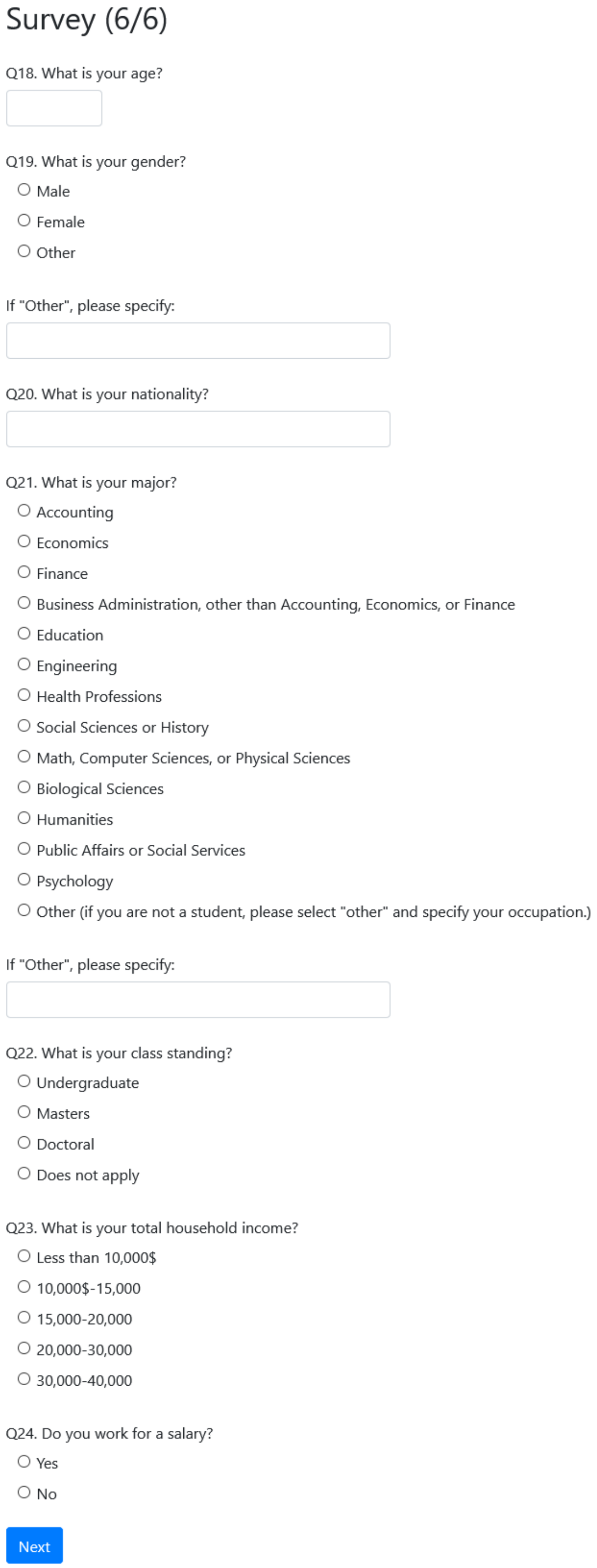
Q15. In another lottery the chance of winning a car is 1 in 1000. What percentage of tickets win a car?

Q16. Out of 1,000 people in a small town 500 are members of a choir. Out of these 500 members in the choir 100 are men. Out of the 500 inhabitants that are not in the choir 300 are men. What is the probability that a randomly drawn man is a member of the choir? Please indicate the probability in percent.

Q17. Imagine we are throwing a five-sided die 50 times. On average, out of these 50 throws how many times would this five sided die show an odd number (1, 3 or 5)?

Next

Figure E.15 Survey (6/6)



Survey (6/6)

Q18. What is your age?

Q19. What is your gender?

- ○ Male
- ○ Female
- ○ Other

If "Other", please specify:

Q20. What is your nationality?

Q21. What is your major?

- ○ Accounting
- ○ Economics
- ○ Finance
- ○ Business Administration, other than Accounting, Economics, or Finance
- ○ Education
- ○ Engineering
- ○ Health Professions
- ○ Social Sciences or History
- ○ Math, Computer Sciences, or Physical Sciences
- ○ Biological Sciences
- ○ Humanities
- ○ Public Affairs or Social Services
- ○ Psychology
- ○ Other (if you are not a student, please select "other" and specify your occupation.)

If "Other", please specify:

Q22. What is your class standing?

- ○ Undergraduate
- ○ Masters
- ○ Doctoral
- ○ Does not apply

Q23. What is your total household income?

- ○ Less than 10,000$
- ○ 10,000$-15,000
- ○ 15,000-20,000
- ○ 20,000-30,000
- ○ 30,000-40,000

Q24. Do you work for a salary?

- ○ Yes
- ○ No

Next

Appendix E.2: Second online experiment

Figure E.16 Instructions (1/3) that is common in all three treatments

Experiment description

The research, led by the academic team of Renmin University of China, focuses on people's risky decision-making behavior, so your performance in this online experiment is very important to our research. Before officially starting, please read the following experiment instructions carefully. Your full understanding of the experimental requirements is the key to the successful completion of this experiment.

During this experiment, you can earn the experimental currency - silver coins. After the experiment is over, the silver coins you get can be converted into RMB, the exchange rate is **1 yuan = 2.5 silver coins.**

During the experiment, you will encounter a total of 29 decision tasks. In each decision task, you need to choose between two options A and B. The amount of rewards in the options is determined by the results of computer-simulated rotation of the lucky wheel with different colored areas. The wheel of fortune may have three, four or six areas of different colors, **each of which has an equal chance of being hit** . **These decisions are based solely on your personal preferences, there is no right or wrong.** Next, we'll show you some examples, please study them carefully.

Next step

Figure E.17 Instructions (2/3) in the baseline treatment

Experiment description

Example task:

○ Option A	**20 (red)**	**40 (blue)**	**70 (orange)**
○ option B	**60 (red)**	**30 (blue)**	**50 (orange)**

In this example, the Wheel of Fortune has three zones. The probability that the lucky wheel stays in any area is the same, that is, 33.33%

- If the lucky wheel stays in the red area **, choose option A and you can get 20** silver coins, choose option B and you can get **60** silver coins
- If the lucky wheel stays in the blue area **, choose option A and you can get 40** silver coins, choose option B and you can get **30** silver coins
- If the lucky wheel stays in the orange area **, choose option A and you can get 70** silver coins, choose option B and you can get **50** silver coins

remuneration:
After the experiment, the computer randomly selects one of the 29 decision-making tasks you completed as a basis for reward. Your exact reward will be determined by the outcome of the wheel of fortune. For example, suppose the sample task is selected as the basis for payment of the payment, and the wheel of fortune is stuck in **the orange** area. If your previous choice was option A, you will get 70 credits; if your previous choice was option B, you will get 50 credits.

There is a one-in-three chance that you will actually receive this extra payment in the end. If you are lucky enough to be drawn, we will give you corresponding rewards through the Jianshu platform .

Please carefully observe the following 29 decision-making tasks, the reward amount and corresponding probability of different tasks will change .

return

Next step

Figure E.18 Instructions (3/3) in the baseline treatment

comprehension test

Before starting the experiment, please answer the following comprehension questions:

○ Option A	**20 (red)**	**150 (blue)**	**30 (orange)**	**10 (green)**
○ option B	**100 (red)**	**50 (blue)**	**30 (orange)**	**40 (green)**

Q1. Suppose you choose option A, the result you will get is:

○
15% chance to get 20 silver coins, 25% chance to get 150 silver coins, 35% chance to get 30 silver coins, 25% chance to get 10 silver coins.
○
25% chance to get 20 silver coins, 25% chance to get 150 silver coins, 25% chance to get 30 silver coins, 25% chance to get 10 silver coins.
○
25% chance to get 40 silver coins, 25% chance to get 100 silver coins, 25% chance to get 50 silver coins, 25% chance to get 30 silver coins.

Q2. Assuming the wheel of fortune stays in **the blue** area, which of the following options is correct:

○ If you choose option A, you will be paid 150 silver coins, and if you choose option B, you will be paid 50 silver coins.
○ If you choose option A, you will get paid 150 silver coins, and if you choose option B, you will get paid 30 silver coins.
○ If you choose option A, you will get paid 20 silver coins, and if you choose option B, you will get paid 100 silver coins.

Q3. Assuming that the outcome of the wheel of fortune is determined randomly, which of the following options is correct:

○ When choosing option A to get a reward of 10 silver coins, choose option B to get a reward of 100 silver coins.
○ When choosing option A to get a reward of 10 silver coins, choose option B to get a reward of 50 silver coins.
○ When choosing option A to get a reward of 10 silver coins, choose option B to get a reward of 40 silver coins.

return Next step

Figure E.19 Example of a choice screen in the baseline treatment

Decision Task (1/29)

Please choose between option A and option B.
The fortune wheel has the same probability of hitting the 4 different color areas. That is, each area has a 25.0% probability of being hit.

○ Option A	**1 (red)**	**150 (blue)**	**51 (orange)**	**17 (green)**
○ option B	**149 (red)**	**50 (blue)**	**16 (orange)**	**0 (green)**

Next step

Figure E.20 Asking participants how they made their choices in the baseline treatment

How do you make decisions?

You just made several decisions similar to the illustration below. Below we ask a few questions about how you make decisions. Note that there are no right or wrong answers here. We simply want to understand how you make decisions.

● Option A	**20** if **red**	**40** if **blue**	**70** if **orange**
○ option B	**60** if **red**	**30** if **blue**	**50** if **orange**

In the table above, vertically aligned cells form a column and horizontally aligned cells form a row. For example, the yellow cells in the table above form a column, while the blue cells form a row. Next, please indicate to what extent the following statement matches your decision-making style.

1. When making a decision between two options, I compare the benefits of the two options column by column (1 means "strongly disagree", and 9 means "very much agree")

○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9

2. When making a decision between two options, I compare the benefits that the two options can bring in each of the same color areas (1 means "very disagree", and 9 means "very much agree")

○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9

3. When making a decision between two options, I look at each option individually on a line-by-line basis (1 being "strongly disagree" and 9 being "very much agree")

○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9

4. When making a decision between the two options, I calculated the expected payoff that each option would generate (1 being "strongly disagree" and 9 being "very much agree").

○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9

5. Are there other factors influencing your decision? If yes, please fill in below

Next step

Figure E.21 Instructions (2/3) in the column-effects treatment

Experiment description

Example task:

○ Option A	**20 (red)**	**40 (blue)**	**70 (orange)**
○ option B	**60 (orange)**	**30 (red)**	**50 (blue)**

In this example, the Wheel of Fortune has three zones. The probability that the lucky wheel stays in any area is the same, that is, 33.33%

- If the lucky wheel stays in the red area **, choose option A and you can get 20** silver coins, choose option B and you can get **30** silver coins
- If the lucky wheel stays in the blue area **, choose option A and you can get 40** silver coins, choose option B and you can get **50** silver coins
- If the lucky wheel stays in the orange area **, choose option A and you can get 70** silver coins, choose option B and you can get **60** silver coins

remuneration:
After the experiment, the computer randomly selects one of the 29 decision-making tasks you completed as a basis for reward. Your exact reward will be determined by the outcome of the wheel of fortune. For example, suppose the sample task is selected as the basis for payment of the payment, and the wheel of fortune is stuck in **the orange** area. If your previous choice was option A, you will get 70 credits; if your previous choice was option B, you will get 50 credits.

There is a one-in-three chance that you will actually receive this extra payment in the end. If you are lucky enough to be drawn, we will give you corresponding rewards through the Jianshu platform .

Please carefully observe the following 29 decision-making tasks, the reward amount and corresponding probability of different tasks will change .

return

Next step

Figure E.22 Instructions (3/3) in the column-effects treatment

comprehension test

Before starting the experiment, please answer the following comprehension questions:

○ Option A	**20 (red)**	**150 (blue)**	**30 (orange)**	**10 (green)**
○ option B	**100 (blue)**	**50 (orange)**	**30 (green)**	**40 (red)**

Q1. Suppose you choose option A, the result you will get is:

○
15% chance to get 20 silver coins, 25% chance to get 150 silver coins, 35% chance to get 30 silver coins, 25% chance to get 10 silver coins.
○
25% chance to get 20 silver coins, 25% chance to get 150 silver coins, 25% chance to get 30 silver coins, 25% chance to get 10 silver coins.
○
25% chance to get 40 silver coins, 25% chance to get 100 silver coins, 25% chance to get 50 silver coins, 25% chance to get 30 silver coins.

Q2. Assuming the wheel of fortune stays in **the blue** area, which of the following options is correct:

○ If you choose option A, you will be paid 150 silver coins, and if you choose option B, you will be paid 100 silver coins.
○ If you choose option A, you will be paid 150 silver coins, and if you choose option B, you will be paid 50 silver coins.
○ If you choose option A, you will get paid 20 silver coins, and if you choose option B, you will get paid 40 silver coins.

Q3. Assuming that the outcome of the wheel of fortune is determined randomly, which of the following options is correct:

○ When choosing option A to get a reward of 10 silver coins, choose option B to get a reward of 40 silver coins.
○ When choosing option A to get a reward of 10 silver coins, choose option B to get a reward of 100 silver coins.
○ When choosing option A to get a reward of 10 silver coins, choose option B to get a reward of 30 silver coins.

return

Next step

Figure E.23 Example of a choice screen in the column-effects treatment

Decision Task (1/29)

Please choose between option A and option B.
The fortune wheel has the same probability of hitting the 4 different color areas. That is, each area has a 25.0% probability of being hit.

○ Option A	**1 (red)**	**150 (blue)**	**51 (orange)**	**17 (green)**
○ option B	**149 (blue)**	**50 (orange)**	**16 (green)**	**0 (red)**

Next step

Figure E.24 Asking participants how they made their choices in the column-effects treatment

How do you make decisions?

You just made several decisions similar to the illustration below. Below we ask a few questions about how you make decisions. Note that there are no right or wrong answers here. We simply want to understand how you make decisions.

● Option A	20 if red	40 if blue	70 if orange
○ option B	60 if orange	30 if red	50 if blue

In the table above, vertically aligned cells form a column and horizontally aligned cells form a row. For example, the yellow cells in the table above form a column, while the blue cells form a row. Next, please indicate to what extent the following statement matches your decision-making style.

1. When making a decision between two options, I compare the benefits of the two options column by column (1 means "strongly disagree", and 9 means "very much agree")

○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9

2. When making a decision between two options, I compare the benefits that the two options can bring in each of the same color areas (1 means "very disagree", and 9 means "very much agree")

○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9

3. When making a decision between two options, I look at each option individually on a line-by-line basis (1 being "strongly disagree" and 9 being "very much agree")

○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9

4. When making a decision between the two options, I calculated the expected payoff that each option would generate (1 being "strongly disagree" and 9 being "very much agree").

○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9

5. Are there other factors influencing your decision? If yes, please fill in below

Next step

Figure E.25 Instructions (2/3) in the state-effects treatment

Experiment description

Example task:

Option A	**20 (red)**	**40 (blue)**	**70 (orange)**
option B	**30 (blue)**	**50 (orange)**	**60 (red)**

In this example, the Wheel of Fortune has three zones. The probability that the lucky wheel stays in any area is the same, that is, 33.33%

- If the lucky wheel stays in the red area **, choose option A and you can get 20** silver coins, choose option B and you can get **60** silver coins
- If the lucky wheel stays in the blue area **, choose option A and you can get 40** silver coins, choose option B and you can get **30** silver coins
- If the lucky wheel stays in the orange area **, choose option A and you can get 70** silver coins, choose option B and you can get **50** silver coins

remuneration:

After the experiment, the computer randomly selects one of the 29 decision-making tasks you completed as a basis for reward. Your exact reward will be determined by the outcome of the wheel of fortune. For example, suppose the sample task is selected as the basis for payment of the payment, and the wheel of fortune is stuck in **the orange** area. If your previous choice was option A, you will get 70 credits; if your previous choice was option B, you will get 50 credits.

There is a one-in-three chance that you will actually receive this extra payment in the end. If you are lucky enough to be drawn, we will give you corresponding rewards through the Jianshu platform .

Please carefully observe the following 29 decision-making tasks, the reward amount and corresponding probability of different tasks will change .

return

Next step

Figure E.26 Instructions (3/3) in the state-effects treatment

comprehension test

Before starting the experiment, please answer the following comprehension questions:

○ Option A	**20 (red)**	**150 (blue)**	**30 (orange)**	**10 (green)**
○ option B	**40 (green)**	**100 (red)**	**50 (blue)**	**30 (orange)**

Q1. Suppose you choose option A, the result you will get is:

○
15% chance to get 20 silver coins, 25% chance to get 150 silver coins, 35% chance to get 30 silver coins, 25% chance to get 10 silver coins.

○
25% chance to get 20 silver coins, 25% chance to get 150 silver coins, 25% chance to get 30 silver coins, 25% chance to get 10 silver coins.

○
25% chance to get 40 silver coins, 25% chance to get 100 silver coins, 25% chance to get 50 silver coins, 25% chance to get 30 silver coins.

Q2. Assuming the wheel of fortune stays in **the blue** area, which of the following options is correct:

○ If you choose option A, you will be paid 150 silver coins, and if you choose option B, you will be paid 50 silver coins.
○ If you choose option A, you will be paid 150 silver coins, and if you choose option B, you will be paid 100 silver coins.
○ If you choose option A, you will get paid 20 silver coins, and if you choose option B, you will get paid 100 silver coins.

Q3. Assuming that the outcome of the wheel of fortune is determined randomly, which of the following options is correct:

○ When choosing option A to get a reward of 10 silver coins, choose option B to get a reward of 30 silver coins.
○ When choosing option A to get a reward of 10 silver coins, choose option B to get a reward of 50 silver coins.
○ When choosing option A to get a reward of 10 silver coins, choose option B to get a reward of 40 silver coins.

return

Next step

Figure E.27 Example of a choice screen in the state-effects treatment

Decision Task (3/29)

Please choose between option A and option B.
The fortune wheel has the same probability of hitting the 3 different color areas. In other words, the probability of each area being hit i 33.33%.

○ Option A	**20 (red)**	**64 (blue)**	**73 (orange)**
○ option B	**20 (blue)**	**64 (orange)**	**73 (red)**

Next step

Figure E.28 Asking participants how they made their choices in the state-effects treatment

How do you make decisions?

You just made several decisions similar to the illustration below. Below we ask a few questions about how you make decisions. Note that there are no right or wrong answers here. We simply want to understand how you make decisions.

Option A	20 if red	40 if blue	70 if orange
option B	30 if blue	50 if orange	60 if red

In the table above, vertically aligned cells form a column and horizontally aligned cells form a row. For example, the yellow cells in the table above form a column, while the blue cells form a row. Next, please indicate to what extent the following statement matches your decision-making style.

1. When making a decision between two options, I compare the benefits of the two options column by column (1 means "strongly disagree", and 9 means "very much agree")

○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9

2. When making a decision between two options, I compare the benefits that the two options can bring in each of the same color areas (1 means "very disagree", and 9 means "very much agree")

○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9

3. When making a decision between two options, I look at each option individually on a line-by-line basis (1 being "strongly disagree" and 9 being "very much agree")

○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9

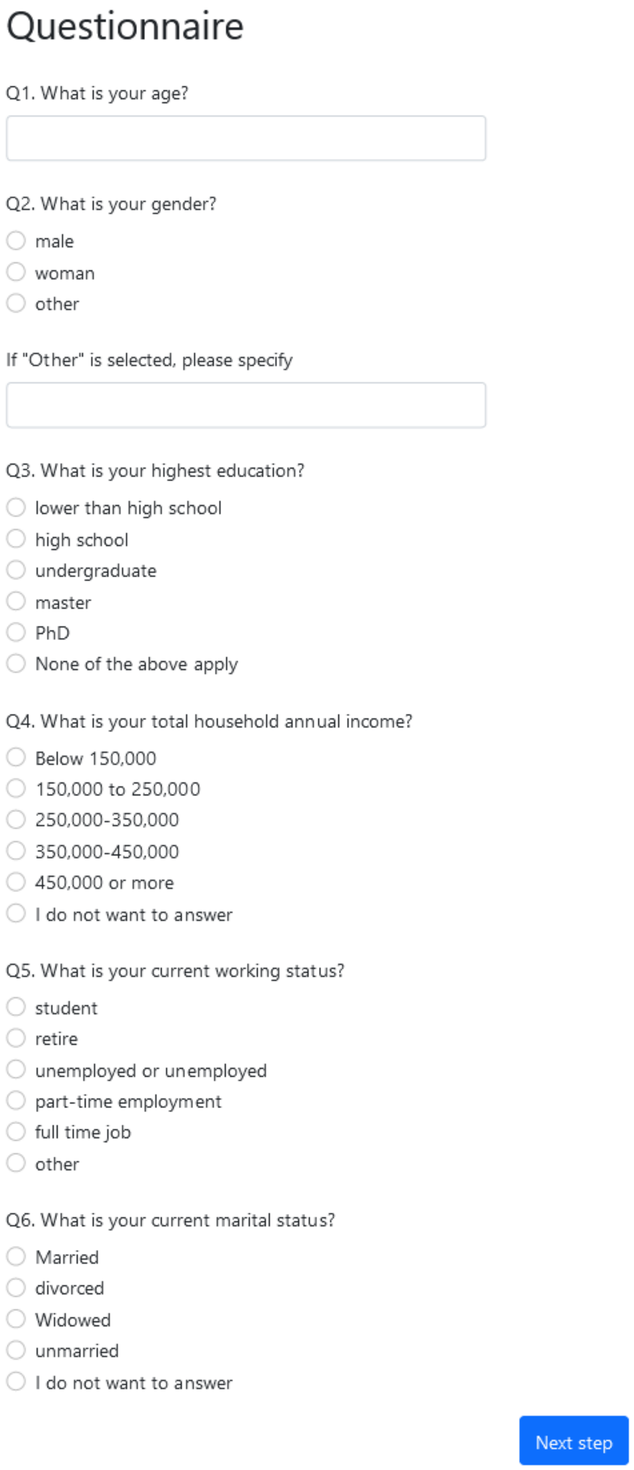
4. When making a decision between the two options, I calculated the expected payoff that each option would generate (1 being "strongly disagree" and 9 being "very much agree").

○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9

5. Are there other factors influencing your decision? If yes, please fill in below

Next step

Figure E.29 The questionnaire that is common in all three treatments



Questionnaire

Q1. What is your age?

Q2. What is your gender?

- male
- woman
- other

If "Other" is selected, please specify

Q3. What is your highest education?

- lower than high school
- high school
- undergraduate
- master
- PhD
- None of the above apply

Q4. What is your total household annual income?

- Below 150,000
- 150,000 to 250,000
- 250,000-350,000
- 350,000-450,000
- 450,000 or more
- I do not want to answer

Q5. What is your current working status?

- student
- retire
- unemployed or unemployed
- part-time employment
- full time job
- other

Q6. What is your current marital status?

- Married
- divorced
- Widowed
- unmarried
- I do not want to answer

Next step