Risk and Rationality: The Relative Importance of Probability Weighting and Choice Set Dependence

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Abstract

The literature suggests that probability weighting and choice set dependence influence risky choices. However, their relative importance has not been tested jointly. We present a joint test that uses binary choices between lotteries provoking Common Consequence and Common Ratio Allais Paradoxes and manipulates their correlation structure. We show non-parametrically that probability weighting and choice set dependence both play a role at describing aggregate choices. To parsimoniously account for heterogeneity, we also estimate a structural model using a finite mixture approach. The model uncovers substantial heterogeneity and classifies subjects into three types: 38% Prospect Theory types whose choices are predominantly driven by probability weighting, 34% Salience Theory types whose choices are predominantly driven by choice set dependence, and 28% Expected Utility Theory types. The model predicts type-specific differences in the frequency of preference reversals out-of-sample. Moreover, the out-of-sample predictions indicate that the choice context shapes the influence of choice set dependence.

Keywords: Choice under Risk, Choice Set Dependence, Probability Weighting, Salience Theory, Prospect Theory, Preference Reversals

JEL Classification: D81, C91, C49

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1 Introduction

The past decades of economic research on choice under risk have revealed systematic violations of expected utility theory (EUT; von Neumann and Morgenstern, 1953). As exposed in the famous Allais Paradoxes, subjects frequently violate EUT's independence axiom as they exhibit both risk loving and risk averse behavior (Allais, 1953). For example, many individuals are risk loving when buying state lottery tickets and risk averse when buying damage insurance (Garrett and Sobel, 1999; Cicchetti and Dubin, 1994; Forrest et al., 2002; Sydnor, 2010). Moreover, subjects often reverse their choice when they have to choose between two lotteries or evaluate them in isolation (Lichtenstein and Slovic, 1971; Lindman, 1971). Some of these preference reversals violate EUT's transitivity axiom (Cox and Epstein, 1989; Loomes et al., 1991). These and other systematic violations of EUT have spurred the development of various alternative decision theories.

These alternative decision theories fit into two major classes. The first major class of decision theories is based on probability weighting and postulates that subjects systematically overweight small probabilities and underweight large probabilites. The most prominent example is Prospect Theory (Kahneman and Tversky, 1979), subsequently generalized to Cumulative Prospect Theory (CPT; Tversky and Kahneman, 1992), which is the best-fitting model for aggregate choices in this class (Starmer, 2000; Wakker, 2010).[1] According to CPT, subjects are risk loving when buying a state lottery ticket because they overweight the small probability of winning and risk averse when buying damage insurance because they underweight the large probability of not suffering any damage. However, CPT fails to explain preference reversals, since subjects always attach the same value to lotteries, regardless whether they have to choose among them or evaluate them in isolation.[2]

The other major class of decision theories postulates that the evaluation of lotteries is choice set dependent.[3] Prominent members of this class are Salience Theory (ST; Bordalo et al., 2012b) and Regret Theory (RT; Loomes and Sugden, 1982).[4] We focus on ST in

[1]Another example in this class of decision theories is Rank Dependent Utility (RDU; Quiggin, 1982). In our paper, RDU and CPT formally coincide, as all our lotteries have non-negative payoffs.

[2]When subjects consider lotteries with non-negative payoffs and derive utility from lottery payoffs rather than absolute wealth levels, then the reference point is equal to zero (Tversky and Kahneman, 1992). In this case, CPT cannot explain preference reversals. However, an extended version of CPT assuming an endogenous reference point can generate preference reversals (Schmidt et al., 2008).

[3]Loomes and Sugden (1987) refer to the two major classes of decision theories as *prospect-based* and *action-based* theories, respectively.

[4]The main difference between ST and RT is how they operationalize choice set dependence. ST focuses on payoff differences while RT focuses on utility differences. Other examples of choice set dependent theories

this paper because it is becoming the main contender to CPT (Dertwinkel-Kalt and Koster, 2017) and, as we show later, exhibits a superior fit to our data. According to ST, individuals focus their limited attention on states of the world with large payoff differences between the alternatives. Hence, a lottery's value is choice set dependent as the weight attached to a state depends on the payoffs of the alternatives in that state. ST can also explain why individuals are often both risk loving and risk averse at the same time, but the intuition is different than in CPT: individuals buy state lottery tickets because they overweight the state where they win the big prize due to the large payoff difference between buying the ticket and winning versus not buying the ticket; at the same time, they buy damage insurance, because they overweight the state in which the damage occurs due to the large payoff difference between being insured and uninsured in that particular state. In contrast to theories based on probability weighting, choice set dependent theories are able to describe preference reversals as they allow for violations of the transitivity axiom.

Discriminating between probability weighting and choice set dependence is relevant in various applications. On the one hand, ST can naturally explain several behavioral phenomena in consumer choice – such as the endowment effect – (Bordalo et al., 2012a, 2013b; Dertwinkel-Kalt et al., 2017), the counter-cyclicality of risk premia on financial markets (Bordalo et al., 2013a), and how legally irrelevant information affects judicial decisions (Bordalo et al., 2015). But on the other hand, and in contrast to CPT, ST can describe the Allais Paradox only in certain choice sets. However, the relative importance of the two major classes of decision theories has not been tested jointly.

In this paper, we address this gap with an experiment and present the first joint test of the relative importance of probability weighting and choice set dependence. Subjects face a series of binary choices between lotteries provoking three versions of the Allais Paradox: the classical and a generalized version of the Common Consequence Allais Paradox as well as the Common Ratio Allais Paradox.

We manipulate the correlation structure of the lotteries' payoffs to discriminate between the different decision theories. That is, every subject faces the lotteries of each binary choice twice. In one case, the lotteries' payoffs are independent of each other, while in the other, they are correlated. This manipulation of the correlation structure affects the joint payoff distribution of the lotteries but leaves their marginal payoff distributions unchanged. If risky choices are driven by probability weighting, the predicted frequency of Allais Paradoxes is

are by Rubinstein (1988); Aizpurua et al. (1990); Leland (1994); and Loomes (2010).

the same, as subjects evaluate each lottery in isolation and focus exclusively on its marginal payoff distribution. Hence, CPT can explain the Allais Paradox regardless of whether lotteries' payoffs are independent or correlated. However, if risky choices are driven by choice set dependence, the predicted frequency of Allais Paradoxes is positive with independent payoffs and zero with correlated payoffs. Thus, ST cannot explain Allais Paradoxes when payoffs are correlated. We can also control for EUT preferences, as EUT can never explain the Allais Paradox. In sum, the experiment yields rich data to discriminate between probability weighting, choice set dependence, and EUT.

Moreover, we present the binary choices to the subjects in two formats. Half of the subjects confronts the "canonical presentation" while the other half confronts the "states of the world presentation". In the canonical presentation, the two lotteries in a binary choice are presented separately by their marginal payoff distributions when their payoffs are independent, and by their joint payoff distribution when their payoffs are correlated. In contrast, in the states of the world presentation, the two lotteries are always presented by their joint payoff distribution, regardless whether payoffs are independent or correlated.[5] Comparing results across the two presentation formats allows us not only to check for robustness but also to control for event-splitting effects, an alternative explanation for choice set dependence (Starmer and Sugden, 1993; Humphrey, 1995).

To obtain our first main result, we analyze the importance of probability weighting and choice set dependence non-parametrically at the aggregate level, i.e., at the level of a representative decision maker. At the aggregate level, both choice set dependence and probability weighting play a role. Probability weighting plays a role, because Allais Paradoxes occur regardless whether lotteries' payoffs are independent or correlated. However, choice set dependence plays a role too, because Allais Paradoxes occur more than twice as often when lotteries' payoffs are independent than when they are correlated. This result holds for all three versions of the Allais Paradox as well as for both presentation formats.

As a next step, we estimate a structural model which offers three conceptual advantages. First, it allows us to take heterogeneity in risk preferences into account. Previous research uncovered substantial heterogeneity in risk preferences (Hey and Orme, 1994; Harless and Camerer, 1994; Starmer, 2000), which may be characterized by a majority of non-EUT-types and a minority of EUT-types (Bruhin et al., 2010; Conte et al., 2011). Taking this heterogeneity into account is important when testing the relative importance of different decision

[5]For screenshots illustrating the two presentation formats, see Figure 1 in Section 3.

theories or when making behavioral predictions – in particular in strategic environments where even small minorities can determine the aggregate outcome (Haltiwanger and Waldman, 1985, 1989; Fehr and Tyran, 2005). Second, since the structural model fully exploits the richness of our data, it can inform us about the specification best suited for representing each major class of decision models. Third, the structural model yields estimated preference parameters which can be used to calibrate theoretical models and to make quantitative predictions about behavior in various choice contexts. This is particularly valuable in theoretical and empirical applications where risk preferences play a role.

The structural model parsimoniously accounts for heterogeneity by using a finite mixture approach. That is, instead of estimating individual-specific parameters – which are typically noisy and may suffer from small sample bias –, it assumes that there exist three types: CPT-types whose behavior is mostly driven by probability weighting, ST-types whose behavior is primarily driven by choice set dependence, and EUT-types. By estimating the three types' relative sizes and their type-specific parameters, the structural model offers a joint test of the relative importance of EUT and of the two most descriptive non-EUT theories. Moreover, it also provides a classification of every subject into the type that best fits her choices.

Another feature of the structural model is that it does not require a particular salience function. More specifically, the binary choices in the experiment allow us to reliably discriminate between the three types as long as subjects exhibit a salience function which satisfies the four general properties of ordering, diminishing sensitivity, symmetry, and zero contrast.

Furthermore, Monte Carlo Simulations confirm that the structural model discriminates remarkably well between the types and remains robust against potential serial correlation in the subjects' errors. This remarkable discriminatory power and robustness result from the model taking all subjects' choices simultaneously into account instead of estimating preference parameters subject by subject.

The structural model yields the second main result. It uncovers vast heterogeneity in subjects' risk preferences and classifies them into 38% CPT-types, 34% ST-types, and 28% EUT-types. This result shows that probability weighting and choice set dependence both play a similarly important role in describing the non-EUT-types' choices. It also highlights that the mix of types can be decisive for understanding and predicting aggregate behavior in applied contexts – such as consumer, investor, and judicial choice.

Finally, we use out-of-sample predictions to test the structural model's power to predict behavior across choice contexts. This is a crucial test of the model since we can only use it to predict behavior in other contexts if the estimated preferences and the classification of subjects into types are stable. To address this question, the experiment exposes subjects to additional lotteries that may trigger preference reversals. Subjects always first choose between two of these additional lotteries and, later, evaluate each of them in isolation. By analyzing the frequency of preference reversals in these additional lotteries, we can assess the structural model's power to predict behavior in choices with a different context than the ones we use for estimating the model.

The predictions about the frequency of preference reversals provide the third main result. The ST-types exhibit roughly 1.5 times more preference reversals than the CPT- and EUT-types, confirming that the ST-types' choices are mostly driven by choice set dependence. The structural model also predicts quantitative differences in the average frequency of preference reversals accurately across the three types. Moreover, the quantitative predictions suggest that the influence of choice set dependence vaires across choice contexts. More specifically, choice set dependence seems to be stronger when subjects trade off a sure amount against a lottery than when they have to choose between two lotteries.

The paper relates directly to the literature that tests the performance of probability weighting and choice set dependence at explaining risky choices. On the one hand, there is considerable evidence suggesting that risky choices depend on outcome probabilities irrespective of the choice set (for examples, see Kahneman and Tversky, 1979; Camerer and Ho, 1994; Loomes and Segal, 1994; Starmer, 2000; Fehr-Duda and Epper, 2012).

On the other hand, the literature also recognizes that risky choices depend on the choice set. Early studies, qualitatively testing the predictions of RT, find "juxtaposition effects", i.e., that systematic manipulations of the correlation structure between lotteries that leave their marginal distributions unchanged can affect subjects' choices. A series of experiments in the 1980s by Loomes and Sugden (1987), Loomes (1988), and Starmer and Sugden (1989) confirm the existence of such juxtaposition effects in common ratio lottery choices using the states of the world presentation format. However, Battalio et al. (1990) and Harless (1992) do not find evidence supporting juxtaposition effects in common ratio lottery choices using the canonical presentation format. More recent studies, testing ST with the same paradigm, confirm the role of choice set dependence in non-incentivized Mturk experiments (Bordalo et al., 2012b) and in two decisions, each involving a choice between a lottery and a sure amount (Booth and Nolen, 2012). Another study by Frydman and Mormann (2018), which is contemporaneous to our paper, finds that the Common Consequence Allais Paradox is less frequent when lotteries' payoffs are correlated and that the evaluation of lotteries changes if one adds an additional "phantom lottery" which subjects can see but not choose.

In sum, the literature has tested probability weighting and choice set dependence separately and found some support for both. However, our paper is the first to test probability weighting and choice set dependence jointly and to assess their relative importance in a heterogeneous population. Since our first main result holds across three different versions of Allais Paradoxes and two presentation formats, the paper confirms the findings from the early experiments qualitatively testing RT and goes against the experiments that found subjects' behavior to be sensitive to the presentation format. Moreover, we can control for event-splitting effects and rule out the concern that making the common consequence more obvious in the states of the world presentation relative to the canonical presentation may influence the frequency of Allais Paradoxes (Keller, 1985; Birnbaum, 2004; Leland, 2010; Birnbaum et al., 2017).

The paper is also the first to feature a structural model taking heterogeneity parsimoniously into account and testing its predictions out-of-sample. Thus, it also contributes to the literature that uses finite mixture models to classify subjects into types. This literature has mostly been focused on discriminating EUT from non-EUT preferences in decision making under risk using a single choice context (Bruhin et al., 2010; Fehr-Duda et al., 2010; Conte et al., 2011; Santos-Pinto et al., 2015).[6] Our second main result enhances this strand of literature by uncovering the relative importance of probability weighting and choice set dependence within the group of non-EUT subjects.

Knowing about this additional heterogeneity within the group of non-EUT subjects matters not only for decision making under risk but also for other domains of individual choice. For instance, taking into account this additional heterogeneity in deterministic consumer choice may shed light on the relative importance of two competing explanations for the famous endowment effect – i.e., the phenomenon that consumers tend to value goods higher as soon as they possess them (Samuelson and Zeckhauser, 1988; Knetsch, 1989; Kahneman et al., 1990; Isoni et al., 2011). One explanation of the endowment effect assumes loss aversion and an endogenous reference point, which shifts as soon as an individual obtains a good and expects to keep it (Kőszegi and Rabin, 2006). Another explanation is choice set

[6] Harrison and Rutström (2009) also apply finite mixture models in order to distinguish EUT from non-EUT behavior. However, they classify decisions instead of subjects. Other studies have also used finite mixture models to analyze strategic decision making in various domains (for examples see El-Gamal and Grether, 1995; Houser et al., 2004; Houser and Winter, 2004; Fischbacher et al., 2013; Bruhin et al., 2018)

dependence and has the following intuition: when the individual receives an endowment, she compares it to the status quo of having nothing which renders the good's best attribute salient and inflates its valuation (Bordalo et al., 2012a). However, experimental evidence based on aggregate choices does not support this explanation (Dertwinkel-Kalt and Köhler, 2016). Since our experimental design and structural model can isolate distinct types of subjects from a heterogeneous population, they offer a way to study the relative importance of choice set dependence for explaining the endowment effect. More precisely, one could investigate whether subjects classified as ST-types are more prone to exhibit the endowment effect than the other types.

Finally, our third main result, derived from the out-of-sample predictions about the frequency of preference reversals enhances the existing literature in three ways. First, it links the aforementioned papers analyzing Allais Paradoxes to the literature about preference reversals (Lichtenstein and Slovic, 1971; Lindman, 1971; Grether and Plott, 1979; Pommerehne et al., 1982; Reilly, 1982; Cox and Epstein, 1989; Loomes et al., 1991) and confirms that both phenomena result from choice set dependence. Second, it shows that a parsimonious structural model has predictive power across different choice contexts – which is essential for modeling and predicting subjects' behavior in different applications of choice under risk. Third, the predictions about the frequency of preference reversals also open an avenue for future research, as they indicate that the choice context shapes the influence of choice set dependence.

The paper has the following structure. Section 2 explains the strategy for discriminating between the different decision theories. Section 3 introduces the experimental design. Section 4 presents the non-parametric results at the aggregate level, while Section 5 discusses the structural model, its results, and its power to predict preference reversals in a different choice context. Finally, Section 6 concludes.

2 Discriminating between Decision Theories

This section describes our empirical strategy for discriminating between EUT, probability weighting, and choice set dependence. We focus on the two most descriptive behavioral theories, i.e., CPT representing probability weighting and ST representing choice set dependence. The empirical strategy (i) relies on a series of binary choices between lotteries that may trigger Common Consequence and Common Ratio Allais Paradoxes and (ii) manipulates the choice set by making the lotteries' payoffs either independent or correlated.

We explain the empirical strategy with the following binary choice between lotteries X and Y, taken from Kahneman and Tversky (1979), which may trigger the Common Consequence Allais Paradox:[7]

$$X = \begin{cases} 2500 & p_1 = 0.33 \\ z & p_2 = 0.66 \\ 0 & p_3 = 0.01 \end{cases} \qquad \text{vs.} \qquad Y = \begin{cases} 2400 & p_1 + p_3 = 0.34 \\ z & p_2 = 0.66 \end{cases} \tag{1}$$

Note that the two lotteries have a common consequence, i.e., a payoff z which occurs with probability p_2 in both lotteries. In this example, the Common Consequence Allais Paradox refers to the robust empirical finding that if $z = 2400$, most individuals prefer Y over X, whereas if $z = 0$, most individuals prefer X over Y.

Next, we show that EUT can never describe the Allais Paradox, CPT can always describe it, and ST can only describe the Allais Paradox when the payoffs of the two lotteries are independent but not when they are correlated.

2.1 EUT

According to EUT, the decision maker evaluates any lottery L with non-negative payoffs $x = (x_1, \ldots, x_J)$ and associated probabilities $p = (p_1, \ldots, p_J)$ as

$$V^{EUT}(L) = \sum_{j=1}^{J} p_j\, v(x_j)\,,$$

where v is an increasing utility function over monetary payoffs with $v(0) = 0$.[8] Note that the value $V^{EUT}(L)$ only depends on the attributes of lottery L and not on the attributes of the other lotteries in the choice set. EUT cannot explain the Common Consequence Allais Paradox since, when comparing the values of the two lotteries $V^{EUT}(X)$ and $V^{EUT}(Y)$, the term involving the common consequence, $p_2\, v(z)$, cancels out. Hence, the decision maker's choice between X and Y does not depend on the value of the common consequence z.

[7]The analogous example for the Common Ratio Allais Paradox can be found in Appendix A.

[8]This assumes that subjects are interested in lottery payoffs and not final wealth states.

2.2 CPT

According to CPT, the decision maker ranks the non-negative monetary payoffs of any lottery L such that $x_1 \geq \ldots \geq x_J$ and evaluates the lottery as

$$V^{CPT}(L) = \sum_{j=1}^{J} \omega_j^{CPT}(p)\, v(x_j)\,,$$

where ω_j is the decision weight attached to the value of payoff x_j. As in EUT, the value $V^{CPT}(L)$ only depends on the attributes of lottery L, i.e., the decision maker evaluates the lottery in isolation. The decision weights are given by

$$\omega_j^{CPT}(p) = \begin{cases} w(p_1) - w(0) & \text{for } \; j = 1 \\ w\left(\sum_{k=1}^{j} p_k\right) - w\left(\sum_{k=1}^{j-1} p_k\right) & \text{for } \; 2 \leq j \leq J-1 \\ w(1) - w\left(\sum_{k=1}^{J-1} p_k\right) & \text{for } \; j = J \end{cases} \,,$$

where p_k is payoff x_k's probability and w is the probability weighting function. Typically, the probability weighting function in CPT exhibits three properties (Kahneman and Tversky, 1979; Prelec, 1998; Wakker, 2010; Fehr-Duda and Epper, 2012):

1. *Strictly increasing and satisfying* $w(0) = 0$ *and* $w(1) = 1$. This ensures that decision weights are non-negative and sum to one.

2. *Inverse S-shape.* The probability weighting function is concave for small probabilities and convex for large probabilities. This property ensures the decision maker overweights small probabilities and underweights large probabilities. It is necessary for CPT to be able to explain the Common Consequence Allais Paradox, as explained further below.

3. *Subproportionality.* For the probabilities $1 \geq q > p > 0$ and the scaling factor $0 < \lambda < 1$, the inequality $\frac{w(q)}{w(p)} > \frac{w(\lambda q)}{w(\lambda p)}$ holds. Subproportionality is needed for CPT to be able to explain the Common Ratio Allais Paradox, as shown in Appendix A.

We now explain how CPT can describe the Common Consequence Allais Paradox in the choice between lotteries X and Y. When $z = 2400$, the choice is

$$X = \begin{cases} 2500 & p_1 = 0.33 \\ 2400 & p_2 = 0.66 \\ 0 & p_3 = 0.01 \end{cases} \qquad \text{vs.} \qquad Y = 2400\,.$$

In this case, the decision maker tends to prefer Y over X. Due to the decision maker's tendency to overestimate small probabilities and underestimate large probabilities, the decision weight attached to the lowest payoff of X, $1-w(0.99)$, is larger than its objective probability $p_3 = 0.01$, which renders X unattractive.

In contrast, when $z = 0$, the choice is

$$X = \begin{cases} 2500 & p_1 = 0.33 \\ 0 & p_2 + p_3 = 0.67 \end{cases} \quad \text{vs.} \quad Y = \begin{cases} 2400 & p_1 + p_3 = 0.34 \\ 0 & p_2 = 0.66 \end{cases}.$$

In this case, the decision maker tends to prefer X over Y. Now, the decision weights of the two lotteries' highest payoffs, $w(0.33)$ and $w(0.34)$, are very close and, therefore, the decision is driven by the difference in utilities between $v(2500)$ and $v(2400)$ rather than the difference in probabilities.

In sum, CPT can always explain the Allais Paradox because the decision weights depend non-linearly on the marginal payoff distribution of the lottery under consideration, which remains unchanged regardless whether the lotteries payoffs are independent or correlated.

2.3 ST

According to ST, cognitive limitations cause the decision maker to be a local thinker who focuses her attention on states of the world in which one payoff stands out relative to the payoffs of the alternative. The decision maker overweights these salient states relative to the others. As the salience of a state directly depends on the payoffs of the alternative, a lottery's value is choice set dependent and – in contrast to EUT and CPT – lotteries are no longer evaluated in isolation.

Formally, if the decision maker has to choose between two lotteries L^1 and L^2, she ranks each possible state $s \in \{1, \ldots, S\}$ according to its salience $\sigma(x_s^1, x_s^2)$, where x_s^1 and x_s^2 are the payoffs of L^1 and L^2, respectively, in state s. The salience function σ satisfies four properties:

1. *Ordering.* For two states s and $\tilde{s}$, we have that if $[x_s^{\min}, x_s^{\max}]$ is a subset of $[x_{\tilde{s}}^{\min}, x_{\tilde{s}}^{\max}]$, then $\sigma(x_{\tilde{s}}^1, x_{\tilde{s}}^2) > \sigma(x_s^1, x_s^2)$. Ordering implies that states with bigger differences in payoffs are more salient.

2. *Diminishing Sensitivity.* For any $\epsilon > 0$, $\sigma(x_s^1, x_s^2) > \sigma(x_s^1 + \epsilon, x_s^2 + \epsilon)$. Diminishing sensitivity implies that, for states with a given difference in payoffs, salience diminishes the further away from zero the difference in payoffs is.

3. *Symmetry:* $\sigma(x_s^1, x_s^2) = \sigma(x_s^2, x_s^1)$. Symmetry implies that permutations of payoffs between lotteries leave the salience of a state unchanged.

4. *Zero Contrast.* For two states s and $\tilde{s}$ where $x_s^1 = x_s^2$ and $x_{\tilde{s}}^1 \neq x_{\tilde{s}}^2$, $\sigma(x_s^1, x_s^2) < \sigma(x_{\tilde{s}}^1, x_{\tilde{s}}^2)$. Zero contrast implies that if two lotteries offer the same payoff in a particular state, this state is the least salient.

The decision weight of each state s depends on the state's salience-rank, $r_s \in \{1, \ldots, S\}$ with lower values being associated with higher salience:

$$\omega_s^{ST}(x^1, x^2) = p_s \frac{\delta^{r_s}}{\sum_{m \in S} \delta^{r_m} \, p_m}, \tag{2}$$

where p_s is the probability that state s is realized, and $0 < \delta \leq 1$ is the decision maker's degree of local thinking. For $\delta = 1$, the decision maker weights states by their objective probabilities, whereas, for $\delta < 1$, the decision maker is a local thinker and overweights salient states. This yields the following values for lotteries L^1 and L^2:

$$V^{ST}(L^1) = \sum_{s=1}^{S} \omega_s^{ST}(x^1, x^2) \, v(x_s^1)$$

and

$$V^{ST}(L^2) = \sum_{s=1}^{S} \omega_s^{ST}(x^1, x^2) \, v(x_s^2) \, .$$

Note that the value of each lottery depends on both lotteries in the choice set $\{L^1, L^2\}$.

We now explain how ST can describe the Common Consequence Allais Paradox in the choice between lotteries X and Y when their payoffs are independent of each other. When $z = 2400$, there are three states of the world which rank in salience as follows: $\sigma(0, 2400) > \sigma(2500, 2400) > \sigma(2400, 2400)$. The decision maker prefers lottery Y over X if $V^{ST}(Y) > V^{ST}(X)$, where

$$V^{ST}(Y) = v(2400) \, ,$$

and

$$V^{ST}(X) = \omega_2^{ST}(2500, 2400) \, v(2500) + \omega_3^{ST}(2400, 2400) \, v(2400) + \omega_1^{ST}(0, 2400) \, v(0) \, .$$

Using $v(0) = 0$ and the decision weights given by equation (2), the condition for preferring Y over X becomes

$$\delta < \frac{0.01}{0.33} \frac{v(2400)}{v(2500) - v(2400)} \, . \tag{3}$$

Intuitively, lottery X provides the lowest payoff in the most salient state which makes lottery Y relatively attractive despite having a lower expected payoff. Hence, when the common consequence is $z = 2400$ and the degree of local thinking is severe enough, the decision maker prefers Y over X.

In contrast, when $z = 0$, there are four states of the world which rank in salience as follows: $\sigma(2500, 0) > \sigma(0, 2400) > \sigma(2500, 2400) > \sigma(0, 0)$. The decision maker prefers lottery X over Y if $V^{ST}(X) > V^{ST}(Y)$, where

$$V^{ST}(X) = \left[\omega_1^{ST}(2500, 0) + \omega_3^{ST}(2500, 2400)\right] \, v(2500) + \left[\omega_2^{ST}(0, 2400) + \omega_4^{ST}(0, 0)\right] \, v(0)\,,$$

and

$$V^{ST}(Y) = \left[\omega_2^{ST}(0, 2400) + \omega_3^{ST}(2500, 2400)\right] \, v(2400) + \left[\omega_1^{ST}(2500, 0) + \omega_4^{ST}(0, 0)\right] \, v(0)\,.$$

Using $v(0) = 0$ and the decision weights given by equation (2), the decision maker prefers X over Y when

$$\begin{aligned}(0.33)\,(0.66)\,v(2500) - \delta\,(0.67)\,(0.34)\,v(2400)& \\ +\delta^2\,(0.33)\,(0.34)\,[v(2500) - v(2400)] &> 0\,. \end{aligned} \tag{4}$$

Now, lottery X provides the highest payoff in the most salient state. Hence, when the common consequence is $z = 0$ and the degree of local thinking is severe enough, the decision maker prefers X over Y.

We now turn to the case in which the two lotteries' payoffs are correlated. In that case, ST can no longer describe the Common Consequence Allais Paradox. When the two lotteries' payoffs are correlated, there are just the following three states of the world:

p_s	0.33	0.66	0.01
x_s	2500	z	0
y_s	2400	z	2400

The ranking in terms of salience of these three states, $\sigma(0, 2400) > \sigma(2500, 2400) > \sigma(z, z)$, is independent of the common consequence z. Hence, regardless of the common consequence, the decision maker tends to prefer Y over X, and the Common Consequence Allais Paradox can no longer be described by ST when the lotteries' payoffs are correlated.

In sum, ST can explain the Allais Paradox only when the lotteries' payoffs are independent but not when they are correlated. This is because decision weights depend on the joint payoff distribution of the two lotteries in the choice set, which changes when we manipulate the correlation structure of the lotteries' payoffs.

2.4 Empirical Strategy

Table 1 summarizes the empirical strategy to discriminate between EUT, probability weighting, and choice set dependence.

Table 1: When can the Allais Paradox occur?

	Lottery Payoffs	
	independent	correlated
EUT	✗	✗
Probability Weighting: CPT	✓	✓
Choice Set Dependence: ST	✓	✗

EUT can never explain the Allais Paradox. In contrast, probability weighting – represented by CPT – can explain the Allais paradox regardless whether the lotteries payoffs are independent or correlated. Finally, choice set dependence – represented by ST – can explain the Allais paradox only when the lotteries' payoffs are independent but not when they are correlated.

3 Experimental Design

This section presents the experimental design which consists of two parts. In the main part, subjects make choices that may trigger three versions of the Allais Paradox: the classical and a generalized version of the Common Consequence Allais Paradox as well as the Common Ratio Allais Paradox. Based on these choices, we discriminate between EUT, probability weighting, as well as choice set dependence, and classify subjects into EUT-, CPT-, and ST-types, respectively. In the additional part, subjects make choices that could lead to preference reversals which allow us to validate our results in a different choice context.

3.1 Main Part

We now present the main part of the experiment. First, we explain how we construct the series of binary choices. Subsequently, we describe the two formats which we use to present the binary choices to the subjects.

3.1.1 Choices between Lotteries

Every subject goes through two blocks of binary choices between lotteries that may trigger the Allais Paradoxes. Both blocks feature the same lotteries, except that in one block the lotteries' payoffs are independent while in the other they are correlated.

The binary choices within each block feature lotteries that vary systematically in payoffs and probabilities. This systematic variation not only allows us to estimate the parameters of each decision theory in the structural model but also ensures that our results are not driven by a particular set of lotteries. To avoid order effects, we randomize (i) the order of the binary choices within each of the two blocks across subjects and (ii) counterbalance the order of the two blocks across subjects.

The binary choices that may trigger the classical and the generalized version of the Common Consequence Allais Paradox are based on a $3 \times 3 \times 2$ design. The design uses the following three different payoff levels:

$$\text{Payoff Level 1:} \qquad X = \begin{cases} 2500 & p_1 \\ z & p_2 \\ 0 & p_3 \end{cases} \qquad \text{vs.} \qquad Y = \begin{cases} 2400 & p_1 + p_3 \\ z & p_2 \end{cases}$$

$$\text{Payoff Level 2:} \qquad X = \begin{cases} 5000 & p_1 \\ z & p_2 \\ 0 & p_3 \end{cases} \qquad \text{vs.} \qquad Y = \begin{cases} 4800 & p_1 + p_3 \\ z & p_2 \end{cases}$$

$$\text{Payoff Level 3:} \qquad X = \begin{cases} 3000 & p_1 \\ z & p_2 \\ 500 & p_3 \end{cases} \qquad \text{vs.} \qquad Y = \begin{cases} 2600 & p_1 + p_3 \\ z & p_2 \end{cases}$$

Varying the payoffs across these three levels while keeping probabilities constant identifies the curvature of the utility function, v. Similarly, the design features three different probability distributions, $p = (p_1, p_2, p_3)$, over the lotteries' payoffs:

$$\begin{aligned} &\text{Probability Distribution 1:} \quad p = (0.33, 0.66, 0.01) \\ &\text{Probability Distribution 2:} \quad p = (0.30, 0.65, 0.05) \\ &\text{Probability Distribution 3:} \quad p = (0.25, 0.60, 0.15) \end{aligned}$$

Varying the probability distributions while keeping the lotteries' payoffs constant identifies the shape of probability weighting function, w, in CPT and the degree of local thinking, δ, in ST. Finally, the design uses the following levels of the common consequence, z, to trigger the two versions of the Common Consequence Allais Paradox:

1. $z = x_3$, i.e., the common consequence is equal to the lowest payoff of lottery X. In this case, lotteries X and Y offer two payoffs each.

2a. $z = y_1$, i.e., the common consequence is equal to the first payoff of lottery Y. In this case, lottery X offers three payoffs and lottery Y is a sure amount.

2b. z is different from any other payoff of the two lotteries and slightly below the first payoff of lottery Y.[9] In this case, lottery X offers three payoffs and lottery Y offers two payoffs.

The first two levels of the common consequence, 1 and 2a, trigger the classical version of the Common Consequence Allais Paradox, as described in the previous section. The first and the third levels, 1 and 2b, trigger a generalized version of the Common Consequence Allais Paradox. The advantage of this generalized version is that the lottery Y does not degenerate into a sure amount which could lead to a specific certainty effect. However, the disadvantage of this generalized version is that, if lottery payoffs are independent, subjects have to consider $2 \times 3 = 6$ possible states of the world resulting in higher cognitive load.

To expose subjects to an even broader variety of decision situations, the design also includes binary choices that may trigger the Common Ratio Allais Paradox. These choices are based on a similar $3 \times 3 \times 2$ design, as shown in Appendix B. To provoke the Common Ratio Allais Paradox, the design scales down probability levels but keeps the lotteries' payoffs unchanged. Moreover, as before, it manipulates the correlation structure of lotteries' payoffs to discriminate between the different classes of decision theories. While CPT can describe the Common Ratio Allais Paradox regardless of the lotteries' correlation structure, ST can describe it only when payoffs are independent but not when they are correlated (see Appendix A for details). The mechanism in ST works as follows: when payoffs are independent, the decision maker's evaluation of the lotteries depends on the salience of the states as well as their objective probabilities. However, when payoffs are correlated, her evaluation no longer depends on the objective probabilities. This mechanism is arguably more subtle than the one behind the Common Consequence Allais Paradox, as the lotteries' payoffs in each binary choice remain unchanged.

[9]For Payoff Level 1: $z = 2000$; for Payoff Level 2: $z = 4000$; for Payoff Level 3: $z = 2000$.

3.1.2 Presentation Format

We present the binary choices between lotteries in two formats, the "canonical presentation" and the "states of the world presentation", exposing half of the subjects to either of them. The two formats differ in the way they present the choices between lotteries with independent payoffs to the subjects. In the canonical presentation, as shown by the screenshot in Panel (a) of Figure 1, the lotteries X and Y are presented side by side as separate lotteries with independent payoff distributions. In the states of the world presentation, as shown by the screenshot in Panel (b) of Figure 1, the lotteries are presented in a table displaying their joint payoff distribution. For choices between lotteries with correlated payoffs, the two presentation formats are identical and display the lotteries' joint payoff distribution.

The two presentation formats have distinct advantages and disadvantages. The main advantages of the canonical presentation are that it emphasizes the difference between lotteries with independent vs. correlated payoffs and that subjects are probably more used to the canonical presentation of lotteries with independent payoffs. However, the main disadvantage of the canonical presentation is that between the two blocks not only the correlation structure of the lotteries' payoffs changes but also their visual presentation. In contrast, the states of the world presentation keeps the visual presentation constant across the two blocks, but presents lotteries with independent payoffs in an unfamiliar way. Ideally, our results should remain valid under both presentation formats.

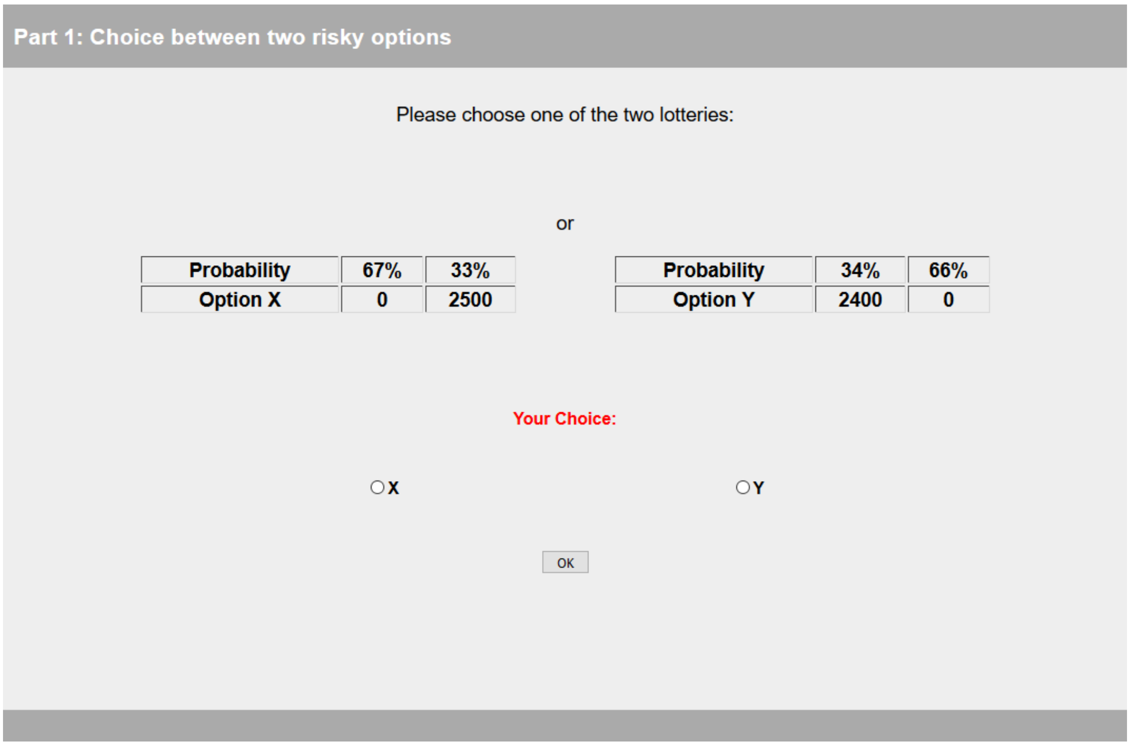
3.2 Additional Part

To validate the classification of subjects into types in a different choice context, we perform out-of-sample predictions about the frequency of preference reversals. To trigger preference reversals we first expose subjects to six binary choices between additional lotteries and, subsequently, let them evaluate these lotteries in isolation by stating their certainty equivalent. We added the six binary choices to the main part of the experiment but used these choices neither for estimating the subject's preferences nor for classifying them into types.

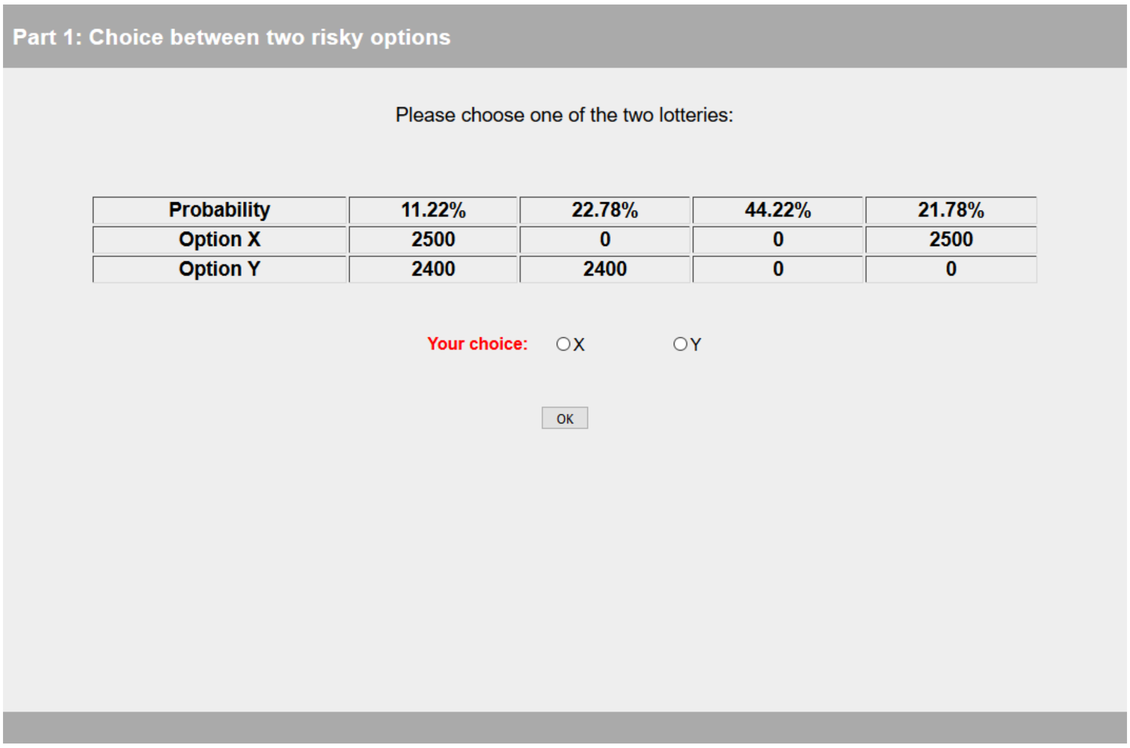
Each of the six binary choices consists of a relatively safe lottery $\tilde{X}$ with a low payoff-variance and a more risky lottery $\tilde{Y}$ with high payoff-variance. The two lotteries have the following format:

$$\tilde{X} = \begin{cases} x & p \\ 0 & 1-p \end{cases} \qquad \text{vs.} \qquad \tilde{Y} = \begin{cases} tx & p/t \\ 0 & 1-p/t \end{cases},$$

Figure 1: Presentation of a Lottery with Independent Payoffs (translated from French)

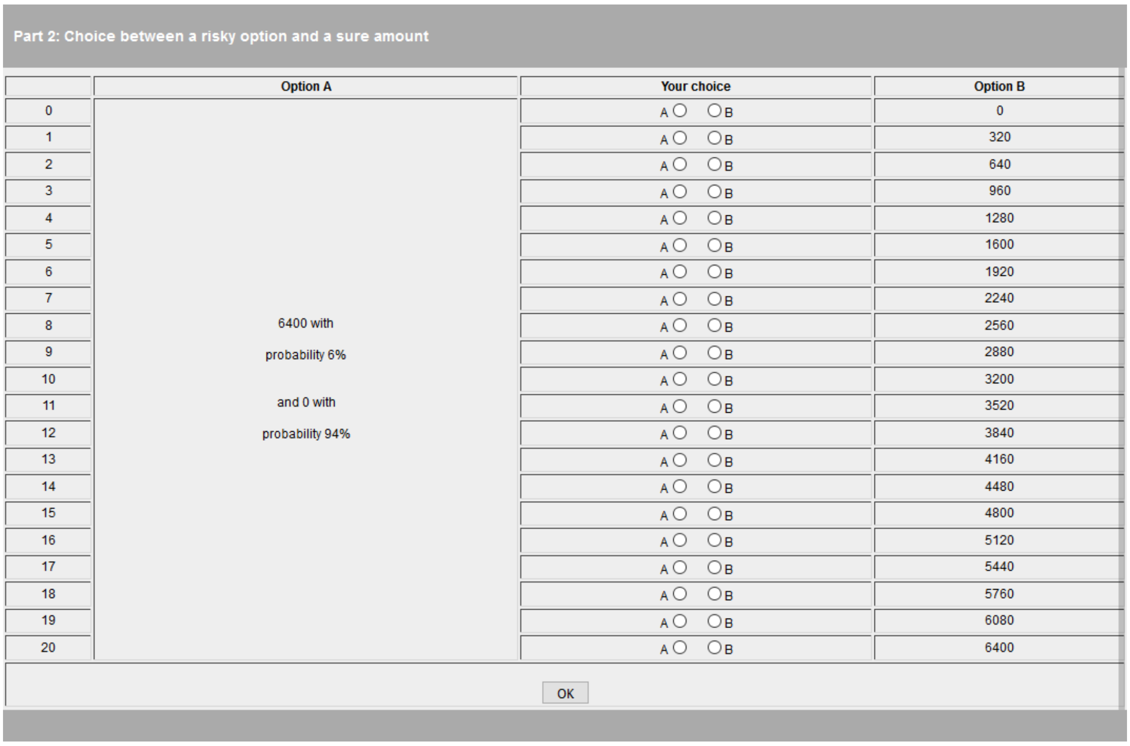


(a) Canonical Presentation



(b) States of the World Presentation

Figure 2: Elicitation of Certainty Equivalents in the Additional Part of the Experiment


Part 2: Choice between a risky option and a sure amount

	Option A	Your choice	Option B
0	6400 with probability 6% and 0 with probability 94%	A ○ ○ B	0
1		A ○ ○ B	320
2		A ○ ○ B	640
3		A ○ ○ B	960
4		A ○ ○ B	1280
5		A ○ ○ B	1600
6		A ○ ○ B	1920
7		A ○ ○ B	2240
8		A ○ ○ B	2560
9		A ○ ○ B	2880
10		A ○ ○ B	3200
11		A ○ ○ B	3520
12		A ○ ○ B	3840
13		A ○ ○ B	4160
14		A ○ ○ B	4480
15		A ○ ○ B	4800
16		A ○ ○ B	5120
17		A ○ ○ B	5440
18		A ○ ○ B	5760
19		A ○ ○ B	6080
20		A ○ ○ B	6400

OK

This screenshot shows an example of the choice menu we used for eliciting the subjects' certainty equivalents, when they had to evaluate lotteries in isolation during the additional part of the experiment. The example is translated from French.

with a scaling factor $t \in \{2, 4, 16\}$. All six binary choices can be found in Appendix C. As Bordalo et al. (2012b) discuss in detail, subjects tend to prefer the relatively safe lottery $\tilde{X}$ over the risky lottery $\tilde{Y}$ in a pairwise choice but, at the same time, indicate a higher certainty equivalent for $\tilde{Y}$ than for $\tilde{X}$ when evaluating the lotteries in isolation. Bordalo et al. (2012b) also explain that ST can describe these so called preference reversals due to the change in the choice set while EUT and CPT can never describe them. Section 1 of the Online Appendix derives for each of the six binary choices the conditions under which ST describes a preference reversal.

To elicit the certainty equivalents in the additional part of the experiment, we present each of the lotteries $\tilde{L} \in \{\tilde{X}, \tilde{Y}\}$ in a choice menu in which the subject has to indicate whether she prefers the lottery or a certain payoff z_r. Figure 2 shows an example fo such a choice menu. The certain payoff increases from the lottery's lowest payoff, $z_1 = 0$, to its highest payoff z_{21} in 21 equal increments. The point where the subject switches from preferring the certain payoff to preferring the lottery allows us to approximate the certainty equivalent by $CE(\tilde{L}_k) = (z_k + z_{k+1})/2$ for $k \in \{1, \dots, 20\}$.[10]

We randomize the order in which we elicit the certainty equivalents of the additional lotteries across subjects. Moreover, since the six binary choices between the additional lotteries appear in the main part of the experiment, subjects should not recall the additional lotteries when stating their certainty equivalents.[11]

By comparing the binary choices between the additional lotteries and their certainty equivalents, we can detect the number of preference reversals of each subject. Since there are six binary choices, each subject can exhibit between 0 and 6 preference reversals.

3.3 Number of Choices

Subjects in the canonical presentation go through a total of 93 binary choices, while subjects in the states of the world presentation go through 84 binary choices. The number of binary choices differs between the presentation formats since the 9 binary choices designed for triggering the Common Consequence Allais Paradox in which lottery X has three payoffs and lottery Y is a sure amount look identical regardless whether the lotteries' payoffs are independent or correlated. Table 4 in Appendix D decomposes the number of choices in each presentation format. Regardless of the presentation format, each subject also evaluates 9 lotteries in isolation during the additional part of the experiment.

3.4 Implementation in the Lab and Incentives

We conducted the experiment in the computer lab at the University of Lausanne (LABEX) using an application based on PHP and MySQL. Most subjects were students of the University of Lausanne and the École Polytechnique Fédérale de Lausanne (EPFL), recruited via ORSEE (Greiner, 2015). The experiment consisted of 14 sessions with 283 subjects in total.

To incentivize subjects' choices in both parts of the experiment, we applied the prior

[10] We did not impose a unique switch-point. 34 of 283 subjects (12.0%) switched more than once and, thus, did not reveal a unique certainty equivalent for at least one lottery. We dropped these subject from the out-of-sample analysis shown in Section 5.4. However, exhibiting more than one switch-point is independent of these subjects' type-membership (χ^2-test of independence: p-value = 0.534).

[11] One way to analyze whether subjects recall some of the choices from the main part of the experiment is to exploit their random order. In particular, we can check whether inconsistencies between the binary choices in the main part and the corresponding choices implied by the certainty equivalents in the additional part are less frequent when the two types of choices are close to each other and, thus, easier to recall. When performing this check, we find no significant correlation between the choice inconsistencies and the order in which the pairwise choices appeared during the main part (t-test: p-value = 0.215). Thus, there is no evidence that subjects recall the choices from the main part.

incentive system (Johnson et al., 2014). This avoids violations of isolation, which may otherwise arise with a random incentive system, as pointed out by Holt (1986). In each part, every subject had to draw a sealed envelope from an urn before making any choices. The envelope contained one of the choices the subject was going to make in that part and which later was used for payment. At the very end of the experiment, the subject went to another room where she opened the envelopes together with an assistant. To determine her payment, which she received in cash at the end, she rolled two dice if the choice in the corresponding envelope involved two lotteries with independent payoffs and only one die if the choice involved two lotteries with correlated payoffs.

At the beginning of the experiment, subjects received general instructions informing them about the structure of the experiment, their anonymity, the show up fee, and the conversion rate of points into Swiss Francs.[12] At the beginning of each part, subjects received additional printed instructions. These additional instructions comprised a description of the choices and the payment procedure for that part. They carefully described the difference between lotteries with independent and correlated payoffs. They also explained that, at the end of the experiment, the subject will open the envelope to determine her payoff and roll one one or two dice, depending on whether the lotteries' payoffs in the payment relevant choice are correlated or independent. The instructions also contained several comprehension questions whose answers the assistants verified before subjects could begin. The additional instructions differed depending on whether a subject was exposed to the canonical presentation or the states of the world presentation. All instructions were written in French. English translations are available in Section 6 of the Online Appendix.

After making their choices, but before determining and receiving their payments, subjects filled in a demographic questionnaire, completed a short version of the Big 5 personality questionnaire, and a cognitive ability test with 12 questions based on Raven's matrices. The instructions were shown on screen at the beginning of each task. The cognitive ability test was also incentivized and subjects received 50 points per correct answer.[13]

Each subject received a show-up fee of 10 Swiss Francs. Total earnings varied between 12.00 and 142.50 Swiss Francs with a mean of 57.66 and a standard deviation of 26.39 Swiss

[12]Payoffs were shown in points. 100 points corresponded to one Swiss Franc. At the time of the experiment, one Swiss Franc corresponded to roughly 1.04 USD.

[13]We find that the classification of subjects into types is neither related to their individual characteristics nor to their average decision time. Results and a brief discussion of this finding are available in Section 3 of the Online Appendix.

Francs. Each session lasted approximately 90 minutes.

4 Non-Parametric Results

In this section, we present the non-parametric results. We start by summarizing the systematic patterns in the frequency of Allais Paradoxes before discussing whether they can be described by EUT, CPT, and ST.

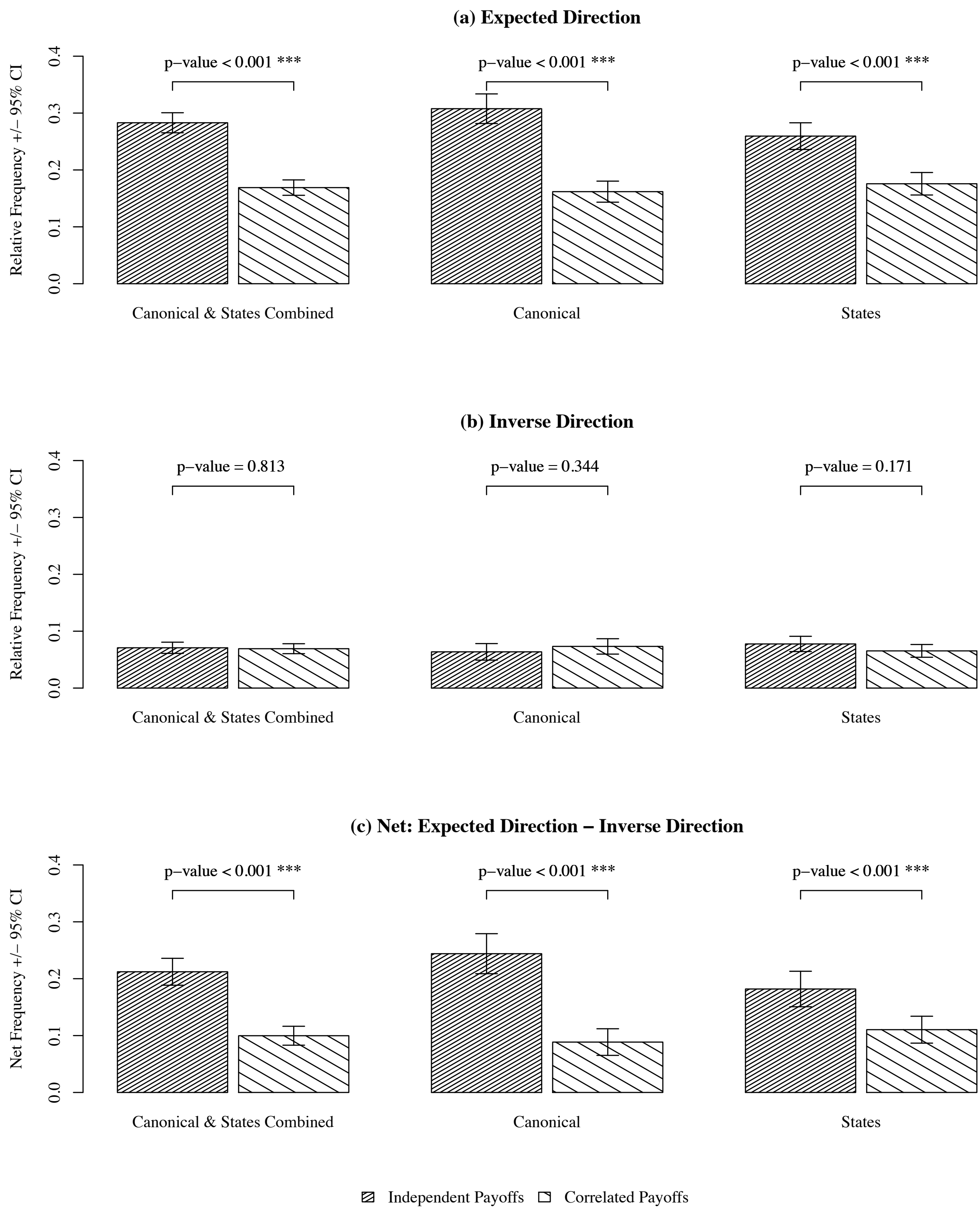
Figure 3 shows the average frequency of Allais Paradoxes relative to their maximum possible number separately for lotteries with independent and correlated payoffs. Panel (a) exhibits the frequency of Allais Paradoxes in the expected direction, that is, the direction predicted by CPT and ST. Regardless of the presentation format, Allais Paradoxes in the expected direction occur often with both correlation structures. However, they are substantially more frequent with independent payoffs than with correlated payoffs. For example, for both presentation formats combined, the frequency of Allais Paradoxes in the expected direction is 28.3% with independent payoffs and 16.9% with correlated payoffs.

Panel (b) exhibits the frequency of Allais Paradoxes in the inverse direction, that is, the direction none of the theories can explain. Regardless of the presentation format, Allais Paradoxes in the inverse direction not only are much less frequent than those in the expected direction but also occur with the same frequency across the two correlation structures.[14] Given that neither theory can describe these Allais Paradoxes in the inverse direction and given that their frequency is constant across presentation formats and correlation structures, we interpret them as the result of decision noise. This interpretation is in line with the literature which acknowledges the existence and relevance of decision noise (e.g. Hey, 2005).

Panel (c) exhibits the difference in the relative frequency of Allais Paradoxes in the expected and in the inverse directions. Under the assumption that the level of decision noise is the same in both directions, we can interpret this difference as the frequency of Allais Paradoxes net of decision noise. These net frequencies confirm that, regardless of the presentation format, Allais Paradoxes occur often and are more than twice as frequent with independent than with correlated payoffs. More specifically, the ratio of Allais Paradoxes between independent and correlated payoffs is 2.127 for both presentation formats combined,

[14]These frequencies are close to those found by Huck and Müller (2012) who analyzed the frequency of Allais Paradoxes both in the lab and in a representative sample of the Dutch population. In the lab, they found the frequency of Allais Paradoxes to be 13.0% in the expected direction and 2.7% in the inverse direction. In the Dutch population, the frequencies are 21.7% in the expected and 9% in the inverse direction.

Figure 3: Relative Frequency of Allais Paradoxes



The figure shows the average frequency of Allais Paradoxes relative to their maximum possible number for lotteries with independent and correlated payoffs. Panel (a) depicts the relative frequency of Allais Paradoxes in the expected direction. Panel (b) shows the relative frequency of Allais Paradoxes in the inverse direction and reflects noise. Panel (c) shows the difference between the relative frequencies of Allais Paradoxes in the expected and inverse directions, i.e., net of noise. The two bars on the left pool the choices from subjects exposed to the canonical presentation with those from subjects exposed to the states of the world presentation. The two bars in the middle and on the right separate the choices by presentation format.

2.755 for the canonical presentation, and 1.648 for the states of the world presentation.

We now discuss which of the three theories is able to describe the above patterns. EUT fails to describe the patterns as it never predicts any Allais Paradoxes and, thus, their net frequencies should always be zero. CPT and ST can each describe some but not all of the above patterns. While CPT can describe the occurrence of Allais Paradoxes for both correlation structures, it cannot describe that their net frequency is higher with independent payoffs than with correlated payoffs. In contrast, ST can describe that Allais Paradoxes are more frequent with independent payoffs than with correlated payoffs. However, it cannot describe the occurrence of Allais Paradoxes with correlated payoffs. In sum, none of the three theories alone can explain all of the above patterns in the aggregate frequency of Allais Paradoxes. However, CPT and ST each describe some of the patterns and, thus, both of them play a role. This non-parametric evidence yields our first main result.

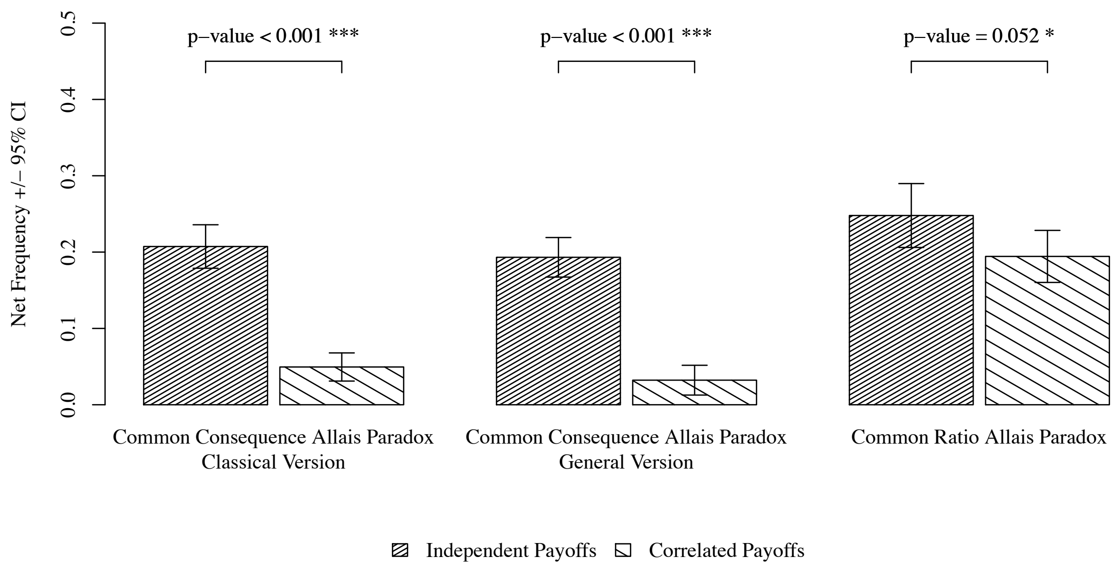
Result 1 *Probability weighting and choice set dependence both play a role in explaining aggregate choices.*

1. *Subjects exhibit a high frequency of Allais Paradoxes no matter if payoffs are independent or correlated.*
2. *However, subjects exhibit a higher frequency of Allais Paradoxes with independent than with correlated payoffs.*
3. *The result is robust across the three versions of the Allais Paradox and the two presentation formats.*

Figure 4 illustrates that Result 1 holds across all three versions of the Allais Paradox. The bars on the left and in the middle show the net frequency of the classical version and the general version of the Common Consequence Allais Paradox, respectively (see Section 3.1.1 for details). The bars on the right show the net frequency of the Common Ratio Allais Paradox. Allais Paradoxes occur often and are more frequent with independent than with correlated payoffs. However, the difference in the net frequencies between independent and correlated payoffs is less pronounced for the Common Ratio than for the Common Consequence Allais Paradox. This is probably because the mechanism in ST behind the Common Ratio Allais Paradox is more subtle than the one behind the Common Consequence Allais Paradox, as mentioned earlier in Section 3.1.1.[15]

[15]Table 7 in Appendix F presents an even more detailed look at the frequency of choices of lotteries X and

Figure 4: Net Frequency of each Version of the Allais Paradox



The figure shows the net frequency of each of the three different versions of the Allais Paradox, separately for lotteries with independent and correlated payoffs. The two bars on the left show the net frequency of the classical version of the Common Consequence Allais Paradox (see Section 3.1.1, level of the common consequence: 1 vs. 2a). The two bars in the middle show the net frequency of the general version of the Common Consequence Allais Paradox (see Section 3.1.1, level of the common consequence: 1 vs. 2b). The two bars on the right show the net frequency of the Common Ratio Allais Paradox. Net frequency of Allais Paradoxes refers to the difference in the relative frequency of Allais Paradoxes in the expected and the inverse directions. Choices from both presentation formats are pooled together.

Result 1 is also robust across the two presentation formats. This robustness allows us to addresses two concerns about the relevance of choice set dependence.

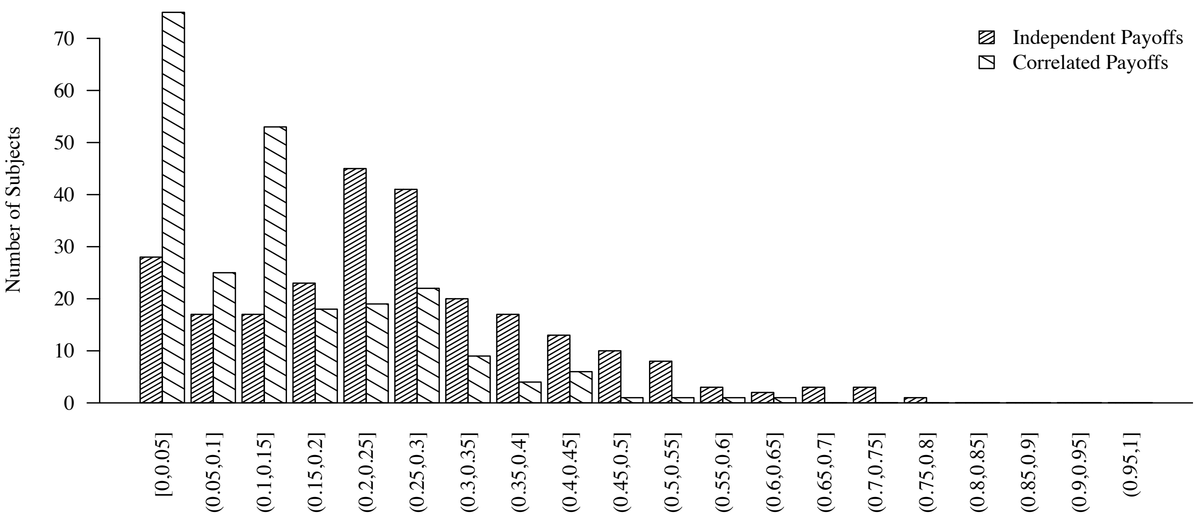
First, it confirms the results by Loomes and Sugden (1987), Loomes (1988), and Starmer and Sugden (1989) who found juxtaposition effects in common ratio lottery choices using the states of the world presentation format. It also rules out the concern that by making the common consequence more obvious, the states of the world presentation influences the frequency of Allais Paradoxes (Keller, 1985; Birnbaum, 2004; Leland, 2010; Birnbaum et al., 2017) or decision times (for details, see Appendix E.1).

Second, the robustness across presentation formats confirms that manipulating the correlation structure of the lotteries' payoffs affects the frequency of Allais Paradoxes primarily through choice set dependence and not through event-splitting effects. An event-splitting occurs when an event with a given payoff is split into sub-events that offer the event's payoff in multiple states of the world. Earlier papers raised the concern that event-splitting could influence subjects' choices if splitting an event into sub-events increases its weight (Starmer and Sugden, 1993; Humphrey, 1995). If such event-splitting effects played a role in our data, their strength would depend on the presentation format: they would be stronger in the states of the world presentation where the number of sub-states in which a payoff appears is particularly prominent. However, our first main result holds across the two presentation formats in our data. Thus, we conclude that event-splitting effects play no significant role in our results (for details, see Appendix E.2).

Next, we analyze the distribution of the net frequency of Allais Paradoxes to get a first glimpse at the potential heterogeneity that may be behind Result 1. Figure 5 depicts the corresponding histograms separately for lotteries with independent and correlated payoffs. Not surprisingly, the distribution for lotteries with independent payoffs is located to the right of the distribution for lotteries with correlated payoffs. However, interestingly, both distributions appear to be bimodal. They both exhibit one mode at the lowest bin, corresponding to a net frequency of Allais Paradoxes between 0 and 5%, and another mode at a bin corresponding to a higher net frequency. This multimodality suggests that Result 1 may be driven by considerable heterogeneity in subjects' risk preferences. In particular, the choices of some subjects may be predominantly influenced by probability weighting whereas

Y, disaggregated by independent and correlated payoffs as well as by each version of the Allais Paradox. As explained in Section 2, opting for Y in the first choice and for X in the second corresponds to the expected direction of the Allais Paradox.

Figure 5: Distribution of the Net Frequency of Allais Paradoxes



The histograms show the distribution of the net frequency of Allais Paradoxes for independent and correlated lottery payoffs. Net frequency of Allais Paradoxes refers to the difference in the relative frequencies of Allais Paradoxes in the expected and the inverse directions. Choices from both presentation formats are pooled together.

the choices of others may be primarily driven by choice set dependence. There may also exist a minority of EUT-subjects who display no or only few Allais Paradoxes. We examine this possibility with the structural model which we present in the next section.

5 Structural Model

In this section, we discuss the set-up and the results of the structural model. It allows us to take heterogeneity into account in a parsimonious way and classify the subjects into distinct preference types. Later, we also validate the model's power to predict preference reversals in a different choice context.

5.1 Set-up

The structural model is based on a finite mixture model (see McLachlan and Peel, 2000, for an overview) and uses a random utility approach for discrete choices (McFadden, 1981). It discriminates between subjects whose preferences are best described by EUT, subjects whose preferences display probability weighting and are best described by CPT, and subjects whose preferences display choice set dependence and are best described by ST. Controlling for the presence of EUT subjects is important, as the behavior of a minority of our subjects may still be best described by EUT, as previously found by other studies (Bruhin et al., 2010; Conte et al., 2011).

5.1.1 Random Utility Approach

The random utility approach allows the structural model to explicitly take decision noise into account. Consider a subject $i \in \{1, \ldots, N\}$ whose preferences are best described by decision model M in the set of decision models $\mathcal{M} = \{EUT, CPT, ST\}$. She prefers lottery X_g over Y_g in binary choice $g \in \{1, \ldots, G\}$ when the random utility of choosing X_g, $V^M(X_g, \theta_M) + \epsilon_X$, is higher than the random utility of choosing Y_g, $V^M(Y_g, \theta_M) + \epsilon_Y$. The random errors, ϵ_X and ϵ_Y, are realizations of an extreme value 1 distribution with scale parameter $1/\sigma_M$, and the vector θ_M comprises decision model M's preference parameters. This implies that the probability of subject i choosing X_g, i.e., $C_{ig} = X$, is given by

$$\begin{aligned} Pr(C_{ig} = X; \theta_M, \sigma_M) &= Pr[V^M(X_g, \theta_M) - V^M(Y_g, \theta_M) \geq \epsilon_Y - \epsilon_X] \\ &= \frac{\exp[\sigma_M V^M(X_g, \theta_M)]}{\exp[\sigma_M V^M(X_g, \theta_M)] + \exp[\sigma_M V^M(Y_g, \theta_M)]} . \end{aligned} \tag{5}$$

The parameter σ_M governs the choice sensitivity with respect to differences in the lotteries' deterministic value. If σ_M is 0, the subject chooses each lottery with probability 50% regardless of the deterministic value it provides. If σ_M is arbitrarily large, the probability of choosing the lottery with the higher deterministic value approaches 1.

Subject i's contribution to the density function of the random utility model corresponds to the product of the choice probabilities over all G binary decisions, i.e.,

$$f_M(C_i; \theta_M, \sigma_M) = \prod_{g=1}^{G} Pr(C_{ig} = X; \theta_M, \sigma_M)^{I(C_{ig}=X)} \, Pr(C_{ig} = Y; \theta_M, \sigma_M)^{1-I(C_{ig}=X)} ,$$

where $I(C_{ig} = X)$ is 1 if subject i chooses lottery X_g and 0 otherwise.

5.1.2 Finite Mixture Model

Since risk preferences may be heterogeneous, we do not directly observe which model best describes subject i's preferences. In other words, we do not know ex-ante whether subject i is an EUT-, CPT-, or ST-type. Hence, we have to weight i's type-specific density contributions by the corresponding ex-ante probabilities of type-membership, π_M, in order to obtain her contribution to the likelihood of the finite mixture model,

$$\begin{aligned}\ell(\Psi; C_i) &= \pi_{EUT}\, f_{EUT}(C_i; \theta_{EUT}, \sigma_{EUT}) + \pi_{CPT}\, f_{CPT}(C_i; \theta_{CPT}, \sigma_{CPT}) \\ &\quad + \pi_{ST}\, f_{ST}(C_i; \theta_{ST}, \sigma_{ST})\,,\end{aligned} \tag{6}$$

where the vector $\Psi = (\theta_{EUT}, \theta_{CPT}, \theta_{ST}, \sigma_{EUT}, \sigma_{CPT}, \sigma_{ST}, \pi_{EUT}, \pi_{CPT})$ comprises all parameters that need to be estimated, and $\pi_{ST} = 1 - \pi_{EUT} - \pi_{CPT}$.[16] Note that the ex-ante probabilities of type-membership are the same across all subjects and correspond to the relative sizes of the types in the population.

Once we estimated the parameters of the finite mixture model, we can classify each subject into the type she most likely belongs to, given her choices and the estimated parameters $\hat{\Psi}$. To do so, we apply Bayes' rule and obtain subject i's individual ex-post probabilities of type-membership,

$$\tau_{iM} = \frac{\hat{\pi}_M\, f_M(C_i; \hat{\theta}_M, \hat{\sigma}_M)}{\sum_{m \in \mathcal{M}} \hat{\pi}_m\, f_m(C_i; \hat{\theta}_m, \hat{\sigma}_m)}\,. \tag{7}$$

Based on these individual ex-post probabilities of type-membership, we can also assess the ambiguity in the classification of subjects into types. If the finite mixture model classifies subjects cleanly into types, most τ_{iM} should be either close to 0 or to 1. In contrast, if the finite mixture model fails to come up with a clean classification of subjects into distinct types, many τ_{iM} will be in the vicinity of 1/3.

5.1.3 Specification of Functional Forms

To keep the model parsimonious and yet flexible in fitting the data, we specify the following functional forms. In all three decision models, we use a power specification for the utility function v, i.e.,

$$v(x) = \begin{cases} \frac{x^{1-\beta}}{1-\beta} & \text{for } \beta \neq 1 \\ \ln x & \text{for } \beta = 1 \end{cases}\,,$$

which has a convenient interpretation, since β measures v's concavity. Moreover, this specification turned out to be a neat compromise between parsimony and goodness of fit (Stott,

[16]Since i's likelihood contribution is highly non-linear, we apply the expectation maximization (EM) algorithm to obtain the model's maximum likelihood estimates $\hat{\Psi}$ (Dempster et al., 1977). The EM algorithm proceeds iteratively in two steps: In the E-step, it computes the individual ex-post probabilities of type-membership given the actual fit of the model (see equation (7)). In the subsequent M-step, it updates the fit of the model by using the previously computed ex-post probabilities to maximize each types' log likelihood contribution separately.

2006). In CPT, we follow the proposal by Prelec (1998) and specify the probability weighting function as

$$w(p) = \exp(-(-\ln(p))^{\alpha}) \, ,$$

where $0 < \alpha$ measures likelihood sensitivity and reflects the shape of the probability weighting function. When $\alpha = 1$, w is linear in probabilities. When α gets closer to zero, w becomes more inversely S-shaped. When α gets larger than one, w becomes more S-shaped. This specification of the probability weighting function satisfies the three properties discussed in Section 2.2. We also tested the two-parameter version of Prelec's probability weighting function. However, as the second parameter measuring the function's net index of convexity is estimated to be almost 1, results remain virtually unchanged (see Appendix G). Hence, we opt for the one-parameter version to keep the total number of parameters the same for CPT and ST. In ST, the decision weights depend on the degree of local thinking $0 < \delta \leq 1$ which we estimate directly using equation (2). In all binary choices we use for triggering Allais Paradoxes, the salience ranking of the states of the world is fully determined by ordering, diminishing sensitivity, symmetry, and zero contrast (Section 2 of the Online Appendix shows this for every binary choice we use). Hence, we do not need to specify a particular salience function.

5.2 Discriminatory Power and Robustness against Serially Correlated Errors

We conduct a series of Monte Carlo Simulations to assess the structural model's power to discriminate between the three preference types and its robustness against potential serial correlation in the subjects' errors. In these simulations, we impose a vector of true parameters which we use to simulate the subjects' choices in each type. Subsequently, we try to recover these true parameters and the subjects' individual type-membership by estimating the structural model on the simulated choices. This allows us to calculate the potential bias in the estimated parameters, their overall precision in terms of Mean Squared Errors, and the fraction of correctly classified subjects. Each simulation is based on 1,000 simulation runs. Section 4 of the Online Appendix discusses the set-up and the results of these Monte Carlo Simulations in detail.

The simulations reveal that the structural model's power to discriminate between the different types is remarkably high. In particular, the structural model provides unbiased and precise estimates even in a situation where discriminating between EUT-, CPT-, and ST-types is extremely hard – that is, when the simulated subjects have an identical utility function and the same choice sensitivity across the three types and only differ slightly in their degrees of likelihood sensitivity and local thinking. In such a situation, the structural model still classifies the vast majority of simulated subjects into the correct type. We suppose that the model's ability to detect even slight behavioral differences between the types is mainly because, instead of estimating at the individual level, the model efficiently exploits the choices of all subjects simultaneously. This allows it to recover the true parameters with high precision as individual noise averages out.

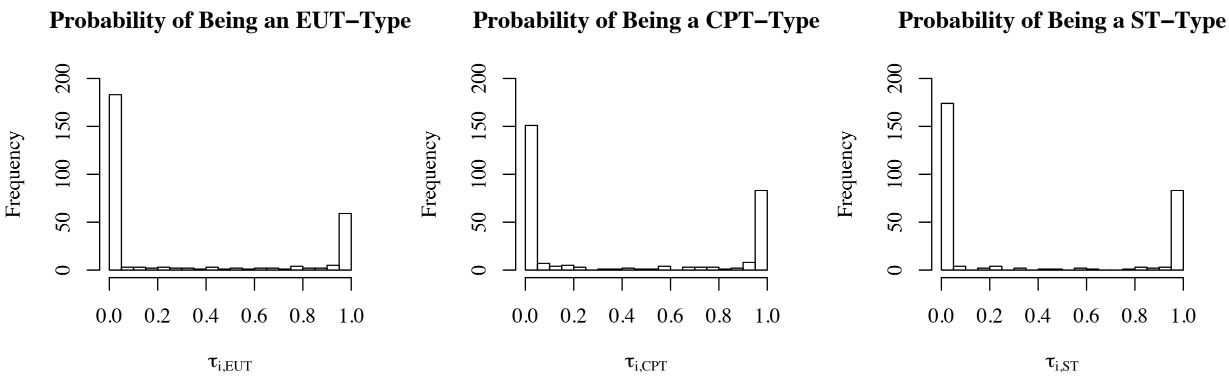
The simulations also confirm the structural model's robustness against potential serial correlation in the subjects' errors. This robustness is an important feature, since we cannot rule out that the errors subjects make when evaluating lotteries are serially correlated across the binary choices. However, the simulations reveal that the estimated parameters remain unbiased and precise, even if the subjects' errors, ϵ_X and ϵ_Y, follow an AR(1) process with a high degree of serial correlation of $\rho = 0.6$. Also, the vast majority of subjects remains classified in the correct type. The reason for this robustness against serially correlated errors is likely because we randomized the order of choices across subjects. Since the finite mixture model exploits the choices of all subjects simultaneously, their random order causes the impact of serial correlation to average out. Furthermore, to ensure that inferences about the estimated parameters are valid even with serially correlated errors, we report cluster-robust standard errors.

In sum, the simulations highlight that the experimental choices contain rich information about subjects' risk preferences and type-membership. By taking the choices of all subjects simultaneously into account, the structural model exploits this information efficiently and is robust against potential serial correlation in the errors.

5.3 Structural Model Results

We now present and interpret the results of the structural model. When classifying subjects into types using their ex-post probabilities of type-membership, we obtain a clean classification of subjects into 80 EUT-types, 108 CPT-types, and 95 ST-types. Most of the ex-post probabilities of individual type-membership are either close to 0 or 1, confirming that almost all subjects can be unambiguously classified into one of these three types. Figure 6 shows

Figure 6: Distribution of Ex-Post Probabilities of Type-Membership



Each panel in the figure shows the distribution over all subjects of the individual ex-post probability, τ_{iM}, of belonging to the corresponding type $M \in \{EUT, CPT, ST\}$ (see equation (7)). The resulting classification of subjects into types is clean as for nearly all subjects these ex-post probabilities of type-membership are either close to 0 or 1.

histograms with the ex-post probabilities of type-membership.

Table 2 exhibits the type-specific parameter estimates of the finite mixture model. The results show that there is substantial heterogeneity in subjects' risk preferences. The choices of 28.4% of subjects are best described by EUT, the choices of 37.9% by CPT, and those of the remaining 33.7% by ST. This classification confirms Result 1 obtained non-parametrically at the aggregate level. The majority of subjects is best described by either CPT or ST, while – consistent with previous evidence (Bruhin et al., 2010; Conte et al., 2011) – only a minority is best described by EUT.

On average, the 80 EUT-types display an almost linear utility function which makes them essentially risk neutral.[17] Although the estimated concavity of $\hat{\beta} = 0.080$ is statistically significant, it is negligible in economic magnitude. Moreover, among the three types, the EUT-types exhibit the highest level of decision noise which translates into a relatively low estimated choice sensitivity.

The 108 CPT-types exhibit, on average, a concave utility function with $\hat{\beta} = 0.572$ and a strongly inverse S-shaped probability weighting function with $\hat{\alpha} = 0.469$. This confirms that the CPT-types' choices are strongly influenced by probability weighting. With these parameter estimates, the average CPT-type displays the Common Consequence Allais Paradox discussed in the motivating example in Section 2.

[17] In fact, EUT evaluated at the type-specific estimates predicts 64.1% of the EUT-types' choices correctly – only slightly more than a comparison of the lotteries' expected payoffs which yields 61.0% correct predictions.

Table 2: Type-Specific Parameter Estimates of the Finite Mixture Model

Type-specific estimates	EUT	CPT	ST
Relative size (π)[a]	0.284	0.379	0.337
	(0.047)	(0.045)	(0.037)
Concavity of utility function (β)	0.080**	0.572***	0.870***
	(0.033)	(0.055)	(0.015)
Likelihood sensitivity (α)		0.469°°°	
		(0.026)	
Degree of local thinking (δ)			0.924°°°
			(0.013)
Choice sensitivity (σ)	0.010***	0.302***	2.756***
	(0.003)	(0.101)	(0.359)
Number of subjects[b]	80	108	95
Number of observations		23,316	
Log Likelihood		-11,458.71	
AIC		22,937.41	
BIC		23,017.98	
Share of correctly predicted choices[c]		0.750	

Subject cluster-robust standard errors are reported in parentheses. Significantly different from 0 (1) at the 1% level: *** (°°°).

[a] The relative group sizes are not tested against zero, since under the null hypothesis that a type's relative size is zero, the preference parameters are meaningless. Consequently, the test statistic would exhibit an unknown distribution (for a more detailed discussion see McLachlan and Peel (2000)).

[b] Subjects are assigned to the best-fitting model according to their ex-post probabilities of type-membership (see equation (7)).

[c] Choices are predicted by using the subjects' classification into types and by calculating the lotteries' values, $V^M(X_g, \hat{\theta}_M)$ and $V^M(Y_g, \hat{\theta}_M)$, for the type-specific parameter estimates $\hat{\theta}_M$.

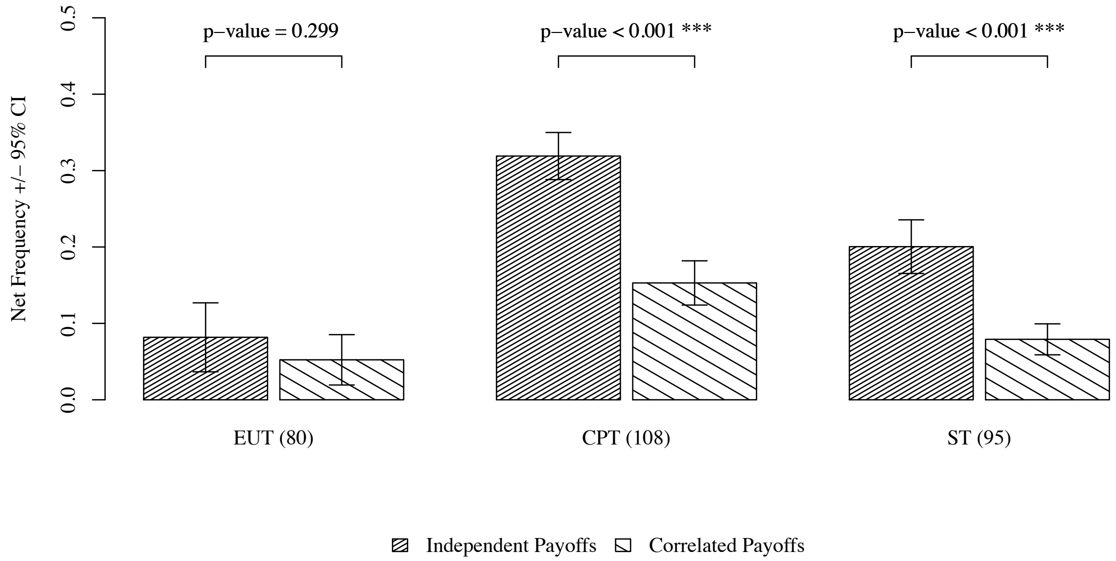
The 95 ST-types display, on average, a strongly concave utility function with $\hat{\beta} = 0.870$ and a seemingly low but statistically significant degree of local thinking corresponding to $\hat{\delta} = 0.924$. Note that, although the average ST-type's degree of local thinking appears to be low, she still exhibits the Common Consequence Allais Paradox discussed in the motivating example in Section 2. The reason is that with a strongly concave utility function, even a low degree of local thinking is sufficient to generate the Common Consequence Allais Paradox.[18]

Next, we analyze how well the structural model fits the subjects' choices compared to aggregate models that neglect any heterogeneity and assume a representative decision maker. The estimation results of the aggregate models can be found in Appendix G. The Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) both indicate that the structural model fits the subjects' choices considerably better than any of the aggregate models. Moreover, when we use the subjects' classification into types and the type-specific parameter estimates to predict choices in-sample, the structural model yields 75.0% correct predictions, that is, 75.0% of the predicted choices coincide with the subjects' empirical choices. This is more than any of the aggregate models and also more than the 50% correct predictions we would expect from purely random behavior. Overall, the analysis reveals that the structural model's parsimonious way of taking heterogeneity into account leads to a superior fit compared to the aggregate models.

An interesting question that the structural model cannot directly address is whether probability weighting and salience exclusively drive the choices of the CPT- and ST-types, or whether they influence the choices of all types to a varying degree. To answer this question, we turn to Figure 7 which shows the net frequency of Allais Paradoxes separately for subjects classified as EUT-, CPT-, and ST-types. First, the net frequency of Allais Paradoxes for EUT-types is the lowest and, more importantly, does not significantly differ across independent and correlated payoffs. This justifies the classification of these subjects as EUT-types. Second, the CPT-types' net frequency of Allais Paradoxes always exceeds those of the other two types, in particular with correlated payoffs. For this reason, the finite mixture model classifies these subjects as CPT-types. However, the CPT-types also exhibit 2.09 times more Allais Paradoxes with independent than with correlated payoffs, indicating that choice set dependence plays a role in their choices too. Third, the ST-types'

[18]This is mainly due to inequality (3), as the difference $v(2500) - v(2400)$ gets smaller. On the other hand, Inequality (4) is less affected by the concavity of the utility function and can still be satisfied with a small degree of local thinking.

Figure 7: Net Frequency of Allais Paradoxes by Preference Type



The figure shows the net frequency of Allais Paradoxes for lotteries with independent and correlated payoffs, separately for EUT-, CPT-, and ST-types. Net frequency of Allais Paradoxes refers to the difference in the relative frequencies of Allais Paradoxes in the expected and the inverse directions. The numbers in parentheses indicate the number of subjects in each of the three types.

net frequency of Allais Paradoxes is 2.53 times higher with independent than with correlated payoffs. Moreover, with correlated payoffs, the ST-types' net frequency of Allais Paradoxes is indistinguishable from the EUT-types'. This is why the finite mixture model classifies these subjects as ST-types. In sum, the ST-types' choices are mainly driven by choice set dependence, while the choices of the subjects labeled as CPT-types seem to be driven by probability weighting as well as choice set dependence.

Overall, the structural estimations and the subjects' type-specific behavior yield our second main result.

Result 2 *There is vast heterogeneity in the subjects' risk preferences.*

1. *Subjects are parsimoniously classified into 28% EUT-types, 38% CPT-types, and 34% ST-types according to the decision theory best describing their behavior.*

2. *While the EUT- and ST-types' behavior is mainly described by the corresponding theories, the CPT-types' behavior is driven by probability weighting as well as choice set dependence.*

Finally, we carried out robustness checks to ensure that this result does not depend on a particular specification of our model. They reveal that the result remains virtually unchanged if we use a Fechner-type error directly affecting subjects' choices instead of the random utility approach. However, the random utility approach yields a superior fit of the structural model. Similarly, modeling choice set dependence with ST yields a superior fit compared to modeling it with RT, the other major choice set dependent theory. Section 5 of the Online Appendix discusses these robustness checks in detail.

5.4 Predictions of Preference Reversals

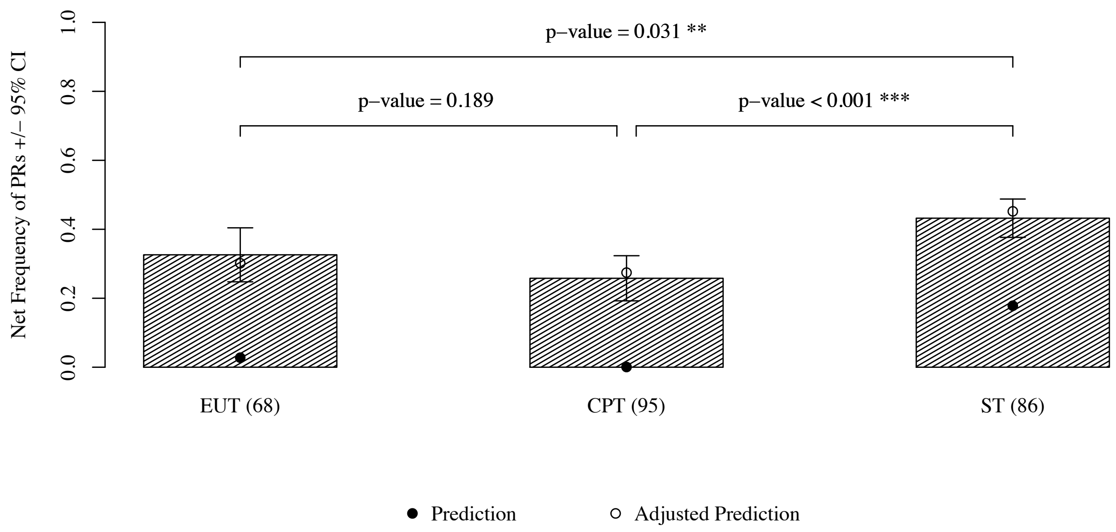
Next, we assess how well the structural model predicts preference reversals in the additional part of the experiment (see Section 3.2). These out-of-sample predictions across choice contexts represent a particularly stringent test of the structural model for two reasons. First, the model needs to predict behavior in choices that differ in payoffs and probabilities from the ones it was estimated on. Second, the model also needs to predict behavior across choice contexts, i.e., in choices that trigger preference reversals instead of Allais Paradoxes.

We start by describing and interpreting the net frequencies of preference reversals for each of the three types. Subsequently, we use the structural model's random utility approach to make quantitative predictions about these net frequencies. Comparing the empirical and the predicted net frequencies of preference reversals will reveal the aspects of behavior the structural model predicts well and potential other aspects which the model does not capture. Such other aspects of behavior which our structural model does not capture would be particularly interesting, as they may provide hints about the instability of certain preference components across choice contexts.

5.4.1 Net Frequencies of Preference Reversals across Types

Figure 8 shows the average net frequency of preference reversals for each of the three preference types, i.e., the difference in the frequencies of preference reversals in the expected and in the inverse direction. It reveals that with a net frequency of 43.3% the ST-types exhibit substantially more preference reversals than the EUT- and the CPT-types whose net frequencies are just 32.6% and 25.8%, respectively. Moreover, the EUT- and CPT-types net frequencies of preference reversals are not significantly different. This evidence is in line with our expectation that choice set dependence mainly drives the ST-types' choices and gener-

Figure 8: Net Frequency of Preference Reversals by Type



The figure shows the net frequency of preference reversals by type for the choices of the additional part of the experiment (see Section 3.2). Net frequency of preference reversals refers to the difference in the relative frequencies of preference reversals in the expected and the inverse directions. The black dots indicate the predicted net frequencies for each type based on the structural model's random utility approach (see Section 5.4.2). The white circles represent the predictions adjusted by the estimated intercept (0.274) as shown in the first column of Table 3. The numbers in parentheses indicate the number of subjects in each of the three types. 34 of the 283 subjects (12.0%) are excluded from the analysis because they exhibit more than one switch-point in at least one of the choice menus used for eliciting the certainty equivalents. Exhibiting more than one switch-point is independent of type-membership (χ^2-test of independence: p-value = 0.534).

ates their preference reversals. However, the positive net frequencies of preference reversals of the EUT- and CPT-types indicate that choice set dependence influences their choices too, although to a lesser extent than the ST-types' choices.

5.4.2 Quantitative Predictions

We now use the structural model's random utility approach to make quantitative predictions about the frequency of preference reversals for each preference type. We start by predicting the probability that a subject belonging to type M with estimated parameters $\hat{\theta}_M$ and $\hat{\sigma}_M$ indicates a higher certainty equivalent for lottery $\tilde{X}$ than for lottery $\tilde{Y}$ when she evaluates the two lotteries separately in a choice menu (see Figure 2). First, we predict for each of the two lotteries $\tilde{L} \in \{\tilde{X}, \tilde{Y}\}$ and for each of the 21 rows r of the corresponding choice menu the probability that the subject prefers the lottery over the sure amount z_r, $z_1 < \ldots < z_{21}$:

$$\hat{Pr}[V^M(\tilde{L}) > v(z_r)] = \frac{\exp[\hat{\sigma}_M\, V^M(\tilde{L}, \hat{\theta}_M)]}{\exp[\hat{\sigma}_M\, V^M(\tilde{L}, \hat{\theta}_M)] + \exp[\hat{\sigma}_M\, V^M(z_r, \hat{\theta}_M)]} \,.$$

Second, by assuming a unique switch-point, we use these predicted probabilities to infer the probability distribution over the $k \in \{1, \ldots, 20\}$ possible certainty equivalents for each lottery.[19] The predicted probability that the certainty equivalent $CE(\tilde{L}) = (z_k + z_{k+1})/2 \equiv \bar{z}_k$, corresponds to

$$\tilde{Pr}[CE(\tilde{L}) = \bar{z}_k] = \prod_{r=1}^{k} \hat{Pr}[V^M(\tilde{L}) > v(z_r)] \times \prod_{r=k+1}^{21} \Big(1 - \hat{Pr}[V^M(\tilde{L}) > v(z_r)]\Big) \,.$$

Since we assume a unique switch-point, we need to normalize these predicted probabilities to $\hat{Pr}[CE(\tilde{L}) = \bar{z}_k] = \tilde{Pr}[CE(\tilde{L}) = \bar{z}_k] / \sum_{m=1}^{20} \tilde{Pr}[CE(\tilde{L}) = \bar{z}_m]$ to obtain a proper probability distribution which sums up to one. Third, by combining the probability distributions over the possible certainty equivalents of the two lotteries, we obtain the joint probability distribution over the $20 \times 20 = 400$ states in which either the certainty equivalent of lottery $\tilde{X}$ or the one of lottery $\tilde{Y}$ is higher. Knowing this joint probability distribution allows us to predict the probability that the subject indicates a higher certainty equivalent for $\tilde{X}$ than $\tilde{Y}$. Subsequently, we evaluate equation (5) to predict the probability that the subject will choose $\tilde{X}$ over $\tilde{Y}$ in the pairwise choice. By applying this procedure to all 6 choices of the additional part (see Appendix C), we can predict the type-specific frequencies of preference reversals in the expected and inverse directions using the structural model and the estimated parameters $\hat{\theta}_M$ and $\hat{\sigma}_M$. Finally, the predicted net frequency of preference reversals is the difference between the predicted frequency of preference reversals in the expected direction and those in the inverse direction.

Table 3 compares the empirical to the predicted net frequencies of preference reversals using OLS regressions. We start by interpreting the estimated coefficients of the regression in the first column, which uses the type-specific parameters $\hat{\theta}_M$ and $\hat{\sigma}_M$ to predict the subjects' net frequencies of preference reversals. The coefficient on the predicted net frequencies of preference reversals is 0.907 and not significantly different from one. This indicates that the structural model captures the behavioral differences between the types remarkably well as, on average, a given change in the predicted frequencies of preference reversals translates nearly one to one into a change in the corresponding empirical frequencies. In other words,

[19] Assuming a unique switch-point is consistent with our approach of excluding the 34 (12.0%) subjects who switched multiple times.

Table 3: OLS Regressions of Empirical on Predicted Net Frequencies of Preference Reversals

	Empirical Net Frequencies of Preference Reversals	
Predictions based on type-specific parameter estimates ($\hat{\theta}_M, \hat{\sigma}_M$)	0.907*** (0.241)	
Predictions based on individual-specific parameter estimates ($\hat{\theta}_{Mi}, \hat{\sigma}_{Mi}$)		0.149** (0.060)
Intercept	0.274*** (0.025)	0.297*** (0.025)
Number of observations	249	249
R^2 for predicting individual differences in net frequencies of preference reversals	0.054	0.025
R^2 for predicting type-specific differences in net frequencies of preference reversals[a]	0.936	0.122
p-value (H_0: coefficient on predictions = 1)	0.699	<0.001

Significantly different from 0 at the 1% level: ***; at the 5% level : **.

[a] The corresponding regressions collapse the data by the type-specific averages.

the structural model predicts the average differences in the empirical net frequencies of preference reversals between the three types almost perfectly.

However, the estimated intercept is positive, revealing that the structural model consistently underestimates the frequency of preference reversals across all three types by 27.4 percentage points. This can be seen when we visualize the type-specific predictions in Figure 8: as indicated by the black dots, the predicted net frequencies of preference reversals are consistently too low across all three types. Moreover, as indicated by the white circles, when we adjust the predicted net frequencies by the estimated intercept of 0.274, they all match the empirical frequencies almost perfectly and fall well within the 95% confidence intervals.

This evidence suggests not only that choice set dependence plays a role across all three types but also that its influence is stronger in the choices of the additional part than in the choices of the main part. We hypothesize that this could be because the influence of choice set dependence may be shaped by the choice context. More specifically, in the additional part, subjects fill out choice menus that always offer choices between a lottery with two payoffs and a series of sure amounts. This specific choice context may shift the subjects' focus of attention towards differences in payoffs and, thus, may inflate the role of choice set dependence. In contrast, in main part, subjects always face binary choices between two lotteries with up to three payoffs. This choice context may shift the subjects' focus of attention towards differences in probabilities and, thus, may dampen the influence of choice set dependence. Overall, the evidence gained from the out-of-sample predictions suggests that exploring how the choice context shapes the role of choice set dependence is an important avenue for future research.

Next, we interpret the fraction of the variance in the empirical net frequencies of preference reversals which the structural model manages to predict. At first glance, the fraction of the predicted variance is disappointingly low with an R^2 of just 0.054. The low R^2 indicates that the structural model is not well suited for predicting *individual* net frequencies of preference reversals since there is apparently a considerable amount of heterogeneity within each of the three preference types. However, as discussed above, the structural model predicts the *average* differences in the net frequencies of preference reversals between the types remarkably well and, in fact, the R^2 of the corresponding regression amounts to 0.936.

Finally, we investigate whether the heterogeneity within each of the three preference types results from systematic differences in individual preferences or rather from noise. To do so, we take the finite mixture model's classification of subjects into types and estimate the parameters of the corresponding decision models separately for each subject i. This yields a distinct set of parameter estimates for every subject, $\hat{\theta}_{Mi}$ and $\hat{\sigma}_{Mi}$, which we use for predicting individual-specific net frequencies of preference reversals. If the heterogeneity within the types results mainly from systematic differences in individual preferences, the predictions based on the individual-specific estimates would pick up these differences and, thus, would exhibit a superior out-of-sample performance than the predictions based on the type-specific estimates. In contrast, if the heterogeneity within the types results mainly from noise, which randomly changes across the two parts of the experiment, the predictions based on the individual-specific estimates would pick up this random noise and, thus, their out-of-sample performance would fall short of the predictions based on the type-specific estimates.

The second column of Table 3 reveals that the performance of the predictions based on the individual-specific estimates falls short of those based on the more parsimonious type-specific estimates in all relevant dimensions. First, the estimated coefficient of the predictions based on the individual-specific estimates (0.149) is far below one, indicating that they severely underestimate differences in the net frequencies of preference reversals across types. With an intercept of 0.297, they also consistently underestimate the level of preference reversals. Second, and even more striking, the predictions based on the individual-specific estimates explain a fraction of just $R^2 = 0.025$ of the variance in the empirical net frequencies of preference reversals – much less than the predictions based on the more parsimonious type-specific estimates. They are also worse at predicting the average differences across types as the corresponding R^2 is just 0.122. Overall, these results indicate not only that the individual heterogeneity within the preference types primarily results from noise but also that, despite their parsimony, the structural model's type-specific estimates pick up most of the relevant heterogeneity across the types.

The analysis of the structural model's power to predict preference reversals yields the third main result.

Result 3 *The structural model has power to predict type-specific behavioral differences across choice contexts.*

1. *Subjects classified as ST-types exhibit significantly more preference reversals than the other subjects*
2. *The structural model accurately predicts the quantitative differences in the average frequencies of preference reversals across types.*
3. *Due to their parsimony, the structural model's type-specific parameter estimates outperform noisy individual estimates.*

Furthermore, the predictions of preference reversals suggest that the choice context shapes the relative importance of choice set dependence.

6 Conclusion

The paper assesses the relative importance of probability weighting and choice set dependence both non-parametrically and with a structural model. This represents the first joint test of the two most descriptive behavioral theories of choice under risk.

There are three main results. First, for aggregate choices, both choice set dependence and probability weighting matter. This result does not rely on specific functional forms and is robust across the three versions of the Allais Paradox as well as across the two presentation formats. Second, there is substantial heterogeneity in risk preferences which can be parsimoniously characterized by three types: 38% CPT-types, 34% ST-types, and 28% EUT-types. Finally, this classification of subjects is valid in a different choice context, as the subjects classified as ST-types exhibit significantly more preference reversals than their peers.

These results are directly relevant for the literature that aims at identifying the main behavioral drivers of risky choices. This literature has so far treated probability weighting and choice set dependence as two mutually exclusive frameworks leading to two corresponding major classes of decision theories. Our results show, however, that both play an important role for non-EUT subjects. While the ST-types' behavior is mainly described by choice set dependence, the behavior of CPT-types is driven by both probability weighting as well as choice set dependence. Knowing about the relative importance of probability weighting and choice set dependence could inspire new decision theories taking both concepts into account and lead to better predictions in various domains of risk taking behavior, such as investment, asset pricing, insurance, and health behavior.

The conclusions also open up avenues for future research. First, our methodology could be used to study how the relative importance of probability weighting and choice set dependence varies with educational background, cognitive ability, and other socio economic characteristics in the general population. Studying this variation in the general population could lead to new explanations for the observed variation in socio-economic outcomes as the different types may fall prey to distinct behavioral traps during their lives. Second, to improve the decision models' predictive power, it would be important to explore how the choice context shapes the role of choice set dependence. Knowing how the choice context influences the role of choice set dependence could lead to more accurate predictions in other domains such as consumer, investor, and judicial choice.

Appendices

A Common Ratio Allais Paradox

We now use an example of two lotteries, X and Y, that may induce the Common Ratio Allais Paradox:

$$X = \begin{cases} 6000 & p = \frac{1}{2}q \\ 0 & 1 - p = 1 - \frac{1}{2}q \end{cases} \qquad \text{vs.} \qquad Y = \begin{cases} 3000 & q \\ 0 & 1 - q \end{cases}$$

In this example, the Common Ratio Allais Paradox refers to the empirical finding that if p is high most individuals prefer Y over X, whereas if p is scaled down by a factor $0 < \lambda < 1$ individuals prefer X over Y for a sufficiently small λ.

A.1 EUT

EUT cannot describe the Common Ratio Allais Paradox in the above example. The decision maker evaluates lottery X as $V^{EUT}(X) = p\, v(6000) + (1-p)\, v(0)$ and lottery Y as $V^{EUT}(Y) = 2p\, v(3000) + (1 - 2p)\, v(0)$. The decision maker chooses lottery X over Y if

$$\begin{aligned} V^{EUT}(X) &> V^{EUT}(Y) \\ p\, v(6000) &> 2p\, v(3000) - p\, v(0) \\ v(6000) &> 2v(3000) - v(0)\,. \end{aligned}$$

Hence, the choice does not depend on the value of the probability p.

A.2 CPT

CPT can describe the Common Ratio Allais Paradox in the above example. The decision maker prefers lottery Y over X if

$$\begin{aligned} V^{CPT}(Y) &> V^{CPT}(X) \\ w(q)\, v(3000) + [1 - w(q)]\, v(0) &> w(p)\, v(6000) + [1 - w(p)]\, v(0) \\ \frac{w(q)}{w(p)} &> \frac{v(6000) - v(0)}{v(3000) - v(0)}\,. \end{aligned}$$

Note that when p is scaled down by the factor λ, the right hand side of the above inequality remains unchanged, while the left hand side decreases due to the probability weighting function's subproportionality, i.e., $\frac{w(q)}{w(p)} > \frac{w(\lambda q)}{w(\lambda p)}$. Hence, for a sufficiently low λ the sign of the above inequality may change, and the decision maker prefers X to Y and exhibits the Common Ratio Allais Paradox.

A.2.1 ST

ST can describe the Common Ratio Allais Paradox in the above example when the two lotteries' payoffs are independent. In this case, there are four states of the world which rank in salience as follows: $\sigma(6000,0) > \sigma(0,3000) > \sigma(6000,3000) > \sigma(0,0)$. Hence, the decision maker evaluates lottery X as

$$V^{ST}(X) = \left[\omega_1^{ST}(6000,0) + \omega_3^{ST}(6000,3000)\right] \, v(6000) + \left[\omega_2^{ST}(0,3000) + \omega_4^{ST}(0,0)\right] \, v(0)\,.$$

and

$$V^{ST}(Y) = \left[\omega_2^{ST}(0,3000) + \omega_3^{ST}(6000,3000)\right] \, v(3000) + \left[\omega_1^{ST}(6000,0) + \omega_4^{ST}(0,0)\right] \, v(0)\,.$$

Using $v(0) = 0$ and the decision weights given by equation (2), the decision maker prefers Y over X when

$$\begin{aligned} v(3000)\left[\delta(1-p)q + \delta^2 pq\right] &> v(6000)\left[p(1-q) + \delta^2 pq\right] \\ v(3000)\, 2\delta \left[1 - p(1-\delta)\right] &> v(6000)\left[1 - 2p(1-\delta^2)\right] \\ \frac{1-p(1-\delta)}{1-2p(1-\delta^2)} &> \frac{v(6000)}{2\delta v(3000)}\,. \end{aligned}$$

Note that when p is scaled down, the right hand side of the above inequality remains unchanged, while the left hand side decreases. Hence, for a sufficiently low λ the sign of the above inequality may change, and the decision maker prefers X to Y and exhibits the Common Ratio Allais Paradox.

However, when the two lotteries are correlated, ST can no longer describe the Common Ration Allais Paradox. In this case, there are just three states of the world:

p_s	p	p	$1-2p$
x_s	6000	0	0
y_s	3000	3000	0

The ranking in terms of salience of these three states is as follows: $\sigma(0,3000) > \sigma(6000,3000) > \sigma(0,0)$. Hence, the decision maker evaluates lottery X as

$$V^{ST}(X) = \omega_2^{ST}(6000,3000)\, v(6000) + \left[\omega_1^{ST}(0,3000) + \omega_3^{ST}(0,0)\right]\, v(0)$$

and evaluates lottery Y as

$$V^{ST}(Y) = \left[\omega_1^{ST}(0,3000) + \omega_2^{ST}(6000,3000)\right]\, v(3000) + \omega_3^{ST}(0,0)\, v(0)$$

Using $v(0) = 0$ and the decision weights given by equation (2), the decision maker prefers X over Y when

$$\begin{aligned} v(6000)\,\delta p &> v(3000)\,(\delta p + p) \\ v(6000)\,\delta p &> v(3000)\,(\delta p + p) \\ \frac{v(6000)}{v(3000)} &> \frac{1+\delta}{\delta}. \end{aligned}$$

Hence, regardless of the value of p, the decision maker always prefers X over Y when the above inequality holds, and otherwise always prefers Y over X. Consequently, the decision maker never exhibits the Common Ratio Allais Paradox when the lotteries' payoffs are correlated.

B Choices to Trigger the Common Ratio Allais Paradox

The binary choices that may trigger the Common Ratio Allais Paradox are based on a subset of a $3 \times 3 \times 2$ design. The design uses the following three different payoff levels:

$$\text{Payoff Level 1:}\quad X = \begin{cases} 6000 & p = \frac{1}{2}q \\ 0 & 1-p = 1-\frac{1}{2}q \end{cases} \quad \text{vs.} \quad Y = \begin{cases} 3000 & q \\ 0 & 1-q \end{cases}$$

$$\text{Payoff Level 2:}\quad X = \begin{cases} 5500 & p = \frac{1}{2}q \\ 500 & 1-p = 1-\frac{1}{2}q \end{cases} \quad \text{vs.} \quad Y = \begin{cases} 3000 & q \\ 500 & 1-q \end{cases}$$

$$\text{Payoff Level 3:}\quad X = \begin{cases} 7000 & p = \frac{1}{2}q \\ 1000 & 1-p = 1-\frac{1}{2}q \end{cases} \quad \text{vs.} \quad Y = \begin{cases} 4000 & q \\ 1000 & 1-q \end{cases}$$

The design features three different probability levels $q \in \{0.90, 0.80, 0.70\}$. To trigger the Common Ratio Allais Paradox each of these three probability levels is scaled down: 0.90 is scaled down to 0.02, 0.80 to 0.10, and 0.70 to 0.20. From the resulting 18 binary choices this design generates, we exclude 3 binary choices which we use for triggering preference reversals and making out-of-sample predictions (see Appendix C).

C Choices to Trigger Preference Reversals

The six binary choices that may trigger preference reversals are based on the following lotteries $\tilde{X}$ and $\tilde{Y}$:

$$\text{Choice 1:} \quad \tilde{X} = \begin{cases} 400 & p = 0.96 \\ 0 & 1-p = 0.04 \end{cases} \quad \text{vs.} \quad \tilde{Y} = \begin{cases} 1600 & q = 0.24 \\ 0 & 1-q = 0.76 \end{cases}$$

$$\text{Choice 2:} \quad \tilde{X} = \begin{cases} 1600 & p = 0.24 \\ 0 & 1-p = 0.76 \end{cases} \quad \text{vs.} \quad \tilde{Y} = \begin{cases} 6400 & q = 0.06 \\ 0 & 1-q = 0.94 \end{cases}$$

$$\text{Choice 3:} \quad \tilde{X} = \begin{cases} 400 & p = 0.96 \\ 0 & 1-p = 0.04 \end{cases} \quad \text{vs.} \quad \tilde{Y} = \begin{cases} 6400 & q = 0.06 \\ 0 & 1-q = 0.94 \end{cases}$$

$$\text{Choice 4:} \quad \tilde{X} = \begin{cases} 3000 & p = 0.90 \\ 0 & 1-p = 0.10 \end{cases} \quad \text{vs.} \quad \tilde{Y} = \begin{cases} 6000 & q = 0.45 \\ 0 & 1-q = 0.55 \end{cases}$$

$$\text{Choice 5:} \quad \tilde{X} = \begin{cases} 3000 & p = 0.80 \\ 0 & 1-p = 0.20 \end{cases} \quad \text{vs.} \quad \tilde{Y} = \begin{cases} 6000 & q = 0.40 \\ 0 & 1-q = 0.60 \end{cases}$$

$$\text{Choice 6:} \quad \tilde{X} = \begin{cases} 3000 & p = 0.70 \\ 0 & 1-p = 0.30 \end{cases} \quad \text{vs.} \quad \tilde{Y} = \begin{cases} 6000 & q = 0.35 \\ 0 & 1-q = 0.65 \end{cases}$$

The first three binary choices are similar to the ones stated in Bordalo et al. (2012b). The last three binary choices are based on Payoff Level 1 of the $3 \times 3 \times 2$ design used for generating choices that may trigger the Common Ratio Allais Paradox (see Appendix B).

D Number of Choices

Table 4: Number of Binary Choices by Presentation Format and Type of Allais Paradox

	Canonical		
Allais Paradox	Independent Payoffs	Correlated Payoffs	Preference Reversal
Common Consequence	27	27	
Common Ratio[a]	15	18	
Total Binary Choices	42	45	6
	States of the World		
Allais Paradox	Independent Payoffs	Correlated Payoffs	Preference Reversal
Common Consequence	18[b]	27	
Common Ratio[a]	15	18	
Total	33	45	6

[a] Three of the $3 \times 3 \times 2 = 18$ binary choices to trigger the Common Ratio Allais Paradox were used to make out-of-sample predictions of preference reversals. These three binary choices were left out in the calculation of the frequencies of Allais Paradoxes and the structural estimations (see Appendices B and C).

[b] In the states of the world presentation, the nine binary choices where lottery X has three possible payoffs and lottery Y is a sure amount look identical regardless whether the lotteries' payoffs are independent or correlated. Since we did not want to present the same choices twice, subjects exposed to the states of the world presentation had to go through nine binary choices less than those exposed to the canonical presentation.

E Comparison between the Two Presentation Formats

This section of compares the subjects' choice patterns across the two presentation formats to rule out two concerns regarding the importance of choice set dependence.

E.1 Prominence of Common Consequence

The first concern is that the states of the world presentation makes the common consequence more prominent, which could influence the number of Allais Paradoxes and the subjects' decision times. When comparing the frequencies of Allais Paradoxes across the two presentation formats, we find one statistically significant but small difference.

Table 5: Differences in the Frequency of Allais Paradoxes between the Canonical Presentation and the States of the World Presentation

Payoffs	independent	correlated
Expected direction	0.048	-0.014
Inverse direction	-0.014	0.008

Table 5 exhibits all differences in the frequencies of Allais Paradoxes. With independent payoffs, the frequency in the expected direction is 4.8 percentage points higher in the canonical presentation than in the states of the world presentation (t-test: p-value = 0.007). However, this difference is much smaller than in Birnbaum et al. (2017) who argue that the states of the world presentation makes the common consequence more prominent and, thus, may lower the frequency of Allais Paradoxes. Perhaps the difference is small in our case because, when presenting the choices to the subjects, Birnbaum et al. (2017) place the common consequence always in the first column while we place it in a random column. This random placement may lower the common consequence's prominence. With correlated payoffs, the frequency of Allais Paradoxes in the expected direction is 1.4 percentage points lower in the canonical presentation than in the states of the world presentation (t-test: p-value = 0.313). In the inverse direction, it is 1.4 percentage points lower in the canonical presentation than in states of the world presentation with independent payoffs (t-test: p-value = 0.169), and 0.8 percentage points higher with correlated payoffs (t-test: p-value = 0.379).

In terms of average decision times, subjects exposed to the canonical presentation needed 12.03 seconds per binary choice, while those exposed to the states of the world presentation needed 14.74 seconds. The difference of 2.71 seconds is significant (t-test: p-value < 0.001) and may reflect the higher complexity of the states of the world presentation. Subjects also required more time with independent than with correlated payoffs: 0.48 seconds more in the canonical presentation (t-test: p-value = 0.034) and 6.50 seconds in the states of the world presentation (t-test: p-value < 0.001).

E.2 Event-Splitting Effects

The second concern is that the change in the frequency of Allais Paradoxes in response to a manipulation of the lotteries' correlation structure may be driven by event-splitting effects rather than choice set dependence. Event-splitting occurs when, depending on the lotteries' correlation structure, some payoffs appear in multiple states of the world. This might affect subjects' choices if they weight payoffs by the number of states in which they appear.

If event-splitting effects play a role in our data, they should be particularly strong in the states of the world presentation of choices provoking the generalized version of the Common Consequence Allais Paradox. For instance, the states of the world presentation of the choice in equation (1) with a common consequence $z = 0$ and independent payoffs is

	$p_1(p_1+p_3)$	$p_1 p_2$	$(p_2+p_3)(p_1+p_3)$	$(p_2+p_3)p_2$
X	2500	2500	0	0
Y	2400	0	2400	0

while with correlated payoffs it is

	p_1	p_2	p_3
X	2500	0	0
Y	2400	0	2400

We see that lottery X offers the highest payoff, 2500, in two states with independent payoffs but in just one state with correlated payoffs. This may render X more attractive with independent payoffs than with correlated payoffs. In addition, lottery Y offers the lowest payoff, 0, in two states with independent payoffs but in just one state with correlated payoffs. This may render Y more attractive with correlated payoffs than with independent payoffs. In contrast, in the canonical presentation, event-splitting effects are absent as the two lotteries are presented side by side as two separate options when payoffs are independent.

To test whether event-splitting effects play a role in our data, we compare the subjects' choice patterns between the two presentation formats. To maximize the chance of finding event-splitting effects, we only look at the choices provoking the generalized version of the Common Consequence Allais Paradox where these effects should be strongest. However, as Table 6 reveals, the choice patterns are virtually identical across the two presentation formats. Hence, we conclude that, in our data, the differences in the frequencies of Allais Paradoxes in response to manipulations of the lotteries' correlation structure are driven by choice set dependence and not by event-splitting effects.

Table 6: Comparing Choice Patterns between Presentation Formats in Lotteries Provoking the Generalized Version of the Common Consequence Allais Paradox

States of the World Presentation ($N = 145$)

Frequency choosing X over Y in Choice 1 with $z = x_3$

	Independent Payoffs	Correlated Payoffs	Difference
Mean	0.166	0.152	0.014
Std. Error	(0.014)	(0.013)	(0.014)

Frequency choosing X over Y in Choice 2 with $z < y_1$

	Independent Payoffs	Correlated Payoffs	Difference
Mean	0.348	0.192	0.156
Std. Error	(0.013)	(0.014)	(0.019)

Difference: Choice 1 - Choice 2

	Independent Payoffs	Correlated Payoffs	Difference
Mean	-0.182	-0.041	-0.142
Std. Error	(0.018)	(0.014)	(0.024)

Canonical Presentation ($N = 138$)

Frequency choosing X over Y in Choice 1 with $z = x_3$

	Independent Payoffs	Correlated Payoffs	Difference
Mean	0.193	0.163	0.030
Std. Error	(0.017)	(0.015)	(0.014)

Frequency choosing X over Y in Choice 2 with $z < y_1$

	Independent Payoffs	Correlated Payoffs	Difference
Mean	0.398	0.187	0.211
Std. Error	(0.014)	(0.014)	(0.017)

Difference: Choice 1 - Choice 2

	Independent Payoffs	Correlated Payoffs	Contrast
Mean	-0.205	-0.023	-0.181
Std. Error	(0.019)	(0.014)	(0.020)

F Frequency of Choices

Table 7: Frequency Choosing Lotteries X and Y by Version of the Allais Paradox

(a) All Allais Paradoxes Combined

Independent Payoffs

		2nd Choice X	2nd Choice Y
1st Choice	X	15.4%	7.1%
	Y	28.3%	49.2%

Correlated Payoffs

		2nd Choice X	2nd Choice Y
1st Choice	X	21.5%	6.9%
	Y	16.9%	54.7%

(b) Only Classical Version of the Common Consequence Allais Paradox

Independent Payoffs

		2nd Choice ($z = y_1$) X	2nd Choice ($z = y_1$) Y
1st Choice	X	10.5%	6.0%
($z = x_3$)	Y	26.7%	56.8%

Correlated Payoffs

		2nd Choice ($z = y_1$) X	2nd Choice ($z = y_1$) Y
1st Choice	X	7.9%	6.1%
($z = x_3$)	Y	11.0%	75.0%

(c) Only General Version of the Common Consequence Allais Paradox

Independent Payoffs

		2nd Choice ($z < y_1$) X	2nd Choice ($z < y_1$) Y
1st Choice	X	11.8%	6.1%
($z = x_3$)	Y	25.4%	56.7%

Correlated Payoffs

		2nd Choice ($z < y_1$) X	2nd Choice ($z < y_1$) Y
1st Choice	X	8.0%	7.7%
($z = x_3$)	Y	11.0%	73.3%

(d) Only Common Ratio Allais Paradox

Independent Payoffs

		2nd Choice (q scaled down) X	2nd Choice (q scaled down) Y
1st Choice	X	28.0%	10.2%
(Pr. q)	Y	35.0%	26.8%

Correlated Payoffs

		2nd Choice (q scaled down) X	2nd Choice (q scaled down) Y
1st Choice	X	44.9%	8.5%
(Pr. q)	Y	28.0%	18.6%

G Structural Estimations at the Aggregate Level

Table 8: Structural Estimations at the Aggregate Level

Specification of Decision Theory	EUT	CPT	CPT2[a]	ST
Concavity of utility function (β)	0.125**	0.489***	0.503***	0.870***
	(0.010)	(0.045)	(0.038)	(0.012)
Likelihood sensitivity (α)		0.681°°°	0.692°°°	
		(0.027)	(0.030)	
Net index of convexity (γ)			0.962°	
			(0.020)	
Degree of local thinking (δ)				0.931°°°
				(0.008)
Choice sensitivity (σ)	0.020***	0.161***	0.186***	0.014***
	(0.001)	(0.044)	(0.041)	(0.001)
Number of subjects	283	283	283	283
Number of observations	23,316	23,316	23,316	23,316
Log Likelihood	-12,714.52	-12,386.13	-12,382.20	-12,650.83
AIC	25,433.03	24,778.25	24,772.39	25,307.65
BIC	25,449.15	24,802.42	24,804.62	25,331.82
Share of correctly predicted choices[b]	0.644	0.727	0.727	0.665

Subject cluster-robust standard errors are reported in parentheses. Significantly different from 0 (1) at the 1% level: *** (°°°); at the 5% level: ** (°°); at the 10% level: * (°)

[a] CPT2 is a specification also based on Cumulative Prospect Theory but uses the more flexible, two-parameter version of the probability weighting function by Prelec (1998): $w(p) = \exp(-\gamma(-\ln(p))^{\alpha})$, where γ is the net index of concavity.

[b] Choices are predicted by calculating the lotteries' values, $V^M(X_g, \hat{\theta}_M)$ and $V^M(Y_g, \hat{\theta}_M)$, for the parameter estimates $\hat{\theta}_M$ of the corresponding model.

Table 8 reveals that, at the aggregate level, all decision models fit the subjects' choices considerably worse than the finite mixture model (Table 2) which accounts for heterogeneity in a parsimonious way. Compared to the estimations at the aggregate level, the finite mixture model not only achieves a higher log likelihood but also lower values of the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC).

Moreover, the alternative specification of Cumulative Prospect Theory, CPT2, using the more flexible, two-parameter version of Prelec's probability weighting function exhibits only a negligibly better fit than the baseline specification of CPT. This is because the estimated net index of concavity, $\hat{\gamma} = 0.962$, is very close to one. Thus, we opt for the baseline specification of CPT, as it exhibits the same number of parameters as ST.

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Risk and Rationality: The Relative Importance of Probability Weighting and Choice Set Dependence

— Online Appendix —

August 23, 2019

Contents

1 Qualitative Predictions for ST

1.1 Binary Choices to Trigger Common Consequence Allais Paradoxes: Independent Payoffs

CC1.independent

$$X = \begin{cases} 2500, & p_1 \\ z, & p_2 \\ 0, & p_3 \end{cases} \quad vs \quad Y = \begin{cases} 2400, & p_1 + p_3 \\ z, & p_2 \end{cases}$$

where $z \in \{0, 2400\}$.

If $z = 2400$ the choice is:

$$X = \begin{cases} 2500, & p_1 \\ 2400, & p_2 \\ 0, & p_3 \end{cases} \quad vs \quad Y = \{2400$$

The salience rankings are $\sigma(0, 2400) > \sigma(2500, 2400) > \sigma(2400, 2400)$ since $\sigma(0, 2400) > \sigma(0, 100) = \sigma(100, 0) > \sigma(2500, 2400)$. This makes lottery Y more attractive.

If $z = 0$ the choice is:

$$X = \begin{cases} 2500, & p_1 \\ 0, & p_2 + p_3 \end{cases} \quad vs \quad Y = \begin{cases} 2400, & p_1 + p_3 \\ 0, & p_2 \end{cases}$$

The salience rankings are $\sigma(2500, 0) > \sigma(0, 2400) > \sigma(2500, 2400) > \sigma(0, 0)$ since $\sigma(2500, 0) = \sigma(0, 2500) > \sigma(0, 2400)$. This makes lottery X more attractive.

CC2.independent

$$X = \begin{cases} 5000, & p_1 \\ z, & p_2 \\ 0, & p_3 \end{cases} \quad vs \quad Y = \begin{cases} 4800, & p_1 + p_3 \\ z, & p_2 \end{cases}$$

where $z \in \{0, 4800\}$. The stake size is double relative to gambles A1.1 so the salience rankings will be the same.

If $z = 4800$ the choice is:

$$X = \begin{cases} 5000, & p_1 \\ 4800, & p_2 \\ 0, & p_3 \end{cases} \quad vs \quad Y = 4800$$

The salience rankings are $\sigma(0,4800) > \sigma(5000,4800) > \sigma(4800,4800)$ since $\sigma(0,4800) > \sigma(0,200) = \sigma(200,0) > \sigma(5000,4800)$. This makes lottery Y more attractive.

If $z = 0$ the choice is:

$$X = \begin{cases} 5000, & p_1 \\ 0, & p_2 + p_3 \end{cases} \quad vs \quad Y = \begin{cases} 4800, & p_1 + p_3 \\ 0, & p_2 \end{cases}$$

The salience rankings are $\sigma(5000,0) > \sigma(0,4800) > \sigma(5000,4800) > \sigma(0,0)$ since $\sigma(5000,0) = \sigma(0,5000) > \sigma(0,4800)$. This makes lottery X more attractive.

CC3.independent

$$X = \begin{cases} 3000, & p_1 \\ z, & p_2 \\ 500, & p_3 \end{cases} \quad vs \quad Y = \begin{cases} 2600, & p_1 + p_3 \\ z, & p_2 \end{cases}$$

where $z \in \{500, 2600\}$.

If $z = 2600$ the choice is:

$$X = \begin{cases} 3000, & p_1 \\ 2600, & p_2 \\ 500, & p_3 \end{cases} \quad vs \quad Y = 2600$$

The salience rankings are $\sigma(500,2600) > \sigma(3000,2600) > \sigma(2600,2600)$. This makes lottery Y more attractive.

If $z = 500$ the choice is:

$$X = \begin{cases} 3000, & p_1 \\ 500, & p_2 + p_3 \end{cases} \quad vs \quad Y = \begin{cases} 2600, & p_1 + p_3 \\ 500, & p_2 \end{cases}$$

The salience rankings are $\sigma(3000,500) > \sigma(500,2600) > \sigma(3000,2600) > \sigma(500,500)$ since $\sigma(3000,500) = \sigma(500,3000) > \sigma(500,2600)$. This makes lottery X more attractive.

CC4.independent

$$X = \begin{cases} 2500, & p_1 \\ z, & p_2 \\ 0, & p_3 \end{cases} \quad vs \quad Y = \begin{cases} 2400, & p_1 + p_3 \\ z, & p_2 \end{cases}$$

where $z \in \{0, 2000\}$.

If $z = 2000$ the choice is:

$$X = \begin{cases} 2500, & p_1 \\ 2000, & p_2 \\ 0, & p_3 \end{cases} \quad vs \quad Y = \begin{cases} 2400, & p_1 + p_3 \\ 2000, & p_2 \end{cases}$$

The salience rankings are $\sigma(0,2400) > \sigma(0,2000) > \sigma(2500,2000) > \sigma(2000,2400) > \sigma(2500,2400) > \sigma(2000,2000)$, since $\sigma(2500,2000) = \sigma(2000,2500) > \sigma(2000,2400)$ and $\sigma(2000,2400) > \sigma(2100,2500) = \sigma(2500,2100) > \sigma(2500,2400)$. This makes lottery Y more attractive.

If $z = 0$ the choice is:

$$X = \begin{cases} 2500, & p_1 \\ 0, & p_2 + p_3 \end{cases} \quad vs \quad Y = \begin{cases} 2400, & p_1 + p_3 \\ 0, & p_2 \end{cases}$$

The salience rankings are $\sigma(2500,0) > \sigma(0,2400) > \sigma(2500,2400) > \sigma(0,0)$ since $\sigma(2500,0) = \sigma(0,2500) > \sigma(0,2400)$. This makes lottery X more attractive.

CC5.independent

$$X = \begin{cases} 5000, & p_1 \\ z, & p_2 \\ 0, & p_3 \end{cases} \quad vs \quad Y = \begin{cases} 4800, & p_1 + p_3 \\ z, & p_2 \end{cases}$$

where $z \in \{0, 4000\}$. The stake size is double relative to gambles B1.1 so the salience rankings will be the same.

If $z = 4000$ the choice is:

$$X = \begin{cases} 5000, & p_1 \\ 4000, & p_2 \\ 0, & p_3 \end{cases} \quad vs \quad Y = \begin{cases} 4800, & p_1 + p_3 \\ 4000, & p_2 \end{cases}$$

The salience rankings are $\sigma(0,4800) > \sigma(0,4000) > \sigma(5000,4000) > \sigma(4000,4800) > \sigma(5000,4800) > \sigma(4000,4000)$ since $\sigma(0,4000) = \sigma(4000,0) > \sigma(5000,100) > \sigma(5000,4000)$ and $\sigma(4000,4800) > \sigma(4200,5000) = \sigma(5000,4200) > \sigma(5000,4800)$. This makes lottery Y more attractive.

If $z = 0$ the choice is:

$$X = \begin{cases} 5000, & p_1 \\ 0, & p_2 + p_3 \end{cases} \quad vs \quad Y = \begin{cases} 4800, & p_1 + p_3 \\ 0, & p_2 \end{cases}$$

The salience rankings are $\sigma(5000,0) > \sigma(0,4800) > \sigma(5000,4800) > \sigma(0,0)$. This makes lottery X more attractive.

CC6.independent

$$X = \begin{cases} 3000, & p_1 \\ z, & p_2 \\ 500, & p_3 \end{cases} \quad vs \quad Y = \begin{cases} 2600, & p_1 + p_3 \\ z, & p_2 \end{cases}$$

where $z \in \{500, 2000\}$.

If $z = 2000$ the choice is:

$$X = \begin{cases} 3000, & p_1 \\ 2000, & p_2 \\ 500, & p_3 \end{cases} \quad vs \quad Y = \begin{cases} 2600, & p_1 + p_3 \\ 2000, & p_2 \end{cases}$$

The salience rankings are $\sigma(500, 2600) > \sigma(500, 2000) > \sigma(3000, 2000) > \sigma(2000, 2600) > \sigma(3000, 2600) > \sigma(2000, 2000)$ since $\sigma(500, 2000) > \sigma(1000, 2000) = \sigma(2000, 1000) > \sigma(3000, 2000)$ and $\sigma(2000, 2600) = \sigma(2600, 2000) > \sigma(3000, 2400) > \sigma(3000, 2600)$. This makes lottery Y more attractive.

If $z = 500$ the choice is:

$$X = \begin{cases} 3000, & p_1 \\ 500, & p_2 + p_3 \end{cases} \quad vs \quad Y = \begin{cases} 2600, & p_1 + p_3 \\ 500, & p_2 \end{cases}$$

The salience rankings are $\sigma(3000, 500) > \sigma(2600, 500) > \sigma(3000, 2600) > \sigma(500, 500)$. This makes lottery X more attractive.

1.2 Binary Choices to Trigger Common Consequence Allais Paradoxes: Correlated Payoffs

CC1.correlated

p_s	p_1	p_2	p_3
x_s	2500	z	0
y_s	2400	z	2400

where $z \in \{0, 2400\}$. The salience rankings are $\sigma(0, 2400) > \sigma(2500, 2400) > \sigma(z, z)$ for $z \in \{0, 2400\}$. This makes lottery Y more attractive.

CC2.correlated

p_s	p_1	p_2	p_3
x_s	5000	z	0
y_s	4800	z	4800

where $z \in \{0, 4800\}$. The salience rankings are $\sigma(0, 4800) > \sigma(5000, 4800) > \sigma(z, z)$ for $z \in \{0, 4800\}$. This makes lottery Y more attractive.

CC3.correlated

p_s	p_1	p_2	p_3
x_s	3000	z	500
y_s	2600	z	2600

where $z \in \{500, 2600\}$. The salience rankings are $\sigma(500, 2600) > \sigma(3000, 2600) > \sigma(z, z)$ for $z \in \{500, 2600\}$. This makes lottery Y more attractive.

CC4.correlated

p_s	p_1	p_2	p_3
x_s	2500	z	0
y_s	2400	z	2400

where $z \in \{0, 2000\}$. The salience rankings are $\sigma(0, 2400) > \sigma(2500, 2400) > \sigma(z, z)$ for $z \in \{0, 2000\}$. This makes lottery Y more attractive.

CC5.correlated

p_s	p_1	p_2	p_3
x_s	5000	z	0
y_s	4800	z	4800

where $z \in \{0, 4000\}$. The salience rankings are $\sigma(0, 4800) > \sigma(5000, 4800) > \sigma(z, z)$ for $z \in \{0, 4000\}$. This makes lottery Y more attractive.

CC6.correlated

p_s	p_1	p_2	p_3
x_s	3000	z	500
y_s	2600	z	2600

where $z \in \{500, 2000\}$. The salience rankings are $\sigma(500, 2600) > \sigma(3000, 2600) > \sigma(z, z)$ for $z \in \{500, 2000\}$. This makes lottery Y more attractive.

1.3 Binary Choices to Trigger Common Ratio Allais Paradoxes: Independent Payoffs

CR1.independent

$$X = \begin{cases} 6000 & p = \frac{1}{2}q \\ 0 & 1 - p = 1 - \frac{1}{2}q \end{cases} \quad \text{vs.} \quad Y = \begin{cases} 3000 & q \\ 0 & 1 - q \end{cases}$$

The salience rankings are $\sigma(6000,0) > \sigma(0,3000) > \sigma(6000,3000) > \sigma(0,0)$. Hence, the decision maker evaluates lottery X as

$$\begin{aligned} V^{ST}(X) &= \left[\omega_1^{ST}(6000,0) + \omega_3^{ST}(6000,3000)\right] \, v(6000) \\ &\quad + \left[\omega_2^{ST}(0,3000) + \omega_4^{ST}(0,0)\right] \, v(0)\,. \end{aligned}$$

and lottery Y as

$$\begin{aligned} V^{ST}(Y) &= \left[\omega_2^{ST}(0,3000) + \omega_3^{ST}(6000,3000)\right] \, v(3000) \\ &\quad + \left[\omega_1^{ST}(6000,0) + \omega_4^{ST}(0,0)\right] \, v(0)\,. \end{aligned}$$

Using $v(0) = 0$ and the decision weights given by equation (2) in the paper, the decision maker prefers Y over X when

$$\begin{aligned} v(3000)\,[\delta(1-p)q + \delta^2 pq] &> v(6000)\,[p(1-q) + \delta^2 pq] \\ v(3000)\,2\delta\,[1 - p(1-\delta)] &> v(6000)\,[1 - 2p(1-\delta^2)] \\ \frac{1-p(1-\delta)}{1-2p(1-\delta^2)} &> \frac{v(6000)}{2\delta v(3000)}\,. \end{aligned}$$

Note that when p is scaled down, the right hand side of the above inequality remains unchanged, while the left hand side decreases. Hence, for a sufficiently low λ the sign of the above inequality may change, and the decision maker prefers X to Y and exhibits the Common Ratio Allais Paradox.

CR2.independent

$$X = \begin{cases} 5500 & p = \frac{1}{2}q \\ 500 & 1-p = 1-\frac{1}{2}q \end{cases} \quad \text{vs.} \quad Y = \begin{cases} 3000 & q \\ 500 & 1-q \end{cases}$$

The salience rankings are $\sigma(5500,500) > \sigma(500,3000) > \sigma(5500,3000) > \sigma(500,500)$. Hence, the decision maker evaluates lottery X as

$$\begin{aligned} V^{ST}(X) &= \left[\omega_1^{ST}(5500,500) + \omega_3^{ST}(5500,3000)\right] \, v(5500) \\ &\quad + \left[\omega_2^{ST}(500,3000) + \omega_4^{ST}(500,500)\right] \, v(500)\,. \end{aligned}$$

and lottery Y as

$$\begin{aligned} V^{ST}(Y) &= \left[\omega_2^{ST}(500,3000) + \omega_3^{ST}(5500,3000)\right] \; v(3000) \\ &\quad + \left[\omega_1^{ST}(5500,500) + \omega_4^{ST}(500,500)\right] \; v(500) \,. \end{aligned}$$

Using the decision weights given by equation (2) in the paper, the decision maker prefers Y over X when

$$\begin{aligned} v(3000)\,[\delta(1-p)q + \delta^2 pq] + v(500)\,p(1-q) &> v(5500)\,[p(1-q) + \delta^2 pq] + v(500)\,\delta(1-p)q \\ 2p &> \frac{v(5500) - 2\delta v(3000) - (1-2\delta)v(500)}{(1-\delta^2)v(5500) - \delta(1-\delta)v(3000) - (1-\delta)v(500)} \,. \end{aligned}$$

Note that when p is scaled down, the right hand side of the above inequality remains unchanged, while the left hand side decreases. Hence, for a sufficiently low λ the sign of the above inequality may change, and the decision maker prefers X to Y and exhibits the Common Ratio Allais Paradox.

CR3.independent

$$X = \begin{cases} 7000 & p = \frac{1}{2}q \\ 1000 & 1-p = 1-\frac{1}{2}q \end{cases} \quad \text{vs.} \quad Y = \begin{cases} 4000 & q \\ 1000 & 1-q \end{cases}$$

The salience rankings are $\sigma(7000,1000) > \sigma(1000,4000) > \sigma(7000,4000) > \sigma(1000,1000)$. Hence, the decision maker evaluates lottery X as

$$\begin{aligned} V^{ST}(X) &= \left[\omega_1^{ST}(7000,1000) + \omega_3^{ST}(7000,4000)\right] \; v(7000) \\ &\quad + \left[\omega_2^{ST}(1000,4000) + \omega_4^{ST}(1000,1000)\right] \; v(1000) \,. \end{aligned}$$

and lottery Y as

$$\begin{aligned} V^{ST}(Y) &= \left[\omega_2^{ST}(1000,4000) + \omega_3^{ST}(7000,4000)\right] \; v(4000) \\ &\quad + \left[\omega_1^{ST}(7000,1000) + \omega_4^{ST}(1000,1000)\right] \; v(1000) \,. \end{aligned}$$

Using the decision weights given by equation (2) in the paper, the decision maker prefers Y over X when

$$
\begin{aligned}
v(4000)\left[\delta(1-p)q+\delta^2 pq\right]+v(1000)\,p(1-q) &> v(7000)\left[p(1-q)+\delta^2 pq\right]+v(1000)\,\delta(1-p)q \\
2p &> \frac{v(7000)-2\delta v(4000)-(1-2\delta)v(1000)}{(1-\delta^2)v(7000)-\delta(1-\delta)v(4000)-(1-\delta)v(1000)}\,.
\end{aligned}
$$

Note that when p is scaled down, the right hand side of the above inequality remains unchanged, while the left hand side decreases. Hence, for a sufficiently low λ the sign of the above inequality may change, and the decision maker prefers X to Y and exhibits the Common Ratio Allais Paradox.

1.4 Binary Choices to Trigger Common Ratio Allais Paradoxes: Correlated Payoffs

CR1.correlated

p_s	p	p	$1-2p$
x_s	6000	0	0
y_s	3000	3000	0

The salience rankings are $\sigma(0,3000) > \sigma(6000,3000) > \sigma(0,0)$. Hence, the decision maker evaluates lottery X as

$$
V^{ST}(X) = \omega_2^{ST}(6000,3000)\,v(6000) + \left[\omega_1^{ST}(0,3000)+\omega_3^{ST}(0,0)\right]\,v(0)
$$

and evaluates lottery Y as

$$
V^{ST}(Y) = \left[\omega_1^{ST}(0,3000)+\omega_2^{ST}(6000,3000)\right]\,v(3000)+\omega_3^{ST}(0,0)\,v(0)
$$

Using $v(0)=0$ and the decision weights given by equation (2) in the paper, the decision maker prefers X over Y when

$$
\begin{aligned}
v(6000)\,\delta p &> v(3000)\,(\delta p + p) \\
v(6000)\,\delta p &> v(3000)\,(\delta p + p) \\
\frac{v(6000)}{v(3000)} &> \frac{1+\delta}{\delta}\,.
\end{aligned}
$$

Hence, regardless of the value of p, the decision maker always prefers X over Y when the above inequality holds, and otherwise always prefers Y over X. Consequently, the decision maker never exhibits the Common Ratio Allais Paradox when the lotteries' payoffs are correlated.

CR2.correlated

p_s	p	p	$1-2p$
x_s	5500	500	500
y_s	3000	3000	500

The salience rankings are $\sigma(500, 3000) > \sigma(5500, 3000) > \sigma(500, 500)$. Hence, the decision maker evaluates lottery X as

$$V^{ST}(X) = \omega_2^{ST}(5500, 3000)\, v(5500) + \left[\omega_1^{ST}(500, 3000) + \omega_3^{ST}(500, 500)\right]\, v(500)$$

and evaluates lottery Y as

$$V^{ST}(Y) = \left[\omega_1^{ST}(500, 3000) + \omega_2^{ST}(5500, 3000)\right]\, v(3000) + \omega_3^{ST}(500, 500)\, v(500)$$

Using the decision weights given by equation (2) in the paper, the decision maker prefers X over Y when

$$\begin{aligned} v(5500)\,\delta p + v(500)\,p &> v(3000)\,(p + \delta p) \\ v(5500)\,\delta + v(500) &> v(3000)\,(1 + \delta) \\ \delta &> \frac{v(3000) - v(500)}{v(5500) - v(3000)}\,. \end{aligned}$$

Hence, regardless of the value of p, the decision maker always prefers X over Y when the above inequality holds, and otherwise always prefers Y over X. Consequently, the decision maker never exhibits the Common Ratio Allais Paradox when the lotteries' payoffs are correlated.

CR3.correlated

p_s	p	p	$1-2p$
x_s	7000	1000	1000
y_s	4000	4000	1000

The salience rankings are $\sigma(1000, 4000) > \sigma(7000, 4000) > \sigma(1000, 1000)$. Hence, the decision maker evaluates lottery X as

$$V^{ST}(X) = \omega_2^{ST}(7000, 4000)\, v(7000) + \left[\omega_1^{ST}(1000, 4000) + \omega_3^{ST}(1000, 1000)\right]\, v(1000)$$

and evaluates lottery Y as

$$V^{ST}(Y) = \left[\omega_1^{ST}(1000, 4000) + \omega_2^{ST}(7000, 4000)\right]\, v(4000) + \omega_3^{ST}(1000, 1000)\, v(1000)$$

Using the decision weights given by equation (2) in the paper, the decision maker prefers X over Y when

$$\begin{aligned} v(7000)\,\delta p + v(1000)\,p &> v(4000)\,(p + \delta p) \\ v(7000)\,\delta + v(1000) &> v(4000)\,(1 + \delta) \\ \delta &> \frac{v(4000) - v(1000)}{v(7000) - v(4000)}\,. \end{aligned}$$

Hence, regardless of the value of p, the decision maker always prefers X over Y when the above inequality holds, and otherwise always prefers Y over X. Consequently, the decision maker never exhibits the Common Ratio Allais Paradox when the lotteries' payoffs are correlated.

2 Occurrence of Preference Reversals in ST

This section describes under which conditions ST describes preference reversals in the 6 binary choices of the experiment's additional part.

2.1 Choices 1 and 2

The binary lottery choices 1 and 2 are as follows:

$$\tilde{X} = \begin{cases} x \text{ with } & p \\ 0 \text{ with } & 1-p \end{cases} \quad \text{vs.} \quad \tilde{Y} = \begin{cases} 4x \text{ with } & q = p/4 \\ 0 \text{ with } & 1-q = 1-p/4 \end{cases},$$

where for choice 1 $x = 400$ and $p = 0.96$ whereas for choice 2 $x = 1600$ and $p = 0.24$. In this case we can have two possible salience rankings:

(i) $\sigma(0, 4x) > \sigma(x, 4x) > \sigma(x, 0) > \sigma(0, 0)$

(ii) $\sigma(0, 4x) > \sigma(x, 0) > \sigma(x, 4x) > \sigma(0, 0)$

We consider each case separately.

(i) If the salience ranking is $\sigma(0, 4x) > \sigma(x, 4x) > \sigma(x, 0) > \sigma(0, 0)$, then

$$\begin{aligned} V^{ST}(\tilde{X}|\{\tilde{X},\tilde{Y}\}) &= [\pi_2^{ST}(x,4x) + \pi_3^{ST}(x,0)]v(x) + [\pi_1^{ST}(0,4x) + \pi_4^{ST}(0,0)]v(0) \\ &= \left[\frac{pq\delta^2}{D} + \frac{p(1-q)\delta^3}{D}\right] v(x) + \left[\frac{(1-p)q\delta}{D} + \frac{(1-p)(1-q)\delta^4}{D}\right] v(0) \\ &= \left[\frac{pq\delta^2}{D} + \frac{p(1-q)\delta^3}{D}\right] v(x) \end{aligned}$$

and

$$\begin{aligned} V^{ST}(\tilde{Y}|\{\tilde{X},\tilde{Y}\}) &= [\pi_1^{ST}(0,4x) + \pi_2^{ST}(x,4x)]v(4x) + [\pi_3^{ST}(x,0) + \pi_4^{ST}(0,0)]v(0) \\ &= \left[\frac{(1-p)q\delta}{D} + \frac{pq\delta^2}{D}\right] v(4x) + \left[\frac{p(1-q)\delta^3}{D} + \frac{(1-p)(1-q)\delta^4}{D}\right] v(0) \\ &= \left[\frac{(1-p)q\delta}{D} + \frac{pq\delta^2}{D}\right] v(4x) \end{aligned}$$

where $D = (1-p)q\delta + pq\delta^2 + p(1-q)\delta^3 + (1-p)(1-q)\delta^4$. The ST decision maker prefers $\tilde{X}$ to $\tilde{Y}$ when

$$\left[\frac{pq\delta^2}{D} + \frac{p(1-q)\delta^3}{D}\right] v(x) > \left[\frac{(1-p)q\delta}{D} + \frac{pq\delta^2}{D}\right] v(4x),$$

or

$$p\left[q\delta + (1-q)\delta^2\right] v(x) > q\left[(1-p) + p\delta\right] v(4x),$$

or

$$\frac{p\delta\left[q + (1-q)\delta\right]}{q\left[(1-p) + p\delta\right]} > \frac{v(4x)}{v(x)},$$

or

$$\frac{p\delta\left[\frac{p}{4}+\left(1-\frac{p}{4}\right)\delta\right]}{\frac{p}{4}\left[(1-p)+p\delta\right]} > \frac{v(4x)}{v(x)},$$

or

$$\frac{\delta\left[p+(4-p)\,\delta\right]}{1-p+p\delta} > \frac{v(4x)}{v(x)}. \tag{1}$$

(ii) If the salience ranking is $\sigma(0,4x) > \sigma(x,0) > \sigma(x,4x) > \sigma(0,0)$, then

$$\begin{aligned}
V^{ST}(\tilde{X}|\{\tilde{X},\tilde{Y}\}) &= [\pi_3^{ST}(x,4x)+\pi_2^{ST}(400,0)]v(x)+[\pi_1^{ST}(0,4x)+\pi_4^{ST}(0,0)]v(0) \\
&= \left[\frac{pq\delta^3}{D}+\frac{p(1-q)\delta^2}{D}\right]v(x)+\left[\frac{(1-p)q\delta}{D}+\frac{(1-p)(1-q)\delta^4}{D}\right]v(0) \\
&= \left[\frac{pq\delta^3}{D}+\frac{p(1-q)\delta^2}{D}\right]v(x),
\end{aligned}$$

and

$$\begin{aligned}
V^{ST}(\tilde{Y}|\{\tilde{X},\tilde{Y}\}) &= [\pi_1^{ST}(0,4x)+\pi_3^{ST}(x,4x)]v(4x)+[\pi_2^{ST}(x,0)+\pi_4^{ST}(0,0)]v(0) \\
&= \left[\frac{(1-p)q\delta}{D}+\frac{pq\delta^3}{D}\right]v(4x)+\left[\frac{p(1-q)\delta^2}{D}+\frac{(1-p)(1-q)\delta^4}{D}\right]v(0) \\
&= \left[\frac{(1-p)q\delta}{D}+\frac{pq\delta^3}{D}\right]v(4x)
\end{aligned}$$

where $D=(1-p)q\delta+p(1-q)\delta^2+pq\delta^3+(1-p)(1-q)\delta^4$. The ST decision maker prefers $\tilde{X}$ to $\tilde{Y}$ when

$$\left[\frac{pq\delta^3}{D}+\frac{p(1-q)\delta^2}{D}\right]v(x) > \left[\frac{(1-p)q\delta}{D}+\frac{pq\delta^3}{D}\right]v(4x),$$

or

$$p\left[q\delta^2+(1-q)\delta\right]v(x) > q\left[(1-p)+p\delta^2\right]v(4x),$$

or

$$\frac{p\delta\left[q\delta+(1-q)\right]}{q\left[(1-p)+p\delta^2\right]} > \frac{v(4x)}{v(x)},$$

or

$$\frac{p\delta\left[\frac{p}{4}\delta+\left(1-\frac{p}{4}\right)\right]}{\frac{p}{4}\left[(1-p)+p\delta^2\right]} > \frac{v(4x)}{v(x)},$$

or

$$\frac{\delta\left[p\delta+(4-p)\right]}{1-p+p\delta^2} > \frac{v(4x)}{v(x)}. \tag{2}$$

Let us now determine the value of the certainty equivalent of lottery $\tilde{X}$. This means that now we need to find out the value of lottery $\tilde{X}$ with respect to the series of sure amounts $\{0,...,x/2,...,x\}$:

$$\tilde{X}=\begin{cases} x \text{ with } & p \\ 0 \text{ with } 1-p \end{cases} \quad \text{vs} \quad \{0,...,x/2,...,x\}.$$

Denote by $CE_{\tilde{X}}$ the certainty equivalent of lottery $\tilde{X}$. If $\sigma(x, CE_{\tilde{X}}) > \sigma(0, CE_{\tilde{X}})$, then

$$\begin{aligned} v(CE_{\tilde{X}}) &= V^{ST}(\tilde{X}|\sigma(x, CE_{\tilde{X}}) > \sigma(0, CE_{\tilde{X}})) \\ &= \pi_1^{ST}(x, CE_{\tilde{X}})v(x) + \pi_2^{ST}(0, CE_{\tilde{X}})v(0) \\ &= \frac{p\delta}{p\delta + (1-p)\delta^2}v(x) + \frac{(1-p)\delta^2}{p\delta + (1-p)\delta^2}v(0) \\ &= \frac{p\delta}{p\delta + (1-p)\delta^2}v(x) = \frac{p}{p + (1-p)\delta}v(x). \end{aligned}$$

If $\sigma(x, CE_{\tilde{X}}) = \sigma(0, CE_{\tilde{X}})$, then

$$\begin{aligned} v(CE_{\tilde{X}}) &= V^{ST}(\tilde{X}|\sigma(x, CE_{\tilde{X}}) = \sigma(0, CE_{\tilde{X}})) \\ &= \pi_1^{ST}(x, CE_{\tilde{X}})v(x) + \pi_1^{ST}(0, CE_{\tilde{X}})v(0) \\ &= \frac{p\delta}{p\delta + (1-p)\delta}v(x) + \frac{p\delta}{p\delta + (1-p)\delta}v(0) = pv(x). \end{aligned}$$

If $\sigma(x, CE_{\tilde{X}}) < \sigma(0, CE_{\tilde{X}})$, then

$$\begin{aligned} v(CE_{\tilde{X}}) &= V^{ST}(\tilde{X}|\sigma(x, CE_{\tilde{X}}) < \sigma(0, CE_{\tilde{X}})) \\ &= \pi_2^{ST}(x, CE_{\tilde{X}})v(x) + \pi_1^{ST}(0, CE_{\tilde{X}})v(0) \\ &= \frac{p\delta^2}{(1-p)\delta + p\delta^2}v(x) + \frac{(1-p)\delta}{(1-p)\delta + p\delta^2}v(0) \\ &= \frac{p\delta^2}{(1-p)\delta + p\delta^2}v(x) = \frac{p\delta}{(1-p) + p\delta}v(x). \end{aligned}$$

Hence, the value of $CE_{\tilde{X}}$ is

$$v(CE_{\tilde{X}}) = \begin{cases} \frac{p}{p+(1-p)\delta}v(x), & \text{if } \sigma(0, CE_{\tilde{X}}) < \sigma(x, CE_{\tilde{X}}) \\ pv(x), & \text{if } \sigma(0, CE_{\tilde{X}}) = \sigma(x, CE_{\tilde{X}}) \\ \frac{p\delta}{(1-p)+p\delta}v(x), & \text{if } \sigma(0, CE_{\tilde{X}}) > \sigma(x, CE_{\tilde{X}}) \end{cases}.$$

Defining as $CE_g^{\tilde{X}}$ the $CE_{\tilde{X}}$ that solves $\sigma(0, CE_{\tilde{X}}) = \sigma(x, CE_{\tilde{X}})$ we have

$$v(CE_{\tilde{X}}) = \begin{cases} \frac{p}{p+(1-p)\delta}v(x), & \text{if } p < \frac{\delta\frac{v(CE_g^{\tilde{X}})}{v(x)}}{1-(1-\delta)\frac{v(CE_g^{\tilde{X}})}{v(x)}} \\ v(CE_g^{\tilde{X}}), & \text{if } p = \frac{v(CE_g^{\tilde{X}})}{v(x)} \\ \frac{p\delta}{(1-p)+p\delta}v(x), & \text{if } p > \frac{\frac{v(CE_g^{\tilde{X}})}{v(x)}}{\delta+(1-\delta)\frac{v(CE_g^{\tilde{X}})}{v(x)}} \end{cases}. \tag{3}$$

Let us now determine the value of the certainty equivalent of lottery $\tilde{Y}$. This means that now we need to find out the value of lottery $\tilde{Y}$ with respect to the series of sure amounts $\{0, ..., 2x, ..., 4x\}$:

$$\tilde{Y} = \begin{cases} 4x \text{ with } & q = p/4 \\ 0 \text{ with } & 1 - q = 1 - p/4 \end{cases} \quad \text{vs} \quad \{0, ..., 2x, ..., 4x\}.$$

Denote by $CE_{\tilde{Y}}$ the certainty equivalent of lottery $\tilde{Y}$. If $\sigma(4x, CE_{\tilde{Y}}) > \sigma(0, CE_{\tilde{Y}})$, then

$$\begin{aligned}
v(CE_{\tilde{Y}}) &= V^{ST}(\tilde{Y}|\sigma(4x, CE_{\tilde{Y}}) > \sigma(0, CE_{\tilde{Y}})) \\
&= \pi_1^{ST}(4x, CE_{\tilde{Y}})v(4x) + \pi_2^{ST}(0, CE_{\tilde{Y}})v(0) \\
&= \frac{q\delta}{q\delta + (1-q)\delta^2}v(4x) + \frac{(1-q)\delta^2}{q\delta + (1-q)\delta^2}v(0) \\
&= \frac{q\delta}{q\delta + (1-q)\delta^2}v(4x) = \frac{q}{q + (1-q)\delta}v(4x).
\end{aligned}$$

If $\sigma(4x, CE_{\tilde{Y}}) = \sigma(0, CE_{\tilde{Y}})$, then

$$\begin{aligned}
v(CE_{\tilde{Y}}) &= V^{ST}(\tilde{Y}|CE_{\tilde{Y}} < 2x, \sigma(4x, CE_{\tilde{Y}}) = \sigma(0, CE_{\tilde{Y}})) \\
&= \pi_1^{ST}(4x, CE_{\tilde{Y}})v(4x) + \pi_1^{ST}(0, CE_{\tilde{Y}})v(0) \\
&= \frac{q\delta}{q\delta + (1-q)\delta}v(4x) + \frac{q\delta}{q\delta + (1-q)\delta}v(0) \\
&= qv(4x).
\end{aligned}$$

If $\sigma(4x, CE_{\tilde{Y}}) < \sigma(0, CE_{\tilde{Y}})$, then

$$\begin{aligned}
v(CE_{\tilde{Y}}) &= V^{ST}(\tilde{Y}|\sigma(4x, CE_{\tilde{Y}}) < \sigma(0, CE_{\tilde{Y}})) \\
&= \pi_2^{ST}(4x, CE_{\tilde{Y}})v(4x) + \pi_1^{ST}(0, CE_{\tilde{Y}})v(0) \\
&= \frac{q\delta^2}{(1-q)\delta + q\delta^2}v(4x) + \frac{(1-q)\delta}{(1-q)\delta + q\delta^2}v(0) \\
&= \frac{q\delta^2}{(1-q)\delta + q\delta^2}v(4x) = \frac{q\delta}{(1-q) + q\delta}v(4x).
\end{aligned}$$

Hence, the value of $CE_{\tilde{Y}}$ is

$$v(CE_{\tilde{Y}}) = \begin{cases} \frac{q}{q+(1-q)\delta}v(4x), & \text{if } \sigma(0, CE_{\tilde{Y}}) < \sigma(4x, CE_{\tilde{Y}}) \\ qv(4x), & \text{if } \sigma(0, CE_{\tilde{Y}}) = \sigma(4x, CE_{\tilde{Y}}) \\ \frac{q\delta}{(1-q)+q\delta}v(4x), & \text{if } \sigma(0, CE_{\tilde{Y}}) > \sigma(4x, CE_{\tilde{Y}}) \end{cases}.$$

Defining as $CE_g^{\tilde{Y}}$ the $CE_{\tilde{Y}}$ that solves $\sigma(0, CE_{\tilde{Y}}) = \sigma(4x, CE_{\tilde{Y}})$ we have

$$v(CE_{\tilde{Y}}) = \begin{cases} \frac{q}{q+(1-q)\delta}v(4x), & \text{if } q < \frac{\delta\frac{v(CE_g^{\tilde{Y}})}{v(4x)}}{1-(1-\delta)\frac{v(CE_g^{\tilde{Y}})}{v(4x)}} \\ v(CE_g^{\tilde{Y}}), & \text{if } q = \frac{v(CE_g^{\tilde{Y}})}{v(4x)} \\ \frac{q\delta}{(1-q)+q\delta}v(4x), & \text{if } q > \frac{\frac{v(CE_g^{\tilde{Y}})}{v(4x)}}{\delta+(1-\delta)\frac{v(CE_g^{\tilde{Y}})}{v(4x)}} \end{cases}.$$

Since $q = p/4$ we have

$$v(CE_{\tilde{Y}}) = \begin{cases} \frac{p}{p+(4-p)\delta} v(4x), & \text{if } \frac{p}{4} < \frac{\delta \frac{v(CE_g^{\tilde{Y}})}{v(4x)}}{1-(1-\delta)\frac{v(CE_g^{\tilde{Y}})}{v(4x)}} \\ v(CE_g^{\tilde{Y}}), & \text{if } \frac{p}{4} = \frac{v(CE_g^{\tilde{Y}})}{v(4x)} \\ \frac{p\delta}{(4-p)+p\delta} v(4x), & \text{if } \frac{p}{4} > \frac{\frac{v(CE_g^{\tilde{Y}})}{v(4x)}}{\delta+(1-\delta)\frac{v(CE_g^{\tilde{Y}})}{v(4x)}} \end{cases}. \tag{4}$$

For a preference reversal to exist the decision maker must prefer lottery $\tilde{X}$ to lottery $\tilde{Y}$ and his certainty equivalent of lottery $\tilde{Y}$ must be greater than his certainty equivalent of lottery $\tilde{X}$, that is, $v(CE_{\tilde{Y}}) > v(CE_{\tilde{X}})$. From (3) and (4) we see that, apart from the knife-hedge cases $p = v(CE_g^{\tilde{X}})/v(x)$ and $p/4 = v(CE_g^{\tilde{Y}})/v(4x)$, we can have $v(CE_{\tilde{Y}}) > v(CE_{\tilde{X}})$ when either

$$p < \frac{\delta \frac{v(CE_g^{\tilde{X}})}{v(x)}}{1-(1-\delta)\frac{v(CE_g^{\tilde{X}})}{v(x)}} \text{ and } \frac{p}{4} < \frac{\delta \frac{v(CE_g^{\tilde{Y}})}{v(4x)}}{1-(1-\delta)\frac{v(CE_g^{\tilde{Y}})}{v(4x)}}, \tag{5}$$

or

$$p > \frac{\frac{v(CE_g^{\tilde{X}})}{v(x)}}{\delta+(1-\delta)\frac{v(CE_g^{\tilde{X}})}{v(x)}} \text{ and } \frac{p}{4} < \frac{\delta \frac{v(CE_g^{\tilde{Y}})}{v(4x)}}{1-(1-\delta)\frac{v(CE_g^{\tilde{Y}})}{v(4x)}}. \tag{6}$$

From (1), (3), and (4), a preference reversal exists when (5) holds and when the salience ranking is (i) $\sigma(0,4x) > \sigma(x,4x) > \sigma(x,0) > \sigma(0,0)$ if and only if

$$\frac{\delta\left[p+(4-p)\,\delta\right]}{1-p+p\delta} > \frac{v(4x)}{v(x)} > \frac{\frac{p}{p+(1-p)\delta}}{\frac{p}{p+(4-p)\delta}} = \frac{p+(4-p)\delta}{p+(1-p)\delta}.$$

In this case a preference reversal does not exist since the term on the LHS, $\frac{\delta[p+(4-p)\delta]}{1-p+p\delta}$, is smaller than the term on the RHS, $\frac{p+(4-p)\delta}{p+(1-p)\delta}$. From (2), (3), and (4), a preference reversal exists when (5) holds and when the salience ranking is (ii) $\sigma(0,4x) > \sigma(x,0) > \sigma(x,4x) > \sigma(0,0)$ if and only if

$$\frac{\delta\left[p\delta+(4-p)\right]}{1-p+p\delta^2} > \frac{v(4x)}{v(x)} > \frac{\frac{p}{p+(1-p)\delta}}{\frac{p}{p+(4-p)\delta}} = \frac{p+(4-p)\delta}{p+(1-p)\delta}.$$

In this case a preference reversal exists when the term on the LHS is greater than the term on the RHS. From (1), (3), and (4) a preference reversal exists when (6) holds and when the salience ranking is (i) $\sigma(0,4x) > \sigma(x,4x) > \sigma(x,0) > \sigma(0,0)$ if and only if

$$\frac{\delta\left[p+(4-p)\,\delta\right]}{1-p+p\delta} > \frac{v(4x)}{v(x)} > \frac{\frac{p\delta}{(1-p)+p\delta}}{\frac{p}{p+(4-p)\delta}} = \frac{\delta\left[p+(4-p)\delta\right]}{1-p+p\delta}.$$

In this case a preference reversal does not exist since the term on the LHS is equal to the term on the RHS. From (2), (3), and (4), a preference reversal exists when (6) holds and when the salience ranking is (ii) $\sigma(0,4x) > \sigma(x,0) > \sigma(x,4x) > \sigma(0,0)$ if and only if

$$\frac{\delta\left[p\delta + (4-p)\right]}{1-p+p\delta^2} > \frac{v(4x)}{v(x)} > \frac{\frac{p\delta}{(1-p)+p\delta}}{\frac{p}{p+(4-p)\delta}} = \frac{\delta\left[p + (4-p)\delta\right]}{1-p+p\delta}.$$

In this case a preference reversal exists since the term on the LHS is always greater than the term on the RHS.

2.2 Choice 3

The binary lottery choice 3 is as follows:

$$\tilde{X} = \begin{cases} x \text{ with } & p \\ 0 \text{ with } 1-p \end{cases} \quad \text{vs.} \quad \tilde{Y} = \begin{cases} 16x \text{ with } & q = p/16 \\ 0 \text{ with } & 1-q = 1-p/16 \end{cases},$$

where $x = 400$ and $p = 0.96$. In this case we can have two possible salience rankings:

(i) $\sigma(0,16x) > \sigma(x,16x) > \sigma(x,0) > \sigma(0,0)$

(ii) $\sigma(0,16x) > \sigma(x,0) > \sigma(x,16x) > \sigma(0,0)$

We consider each case separately.

(i) If the salience ranking is $\sigma(0,16x) > \sigma(x,16x) > \sigma(x,0) > \sigma(0,0)$, then

$$\begin{aligned} V^{ST}(\tilde{X}|\{\tilde{X},\tilde{Y}\}) &= [\pi_2^{ST}(x,16x) + \pi_3^{ST}(x,0)]v(x) + [\pi_1^{ST}(0,16x) + \pi_4^{ST}(0,0)]v(0) \\ &= \left[\frac{pq\delta^2}{D} + \frac{p(1-q)\delta^3}{D}\right]v(x) + \left[\frac{(1-p)q\delta}{D} + \frac{(1-p)(1-q)\delta^4}{D}\right]v(0) \\ &= \left[\frac{pq\delta^2}{D} + \frac{p(1-q)\delta^3}{D}\right]v(x), \end{aligned}$$

and

$$\begin{aligned} V^{ST}(\tilde{Y}|\{\tilde{X},\tilde{Y}\}) &= [\pi_1^{ST}(0,16x) + \pi_2^{ST}(x,16x)]v(16x) + [\pi_3^{ST}(x,0) + \pi_4^{ST}(0,0)]v(0) \\ &= \left[\frac{(1-p)q\delta}{D} + \frac{pq\delta^2}{D}\right]v(16x) + \left[\frac{p(1-q)\delta^3}{D} + \frac{(1-p)(1-q)\delta^4}{D}\right]v(0) \\ &= \left[\frac{(1-p)q\delta}{D} + \frac{pq\delta^2}{D}\right]v(16x) \end{aligned}$$

where $D = (1-p)q\delta + pq\delta^2 + p(1-q)\delta^3 + (1-p)(1-q)\delta^4$. The ST decision maker prefers $\tilde{X}$ to $\tilde{Y}$ when

$$\left[\frac{pq\delta^2}{D} + \frac{p(1-q)\delta^3}{D}\right]v(x) > \left[\frac{(1-p)q\delta}{D} + \frac{pq\delta^2}{D}\right]v(16x)$$

or

$$\left[pq\delta + p(1-q)\delta^2\right]v(x) > \left[(1-p)q + pq\delta\right]v(16x)$$

or

$$p\delta\left[q+(1-q)\delta\right]v(x)>q\left[(1-p)+p\delta\right]v(16x)$$

or

$$\frac{p\delta\left[q+(1-q)\delta\right]}{q\left[(1-p)+p\delta\right]}>\frac{v(16x)}{v(x)},$$

or

$$\frac{p\delta\left[\frac{p}{16}+(1-\frac{p}{16})\delta\right]}{\frac{p}{16}\left[(1-p)+p\delta\right]}>\frac{v(16x)}{v(x)},$$

or

$$\frac{\delta\left[p+(16-p)\delta\right]}{1-p+p\delta}>\frac{v(16x)}{v(x)}. \tag{7}$$

(ii) If the salience ranking is $\sigma(0,16x)>\sigma(x,0)>\sigma(x,16x)>\sigma(0,0)$, then

$$\begin{aligned}
V^{ST}(\tilde{X}|\{\tilde{X},\tilde{Y}\}) &= [\pi_3^{ST}(x,16x)+\pi_2^{ST}(x,0)]v(x)+[\pi_1^{ST}(0,16x)+\pi_4^{ST}(0,0)]v(0)\\
&= \left[\frac{pq\delta^3}{D}+\frac{p(1-q)\delta^2}{D}\right]v(x)+\left[\frac{(1-p)q\delta}{D}+\frac{(1-p)(1-q)\delta^4}{D}\right]v(0)\\
&= \left[\frac{pq\delta^3}{D}+\frac{p(1-q)\delta^2}{D}\right]v(x),
\end{aligned}$$

and

$$\begin{aligned}
V^{ST}(\tilde{Y}|\{\tilde{X},\tilde{Y}\}) &= [\pi_1^{ST}(0,16x)+\pi_3^{ST}(x,16x)]v(16x)+[\pi_2^{ST}(x,0)+\pi_4^{ST}(0,0)]v(0)\\
&= \left[\frac{(1-p)q\delta}{D}+\frac{pq\delta^3}{D}\right]v(16x)+\left[\frac{p(1-q)\delta^2}{D}+\frac{(1-p)(1-q)\delta^4}{D}\right]v(0)\\
&= \left[\frac{(1-p)q\delta}{D}+\frac{pq\delta^3}{D}\right]v(16x)
\end{aligned}$$

where $D=(1-p)q\delta+p(1-q)\delta^2+pq\delta^3+(1-p)(1-q)\delta^4$. The ST decision maker prefers $\tilde{X}$ to $\tilde{Y}$ when

$$\left[\frac{pq\delta^3}{D}+\frac{p(1-q)\delta^2}{D}\right]v(x)>\left[\frac{(1-p)q\delta}{D}+\frac{pq\delta^3}{D}\right]v(16x),$$

or

$$p\delta\left[q\delta+(1-q)\right]v(x)>q\left[(1-p)+p\delta^2\right]v(16x),$$

or

$$\frac{p\delta\left[q\delta+(1-q)\right]}{q\left[(1-p)+p\delta^2\right]}>\frac{v(16x)}{v(x)},$$

or

$$\frac{p\delta\left[\frac{p}{16}\delta+(1-\frac{p}{16})\right]}{\frac{p}{16}\left[(1-p)+p\delta^2\right]}>\frac{v(16x)}{v(x)},$$

or

$$\frac{\delta\left[p\delta+(16-p)\right]}{1-p+p\delta^2}>\frac{v(16x)}{v(x)}. \tag{8}$$

The value of the certainty equivalent of lottery $\tilde{X}$ is given by (3). Let us now determine the value of the certainty equivalent of lottery $\tilde{Y}$. This means that we need to find out the value of lottery $\tilde{Y}$ with respect to the series of sure amounts $\{0, ..., 8x, ..., 16x\}$:

$$\tilde{Y} = \begin{cases} 16x \text{ with } & q = p/16 \\ 0 \text{ with } & 1-q = 1-p/16 \end{cases} \quad \text{vs} \quad \{0, ..., 8x, ..., 16x\}$$

If $\sigma(16x, CE_{\tilde{Y}}) > \sigma(0, CE_{\tilde{Y}})$, then

$$\begin{aligned} v(CE_{\tilde{Y}}) &= V^{ST}(\tilde{Y}|\sigma(16x, CE_{\tilde{Y}}) > \sigma(0, CE_{\tilde{Y}})) \\ &= \pi_1^{ST}(16x, CE_{\tilde{Y}})v(16x) + \pi_2^{ST}(0, CE_{\tilde{Y}})v(0) \\ &= \frac{q\delta}{q\delta + (1-q)\delta^2}v(16x) + \frac{(1-q)\delta^2}{q\delta + (1-q)\delta^2}v(0) \\ &= \frac{q\delta}{q\delta + (1-q)\delta^2}v(16x) = \frac{q}{q + (1-q)\delta}v(16x). \end{aligned}$$

If $\sigma(16x, CE_{\tilde{Y}}) = \sigma(0, CE_{\tilde{Y}})$, then

$$\begin{aligned} v(CE_{\tilde{Y}}) &= V^{ST}(\tilde{Y}|\sigma(16x, CE_{\tilde{Y}}) = \sigma(0, CE_{\tilde{Y}})) \\ &= \pi_1^{ST}(16x, CE_{\tilde{Y}})v(16x) + \pi_1^{ST}(0, CE_{\tilde{Y}})v(0) \\ &= \frac{q\delta}{q\delta + (1-q)\delta}v(16x) + \frac{q\delta}{q\delta + (1-q)\delta}v(0) = qv(16x). \end{aligned}$$

If $\sigma(16x, CE_{\tilde{Y}}) < \sigma(0, CE_{\tilde{Y}})$, then

$$\begin{aligned} v(CE_{\tilde{Y}}) &= V^{ST}(\tilde{Y}|\sigma(16x, CE_{\tilde{Y}}) > \sigma(0, CE_{\tilde{Y}})) \\ &= \pi_2^{ST}(16x, CE_{\tilde{Y}})v(16x) + \pi_1^{ST}(0, CE_{\tilde{Y}})v(0) \\ &= \frac{q\delta^2}{(1-q)\delta + q\delta^2}v(16x) + \frac{(1-q)\delta}{(1-q)\delta + q\delta^2}v(0) \\ &= \frac{q\delta^2}{(1-q)\delta + q\delta^2}v(16x) = \frac{q\delta}{(1-q) + q\delta}v(16x). \end{aligned}$$

Hence, the value of $CE_{\tilde{Y}}$ is

$$v(CE_{\tilde{Y}}) = \begin{cases} \frac{q}{q+(1-q)\delta}v(16x), & \text{if } \sigma(0, CE_{\tilde{Y}}) < \sigma(16x, CE_{\tilde{Y}}) \\ qv(16x), & \text{if } \sigma(0, CE_{\tilde{Y}}) = \sigma(16x, CE_{\tilde{Y}}) \\ \frac{q\delta}{(1-q)+q\delta}v(16x), & \text{if } \sigma(0, CE_{\tilde{Y}}) > \sigma(16x, CE_{\tilde{Y}}) \end{cases}.$$

Defining as $CE_g^{\tilde{Y}}$ the $CE_{\tilde{Y}}$ that solves $\sigma(0, CE_{\tilde{Y}}) = \sigma(16x, CE_{\tilde{Y}})$ we have

$$v(CE_{\tilde{Y}}) = \begin{cases} \frac{q}{q+(1-q)\delta}v(16x), & \text{if } q < \frac{\delta\frac{v(CE_g^{\tilde{Y}})}{v(16x)}}{1-(1-\delta)\frac{v(CE_g^{\tilde{Y}})}{v(16x)}} \\ v(CE_g^{\tilde{Y}}), & \text{if } q = \frac{v(CE_g^{\tilde{Y}})}{v(16x)} \\ \frac{q\delta}{(1-q)+q\delta}v(16x), & \text{if } q > \frac{\frac{v(CE_g^{\tilde{Y}})}{v(16x)}}{\delta+(1-\delta)\frac{v(CE_g^{\tilde{Y}})}{v(16x)}} \end{cases}.$$

Since $q = p/16$ we have

$$v(CE_{\tilde{Y}}) = \begin{cases} \frac{p}{p+(16-p)\delta} v(16x), & \text{if } \frac{p}{16} < \frac{\delta \frac{v(CE_g^{\tilde{Y}})}{v(16x)}}{1-(1-\delta)\frac{v(CE_g^{\tilde{Y}})}{v(16x)}} \\ v(CE_g^{\tilde{Y}}), & \text{if } \frac{p}{16} = \frac{v(CE_g^{\tilde{Y}})}{v(16x)} \\ \frac{p\delta}{(16-p)+p\delta} v(16x), & \text{if } \frac{p}{16} > \frac{\frac{v(CE_g^{\tilde{Y}})}{v(16x)}}{\delta+(1-\delta)\frac{v(CE_g^{\tilde{Y}})}{v(16x)}} \end{cases}. \tag{9}$$

For a preference reversal to exist the decision maker must prefer lottery $\tilde{X}$ to lottery $\tilde{Y}$ and his certainty equivalent of lottery $\tilde{Y}$ must be greater than his certainty equivalent of lottery $\tilde{X}$, that is, $v(CE_{\tilde{Y}}) > v(CE_{\tilde{X}})$. From (3) and (9) we see that, apart from the knife-hedge cases $p = v(CE_g^{\tilde{X}})/v(x)$ and $p/16 = v(CE_g^{\tilde{Y}})/v(16x)$, we can have $v(CE_{\tilde{Y}}) > v(CE_{\tilde{X}})$ when either

$$p < \frac{\delta \frac{v(CE_g^{\tilde{X}})}{v(x)}}{1-(1-\delta)\frac{v(CE_g^{\tilde{X}})}{v(x)}} \text{ and } \frac{p}{16} < \frac{\delta \frac{v(CE_g^{\tilde{Y}})}{v(16x)}}{1-(1-\delta)\frac{v(CE_g^{\tilde{Y}})}{v(16x)}}, \tag{10}$$

or

$$p > \frac{\frac{v(CE_g^{\tilde{X}})}{v(x)}}{\delta+(1-\delta)\frac{v(CE_g^{\tilde{X}})}{v(x)}} \text{ and } \frac{p}{16} < \frac{\delta \frac{v(CE_g^{\tilde{Y}})}{v(16x)}}{1-(1-\delta)\frac{v(CE_g^{\tilde{Y}})}{v(16x)}}. \tag{11}$$

From (7), (3), and (9), a preference reversal exists when (10) holds and when the salience ranking is (i) $\sigma(0,16x) > \sigma(x,16x) > \sigma(x,0) > \sigma(0,0)$ if and only if

$$\frac{\delta\left[p+(16-p)\delta\right]}{1-p+p\delta} > \frac{v(16x)}{v(x)} > \frac{\frac{p}{p+(1-p)\delta}}{\frac{p}{p+(16-p)\delta}} = \frac{p+(16-p)\delta}{p+(1-p)\delta}.$$

In this case a preference reversal does not exist since the term on the LHS, $\frac{\delta[p+(16-p)\delta]}{1-p+p\delta}$, is smaller than the term on the RHS, $\frac{p+(16-p)\delta}{p+(1-p)\delta}$. From (8), (3), and (9), a preference reversal exists when (10) holds and when the salience ranking is (ii) $\sigma(0,16x) > \sigma(x,0) > \sigma(x,16x) > \sigma(0,0)$ if and only if

$$\frac{\delta\left[p\delta+(16-p)\right]}{1-p+p\delta^2} > \frac{v(16x)}{v(x)} > \frac{\frac{p}{p+(1-p)\delta}}{\frac{p}{p+(16-p)\delta}} = \frac{p+(16-p)\delta}{p+(1-p)\delta}.$$

In this case a preference reversal exists when the term on the LHS is greater than the term on the RHS. From (7), (3), and (9) a preference reversal exists when (11) holds and when the salience ranking is (i) $\sigma(0,16x) > \sigma(x,16x) > \sigma(x,0) > \sigma(0,0)$ if and only if

$$\frac{\delta\left[p+(16-p)\delta\right]}{1-p+p\delta} > \frac{v(16x)}{v(x)} > \frac{\frac{p\delta}{(1-p)+p\delta}}{\frac{p}{p+(16-p)\delta}} = \frac{\delta\left[p+(16-p)\delta\right]}{1-p+p\delta}.$$

In this case a preference reversal does not exist since the term on the LHS is equal to the term on the RHS. From (8), (3), and (9), a preference reversal exists when (11) holds and when the salience ranking is (ii) $\sigma(0,16x) > \sigma(x,0) > \sigma(x,16x) > \sigma(0,0)$ if and only if

$$\frac{\delta\left[p\delta + (16-p)\right]}{1-p+p\delta^2} > \frac{v(16x)}{v(x)} > \frac{\frac{p\delta}{(1-p)+p\delta}}{\frac{p}{p+(16-p)\delta}} = \frac{\delta\left[p + (16-p)\delta\right]}{1-p+p\delta}.$$

In this case a preference reversal exists since the term on the LHS is always greater than the term on the RHS.

2.3 Choices 4, 5, and 6

The binary lottery choices 4, 5, and 6 are as follows:

$$\tilde{X} = \begin{cases} x \text{ with prob. } & p \\ 0 \text{ with prob. } & 1-p \end{cases} \quad \text{vs.} \quad \tilde{Y} = \begin{cases} 2x \text{ with prob. } & q = p/2 \\ 0 \text{ with prob. } & 1-q = 1-p/2 \end{cases},$$

where $x = 3000$, $p = 0.9$ for choice 4, $p = 0.8$ for choice 5, and $p = 0.7$ for choice 6. The salience ranking is:

$$\sigma(0,2x) > \sigma(x,0) > \sigma(x,2x) > \sigma(0,0).$$

Hence, we have

$$\begin{aligned} V^{ST}(\tilde{X}|\{\tilde{X},\tilde{Y}\}) &= [\pi_3^{ST}(x,2x) + \pi_2^{ST}(x,0)]v(x) + [\pi_1^{ST}(0,2x) + \pi_4^{ST}(0,0)]v(0) \\ &= \left[\frac{pq\delta^3}{D} + \frac{p(1-q)\delta^2}{D}\right]v(x) + \left[\frac{(1-p)q\delta}{D} + \frac{(1-p)(1-q)\delta^4}{D}\right]v(0) \\ &= \left[\frac{pq\delta^3}{D} + \frac{p(1-q)\delta^2}{D}\right]v(x), \end{aligned}$$

and

$$\begin{aligned} V^{ST}(\tilde{Y}|\{\tilde{X},\tilde{Y}\}) &= [\pi_1^{ST}(0,2x) + \pi_3^{ST}(x,2x)]v(2x) + [\pi_2^{ST}(x,0) + \pi_4^{ST}(0,0)]v(0) \\ &= \left[\frac{(1-p)q\delta}{D} + \frac{pq\delta^3}{D}\right]v(2x) + \left[\frac{p(1-q)\delta^2}{D} + \frac{(1-p)(1-q)\delta^4}{D}\right]v(0) \\ &= \left[\frac{(1-p)q\delta}{D} + \frac{pq\delta^3}{D}\right]v(2x) \end{aligned}$$

where $D = (1-p)q\delta + p(1-q)\delta^2 + pq\delta^3 + (1-p)(1-q)\delta^4$. The ST decision maker prefers $\tilde{X}$ to $\tilde{Y}$ when

$$\left[\frac{pq\delta^3}{D} + \frac{p(1-q)\delta^2}{D}\right]v(x) > \left[\frac{(1-p)q\delta}{D} + \frac{pq\delta^3}{D}\right]v(2x),$$

or

$$p\left[q\delta^2 + (1-q)\delta\right]v(x) > q\left[(1-p) + p\delta^2\right]v(2x),$$

or

$$\frac{p\delta\left[q\delta+(1-q)\right]}{q\left[(1-p)+p\delta^2\right]} > \frac{v(2x)}{v(x)},$$

or

$$\frac{p\delta\left[\frac{p}{2}\delta+\left(1-\frac{p}{2}\right)\right]}{\frac{p}{2}\left[(1-p)+p\delta^2\right]} > \frac{v(2x)}{v(x)},$$

or

$$\frac{\delta\left[(2-p)+p\delta\right]}{(1-p)+p\delta^2} > \frac{v(2x)}{v(x)}. \tag{12}$$

The value of the certainty equivalent of lottery $\tilde{X}$ is given by (3). Let us now determine the value of the certainty equivalent of lottery $\tilde{Y}$. This means that we need to find out the value of lottery $\tilde{Y}$ with respect to the series of sure amounts $\{0, ..., x, ..., 2x\}$:

$$\tilde{Y} = \begin{cases} 2x \text{ with } & q = p/2 \\ 0 \text{ with } & 1-q = 1-p/2 \end{cases} \quad \text{vs} \quad \{0, ..., x, ..., 2x\}$$

If $\sigma(2x, CE_{\tilde{Y}}) < \sigma(0, CE_{\tilde{Y}})$, then

$$\begin{aligned} v(CE_{\tilde{Y}}) &= V^{ST}(\tilde{Y}|\sigma(2x, CE_{\tilde{Y}}) < \sigma(0, CE_{\tilde{Y}})) \\ &= \pi_2^{ST}(2x, CE_{\tilde{Y}})v(2x) + \pi_1^{ST}(0, CE_{\tilde{Y}})v(0) \\ &= \frac{q\delta^2}{(1-q)\delta+q\delta^2}v(2x) + \frac{(1-q)\delta}{(1-q)\delta+q\delta^2}v(0) \\ &= \frac{q\delta^2}{(1-q)\delta+q\delta^2}v(2x) = \frac{q\delta}{(1-q)+q\delta}v(2x). \end{aligned}$$

If $\sigma(2x, CE_{\tilde{Y}}) > \sigma(0, CE_{\tilde{Y}})$, then

$$\begin{aligned} v(CE_{\tilde{Y}}) &= V^{ST}(\tilde{Y}|\sigma(2x, CE_{\tilde{Y}}) > \sigma(0, CE_{\tilde{Y}})) \\ &= \pi_1^{ST}(2x, CE_{\tilde{Y}})v(2x) + \pi_2^{ST}(0, CE_{\tilde{Y}})v(0) \\ &= \frac{q\delta}{q\delta+(1-q)\delta^2}v(2x) + \frac{(1-q)\delta^2}{q\delta+(1-q)\delta^2}v(0) \\ &= \frac{q\delta}{q\delta+(1-q)\delta^2}v(2x) = \frac{q}{q+(1-q)\delta}v(2x). \end{aligned}$$

If $\sigma(2x, CE_{\tilde{Y}}) = \sigma(0, CE_{\tilde{Y}})$, then

$$\begin{aligned} v(CE_{\tilde{Y}}) &= V^{ST}(\tilde{Y}|\sigma(2x, CE_{\tilde{Y}}) = \sigma(0, CE_{\tilde{Y}})) \\ &= \pi_1^{ST}(2x, CE_{\tilde{Y}})v(2x) + \pi_1^{ST}(0, CE_{\tilde{Y}})v(0) \\ &= \frac{q\delta}{q\delta+(1-q)\delta}v(2x) + \frac{q\delta}{q\delta+(1-q)\delta}v(0) = qv(2x). \end{aligned}$$

Hence, the value of $CE_{\tilde{Y}}$ is

$$v(CE_{\tilde{Y}}) = \begin{cases} \frac{q}{q+(1-q)\delta} v(2x), & \text{if } \sigma(0, CE_{\tilde{Y}}) < \sigma(2x, CE_{\tilde{Y}}) \\ qv(2x), & \text{if } \sigma(0, CE_{\tilde{Y}}) = \sigma(2x, CE_{\tilde{Y}}) \\ \frac{q\delta}{(1-q)+q\delta} v(2x), & \text{if } \sigma(0, CE_{\tilde{Y}}) > \sigma(2x, CE_{\tilde{Y}}) \end{cases}.$$

Defining as $CE_g^{\tilde{Y}}$ the $CE_{\tilde{Y}}$ that solves $\sigma(0, CE_{\tilde{Y}}) = \sigma(2x, CE_{\tilde{Y}})$ we have

$$v(CE_{\tilde{Y}}) = \begin{cases} \frac{q}{q+(1-q)\delta} v(2x), & \text{if } q < \frac{\delta \frac{v(CE_g^{\tilde{Y}})}{v(2x)}}{1-(1-\delta)\frac{v(CE_g^{\tilde{Y}})}{v(2x)}} \\ v(CE_g^{\tilde{Y}}), & \text{if } q = \frac{v(CE_g^{\tilde{Y}})}{v(2x)} \\ \frac{q\delta}{(1-q)+q\delta} v(2x), & \text{if } q > \frac{\frac{v(CE_g^{\tilde{Y}})}{v(2x)}}{\delta+(1-\delta)\frac{v(CE_g^{\tilde{Y}})}{v(2x)}} \end{cases}.$$

Since $q = p/2$ we have

$$v(CE_{\tilde{Y}}) = \begin{cases} \frac{p}{p+(2-p)\delta} v(2x), & \text{if } \frac{p}{2} < \frac{\delta \frac{v(CE_g^{\tilde{Y}})}{v(2x)}}{1-(1-\delta)\frac{v(CE_g^{\tilde{Y}})}{v(2x)}} \\ v(CE_g^{\tilde{Y}}), & \text{if } \frac{p}{2} = \frac{v(CE_g^{\tilde{Y}})}{v(2x)} \\ \frac{p\delta}{(2-p)+p\delta} v(2x), & \text{if } \frac{p}{2} > \frac{\frac{v(CE_g^{\tilde{Y}})}{v(2x)}}{\delta+(1-\delta)\frac{v(CE_g^{\tilde{Y}})}{v(2x)}} \end{cases}. \tag{13}$$

For a preference reversal to exist the decision maker must prefer lottery $\tilde{X}$ to lottery $\tilde{Y}$ and his certainty equivalent of lottery $\tilde{Y}$ must be greater than his certainty equivalent of lottery $\tilde{X}$, that is, $v(CE_{\tilde{Y}}) > v(CE_{\tilde{X}})$. From (3) and (13) we see that, apart from the knife-hedge cases $p = v(CE_g^{\tilde{X}})/v(x)$ and $p/2 = v(CE_g^{\tilde{Y}})/v(2x)$, we can have $v(CE_{\tilde{Y}}) > v(CE_{\tilde{X}})$ when either

$$p < \frac{\delta \frac{v(CE_g^{\tilde{X}})}{v(x)}}{1-(1-\delta)\frac{v(CE_g^{\tilde{X}})}{v(x)}} \text{ and } \frac{p}{2} < \frac{\delta \frac{v(CE_g^{\tilde{Y}})}{v(2x)}}{1-(1-\delta)\frac{v(CE_g^{\tilde{Y}})}{v(2x)}}, \tag{14}$$

or

$$p > \frac{\frac{v(CE_g^{\tilde{X}})}{v(x)}}{\delta+(1-\delta)\frac{v(CE_g^{\tilde{X}})}{v(x)}} \text{ and } \frac{p}{2} < \frac{\delta \frac{v(CE_g^{\tilde{Y}})}{v(2x)}}{1-(1-\delta)\frac{v(CE_g^{\tilde{Y}})}{v(2x)}}. \tag{15}$$

From (12), (3), and (13), a preference reversal exists when (14) holds if and only if

$$\frac{\delta\left[p\delta + (2-p)\right]}{1-p+p\delta^2} > \frac{v(2x)}{v(x)} > \frac{\frac{p}{p+(1-p)\delta}}{\frac{p}{p+(2-p)\delta}} = \frac{p+(2-p)\delta}{p+(1-p)\delta}.$$

In this case a preference reversal exists when the term on the LHS is greater than the term on the RHS. From (12), (3), and (13), a preference reversal exists when (15) holds if and only if

$$\frac{\delta\left[p\delta + (2-p)\right]}{1-p+p\delta^2} > \frac{v(2x)}{v(x)} > \frac{\frac{p\delta}{(1-p)+p\delta}}{\frac{p}{p+(2-p)\delta}} = \frac{\delta\left[p+(2-p)\delta\right]}{1-p+p\delta}.$$

In this case a preference reversal exists since the term on the LHS is always greater than the term on the RHS.

3 Relationship between Type-Membership and Individual Characteristics

This section shows the results of a multinomial logit regression investigating the relationship between the subjects' type-membership and their individual characteristics. The dependent variable is an indicator for the subjects' type-membership – EUT, CPT, or ST – which follows form equation (7) in the paper. The independent variables comprise the subjects' gender, cognitive ability score based on 12 Raven's matrices, scores in the five main categories of the Big 5 personality questionnaire, and average decision time. The basis category is membership in the EUT-type. Two subjects are missing as they did not complete the Big 5 personality questionnaire.

Online Table 1 shows the results. All characteristics are insignificant, both when tested individually and jointly. Hence there is no correlation between the subjects' type-membership and their individual characteristics.

This null result may be surprising at first glance – in particular, the fact that cognitive ability is not correlated with individual type-membership. We may hypothesize that ST-types have lower cognitive ability than the other types since they are local thinkers unable to take all possible states of the world into account. However, the following argument weakens this hypothesis. Cognitive ability is measured with 12 Raven's matrices which require subjects to recognize repeated patterns that stand out. Hence, ST-types who overweight salient states where the payoffs stand out relative to other states may not have a disadvantage in this test at all.

Online Table 1: Multinomial Logit of Type-Membership and Individual Characteristics

Individual characteristic	CPT	ST
Female	0.203	-0.020
	(0.346)	(0.362)
Cognitive ability score	0.090	-0.028
	(0.075)	(0.074)
Big 5: Extraversion	-0.005	-0.021
	(0.042)	(0.044)
Big 5: Agreeableness	0.077	0.064
	(0.054)	(0.056)
Big 5: Conscenciousness	0.015	0.035
	(0.049)	(0.051)
Big 5: Neuroticism	-0.038	0.005
	(0.037)	(0.039)
Big 5: Openness	-0.016	-0.105
	(0.036)	(0.037)
Average Decision Time (in seconds)	-0.000	0.000
	(0.000)	(0.000)
Constant	-0.606	1.410
	(1.523)	(1.554)
Number of subjects/observations	281	
Log Likelihood	-296.09	
P-values of joint tests		
H_0 : all coefficients = 0	0.205	
H_0 : all type-specific coefficients = 0	0.722	0.201
H_0 : all Big 5 coefficients = 0	0.642	0.067

2 of the 283 subjects are missing as they did not complete the Big 5 personality questionnaire.

4 Monte Carlo Simulations

This section presents a series of Monte Carlo Simulations. They allow us to assess (i) the structural model's power to discriminate between the three preference types and (ii) its robustness against potential serial correlations in the error term.

4.1 General Set-up

All Monte Carlo Simulations share an identical general set-up. First, we define the true number of subjects in each type, N_{EUT}, N_{CPT}, and N_{ST}, and the vector

$$\Psi = (\theta_{EUT}, \theta_{CPT}, \theta_{ST}, \sigma_{EUT}, \sigma_{CPT}, \sigma_{ST}, \pi_{EUT}, \pi_{CPT})$$

which contains the true preference parameters, choice sensitivities, and relative sizes for each type. We use these true parameters to simulate the subjects' choices. The types' relative sizes π_M follow from the true number of subjects in each type.

After defining the number of subjects in each type and the vector of true parameters, we conduct $R = 1,000$ simulation runs. Each simulation run r consists of two steps.

1. We simulate the choices of all $N = N_{EUT} + N_{CPT} + N_{ST}$ subjects in the main part of the experiment (see Section 3.1 of the paper) based on the true type-specific parameters Ψ and the random utility model presented in Section 5.1 of the paper. To represent the experiment as closely as possible, we simulate that in each type, one half of the subjects is exposed to the 87 choices in the canonical presentation while the other half is exposed to the 78 choices in the states of the world presentation.

   As in the experiment, the order in which the simulated subjects make their choices is randomized. Simulating this random order is important, as we also intend to assess the extent to which serial correlation in the random errors errors across choices can bias our results. Thus, the simulated random errors in a subject's utility follow an AR(1) process across choices with serial correlation ρ and type-1-extreme-value-distributed innovations. The simulations in Section 4.2 use independent errors ($\rho = 0$) as assumed by the structural model. However, the simulations in Section 4.4 use serially correlated errors ($\rho > 0$) to test whether the structural model is robust against this type of misspecification.

2. We try to recover the true parameters by estimating the structural model on the simulated choices. This yields a vector of estimated parameters $\hat{\Psi}^{(r)}$ for each simulation run r.

   Moreover, we classify the subjects into types according to their behavior and the model's estimated parameters by using the individual ex-post probabilities of type-membership $\tau_{i,M}^{(r)}$ (see equation (7) in the paper). This yields the fraction of correctly classified subjects, $f_{correct,M}^{(r)}$, in each type.

After finishing all R simulation runs, we compare the true and the estimated parameters to assess the potential bias and the overall accuracy of our estimators. The bias in the estimator of the j-th parameter,

$$Bias(\hat{\Psi}_j) = \frac{1}{R}\sum_{r=1}^{R} \hat{\Psi}_j^{(r)} - \Psi_j \,,$$

indicates whether, on average, we can recover the true parameter, or whether the estimated parameter systematically deviates from the true value. The overall accuracy of the estimator is given by its Mean Squared Error (MSE),

$$MSE(\hat{\Psi}_j) = Bias(\hat{\Psi}_j)^2 + Var(\hat{\Psi}_j) = \frac{1}{R}\sum_{r=1}^{R} \left(\hat{\Psi}_j^{(r)} - \Psi_j\right)^2 ,$$

and corresponds to the sum of the estimator's squared bias plus its variance - an inverse measure for its precision. A MSE close to zero indicates great overall accuracy, while a large MSE indicates a low overall accuracy due to a bias in the estimator and/or a high variance. Considering the overall accuracy and not just bias is relevant, as a biased estimator with a relatively low variance may be overall more accurate than an unbiased estimator with a relatively high variance.

We also assess how well the structural model performs at classifying subjects into types. To do so, we calculate the average fraction of correctly classified subjects,

$$f_{correct,M} = \frac{1}{R}\sum_{r=1}^{R} f_{correct,M}^{(r)} \,,$$

for each type.

4.2 Discriminatory Power

This section discusses the set-up and the results of four Monte Carlo Simulations to assess the structural model's power to discriminate between the three preference types in the choices of our experiment.

4.2.1 Set-up

Online Table 2 shows the types' sizes and the true parameters in the four simulations.

- In simulations S1 to S3, the simulated types are increasingly difficult to discriminate. Each of the simulated types consists of 80 subjects who exhibit the same mildly concave utility function ($\beta = 0.2$) and low choice sensitivity ($\rho = 0.3$). The only systematic differences between the simulated types lie in the CPT-type's degree of likelihood sensitivity (α) and the ST-type's degree of local thinking (δ). However, these differences decrease from S1 to S3, making the types increasingly difficult to discriminate. From S1 to S3, the CPT-type gets increasingly similar to the EUT-type as its degree of likelihood sensitivity increases in three equally sized steps from $\alpha = 0.4$ to $\alpha = 0.8$. Similarly, the ST-type also gets increasingly similar to the EUT-types as its degree of local thinking increases in three equally sized steps from $\delta = 0.5$ to $\delta = 0.9$. Consequently, simulations S1 to S3 allow us to assess the structural model's power at discriminating the types in our experiment when this task becomes increasingly difficult.

- In simulation S4, the simulated types are very similar to the ones uncovered in the paper. Hence, simulation S4 gives us an idea about the structural model's power at discriminating the types in a situation similar to the one in the actual experiment.

4.3 Results

Online Table 3 shows the results of simulations S1 to S4.

- In simulations S1, S2, and S4, there is virtually no bias in the estimated parameters and the MSEs indicate great overall precision. Moreover, the structural model classifies almost all subjects into the correct type.

- In simulation S3 – i.e., the simulation where the CPT- and ST-types are almost indistinguishable from the EUT-type – there is some bias in the estimated parameters

Online Table 2: Types' Sizes and True Parameters in Simulations to Assess Discriminatory Power

S1					
Type	N (π)	β	α	δ	σ
EUT	80 (0.3333)	0.2000			0.3000
CPT	80 (0.3333)	0.2000	0.4000		0.3000
ST	80 (0.3333)	0.2000		0.5000	0.3000
S2					
Type	N (π)	β	α	δ	σ
EUT	80 (0.3333)	0.2000			0.3000
CPT	80 (0.3333)	0.2000	0.6000		0.3000
ST	80 (0.3333)	0.2000		0.7000	0.3000
S3					
Type	N (π)	β	α	δ	σ
EUT	80 (0.3333)	0.2000			0.3000
CPT	80 (0.3333)	0.2000	0.8000		0.3000
ST	80 (0.3333)	0.2000		0.9000	0.3000
S4					
Type	N (π)	β	α	δ	σ
EUT	80 (0.2963)	0.1000			0.0100
CPT	100 (0.3704)	0.5500	0.4500		0.3000
ST	90 (0.3333)	0.8500		0.9000	2.5000

In S1 to S3, the types differ only in the degrees of likelihood sensitivity (α) and local thinking (δ). They become increasingly similar in preferences, i.e., hard to discriminate. In S4, the types are similar to the ones uncovered in the paper. Simulation results can be found in Online Table 3.

Online Table 3: Results of Simulations to Assess Discriminatory Power

S1	Bias					Mean Squared Error (MSE)					
Type	π	β	α	δ	σ	π	β	α	δ	σ	$f_{correct}$
EUT	0.0000	0.0003			0.0020	0.0000	0.0001			0.0004	1.0000
CPT	0.0000	-0.0092	0.0016		-0.0079	0.0000	0.0011	0.0001		0.0054	1.0000
ST	0.0000	-0.0014		-0.0009	-0.0006	0.0000	0.0002		0.0000	0.0008	1.0000
S2	Bias					Mean Squared Error (MSE)					
Type	π	β	α	δ	σ	π	β	α	δ	σ	$f_{correct}$
EUT	0.0000	0.0002			0.0020	0.0000	0.0001			0.0004	1.0000
CPT	0.0000	-0.0002	0.0002		0.0001	0.0000	0.0000	0.0000		0.0003	1.0000
ST	0.0000	0.0005		0.0027	0.0111	0.0000	0.0002		0.0002	0.0021	1.0000
S3	Bias					Mean Squared Error (MSE)					
Type	π	β	α	δ	σ	π	β	α	δ	σ	$f_{correct}$
EUT	0.0135	0.0015			-0.0008	0.0097	0.0013			0.0008	0.9338
CPT	0.0140	0.0000	0.0001		0.0012	0.0093	0.0001	0.0001		0.0002	1.0000
ST	-0.0275	-0.1836		-0.0188	-0.0036	0.0377	1.6935		0.0170	0.0023	0.9362
S4	Bias					Mean Squared Error (MSE)					
Type	π	β	α	δ	σ	π	β	α	δ	σ	$f_{correct}$
EUT	-0.0002	-0.0083			0.0000	0.0000	0.0836			0.0000	0.9949
CPT	0.0002	0.0002	-0.0003		0.0014	0.0000	0.0003	0.0001		0.0008	0.9984
ST	0.0000	-0.0002		-0.0002	0.0005	0.0000	0.0001		0.0001	0.0180	0.9989

Simulated number of subjects and true parameters for all four simulations can be found in Online Table 2. In each simulation, biases and Mean Squared Errors (MSE) are calculated based on $R = 1,000$ simulation runs. $f_{correct}$ denotes the fraction of correctly classified subjects in each type.

of the ST-type. The MSEs also indicate that the ST-type's parameters are estimated only with low overall precision, in particular the estimator for the concavity of the utility function is quite imprecise. However, the model still manages to classify almost all subjects into the correct type.

Overall, simulations S1 to S4 reveal that the structural model's power to discriminate between the different types is very high. Even in simulation S3, where the three types are so similar that they are at the edge of being indistinguishable, the model still manages to classify almost all subjects into the correct type. These results also confirm that the experimental choices contain rich information about a subjects' type-membership and that the structural model exploits this information efficiently.

4.4 Effects of Serially Correlated Errors

This section discusses the set-up and the results of four simulations to investigate the robustness of the structural model against potential serial correlation in the errors. This investigation is important since, in the experiment, subjects make a series of binary choices. Thus, the random errors subjects make when evaluating the lotteries may be serially correlated across the binary choices. Such serial correlation would imply that our structural model is misspecified as it assumes independent errors and, thus, could yield biased parameter estimates. However, as explained in the paper, the order of the binary choices was randomized across subjects. Hence, since the structural model does not estimate at the individual level but takes into account the choices of all subjects simultaneously, the serial correlations in the subjects' errors may average out due to the random order in which the choices were presented.

4.4.1 Set-up

Online Table 4 shows the types' sizes and the true parameters in the four simulations. Across all four simulations S5-S8, the simulated types are identical. They are very similar in terms of relative size and parameters to the ones uncovered in the paper. However, the serial correlation across choices in the random errors the simulated subjects make when evaluating the lotteries increases in four equally sized steps from $\rho = 0$ to $\rho = 0.6$.

Online Table 4: Types' Sizes, True Parameters, and Serial Correlation (ρ) in Simulations to Assess the Effects of Serially Correlated Errors

Types' sizes & true parameters: common in simulations **S5-S8**					
Type	N (π)	β	α	δ	σ
EUT	80 (0.2963)	0.1000			0.0100
CPT	100 (0.3704)	0.5500	0.4500		0.3000
ST	90 (0.3333)	0.8500		0.9000	2.5000
Serial correlation of errors		**S5**	**S6**	**S7**	**S8**
ρ		0.0	0.2	0.4	0.6

In S4-S7, the types are similar in size and parameters to the ones uncovered in the paper. Simulation results can be found in Online Table 5.

Online Table 5: Results of Simulations to Assess the Effects of Serially Correlated Errors

S5 ($\rho = 0.0$)	Bias					Mean Squared Error (MSE)					
Type	π	β	α	δ	σ	π	β	α	δ	σ	$f_{correct}$
EUT	-0.0002	-0.0083			0.0000	0.0000	0.0836			0.0000	0.9949
CPT	0.0002	0.0002	-0.0003		0.0014	0.0000	0.0003	0.0001		0.0008	0.9984
ST	0.0000	-0.0002		-0.0002	0.0005	0.0000	0.0001		0.0001	0.0180	0.9989

S6 ($\rho = 0.2$)	Bias					Mean Squared Error (MSE)					
Type	π	β	α	δ	σ	π	β	α	δ	σ	$f_{correct}$
EUT	-0.0005	-0.0001			-0.0003	0.0000	0.0012			0.0000	0.9930
CPT	0.0003	0.0018	-0.0009		-0.0031	0.0000	0.0002	0.0001		0.0007	0.9974
ST	0.0001	-0.0006		0.0009	-0.0591	0.0000	0.0001		0.0001	0.0196	0.9988

S7 ($\rho = 0.4$)	Bias					Mean Squared Error (MSE)					
Type	π	β	α	δ	σ	π	β	α	δ	σ	$f_{correct}$
EUT	-0.0010	0.0023			-0.0010	0.0000	0.0022			0.0000	0.9878
CPT	0.0011	0.0035	-0.0020		-0.0229	0.0000	0.0003	0.0001		0.0012	0.9950
ST	-0.0002	0.0010		-0.0002	-0.2305	0.0000	0.0001		0.0001	0.0675	0.9976

S8 ($\rho = 0.6$)	Bias					Mean Squared Error (MSE)					
Type	π	β	α	δ	σ	π	β	α	δ	σ	$f_{correct}$
EUT	-0.0039	-0.0061			-0.0022	0.0001	0.1725			0.0000	0.9676
CPT	0.0053	0.0022	-0.0021		-0.0622	0.0001	0.0004	0.0001		0.0045	0.9855
ST	-0.0014	0.0011		-0.0003	-0.5564	0.0000	0.0001		0.0001	0.3210	0.9914

Simulated number of subjects and true parameters for all four simulations can be found in Online Table 4. In each simulation, biases and Mean Squared Errors (MSE) are calculated based on $R = 1,000$ simulation runs. $f_{correct}$ denotes the fraction of correctly classified subjects in each type.

4.4.2 Results

Online Table 5 shows the results of the four simulations. Simulations S5 to S8 reveal that, regardless of the degree of serial correlation in the errors, the types' estimated relative sizes and preference parameters are virtually unbiased and highly precise. The structural model also classifies the vast majority of subjects into the correct type. Only the estimated choice sensitivities exhibit an increasing downward bias when the serial correlation in the errors increases.

In sum, the structural model turns out to be remarkably robust against serial correlation in the subjects' errors. Hence, even if the subjects' errors in the experiment were serially correlated across choices, this would neither bias the types' estimated sizes, nor their preference parameters, nor the classification of subjects into types. Note that we also use cluster-robust standard errors in the paper to ensure that our inferences about the structural model's parameters remain valid even if the subjects' errors in the experiment were serially correlated across choices.

Again, we suppose the reason why the structural model is so robust against serial correlation in the subjects' errors is because the order of the choices is randomized across subjects. Since the finite mixture model does not operate at the individual level but uses the choices of all subjects simultaneously when estimating its parameters, the random order of the choices across subjects may cause the serial correlations in the errors to average each other out.

5 Alternative Error Specification and Modeling of Choice Set Dependence

This section of the Online Appendix explores how an alternative specification using a Fechner-type error and modeling choice set dependence by RT instead of ST affects the structural model's fit.

5.1 Fechner-Type Errors

Although the random utility approach presented in Section 5.1.1 of the paper offers an intuitive way to estimate preference parameters in binary choices, an alternative approach is to specify a Fechner-type error that directly affects a subject's choices instead of her utility. With a normally distributed Fechner-type error ν_g with standard deviation σ_M, the probability that subject i of type M chooses lottery X_g in binary choice g, i.e. X_g, i.e., $C_{ig} = X$, is given by

$$\begin{aligned} Pr(C_{ig} = X; \theta_M, \sigma_M) &= Pr\left[V^M(X_g, \theta_M) - V^M(Y_g, \theta_M) + \nu \geq 0\right] \\ &= \Phi\left(\frac{V^M(X_g, \theta_M) - V^M(Y_g, \theta_M)}{\sigma_M}\right), \end{aligned}$$

where Φ is the cdf of the standard normal distribution. By using this probability in equation (6), we obtain subject i's type-specific density contribution to the structural model.

Online Table 6 shows the estimation results of the structural model when we specify such a Fechner-type error instead of applying the random utility approach. Although the parameter estimates and the percentage of correctly predicted choices remain remarkably similar, the AIC and BIC indicate that the model with a Fechner-type error fits the data substantially worse than the one applying the random utility approach.[1] Moreover, when we compare the individual classification of subjects into types between the two models, they are mostly identical as 94.7% of subjects are classified into the same type. In conclusion, even though the two models yield essentially the same results, we select the model using the random utility approach in the paper due to its superior fit.

[1] Since the two models have the same number of parameters, we can also directly compare the achieved log likelihood which is substantially lower for the model with the Fechner-type error.

Online Table 6: Type-Specific Parameter Estimates of the Finite Mixture Model with a Fechner-Type Error

Type-specific estimates	EUT	CPT	ST
Relative size (π)[a]	0.294	0.362	0.345
	(0.040)	(0.039)	(0.037)
Concavity of utility function (β)	0.095***	0.554***	0.860***
	(0.029)	(0.049)	(0.013)
Likelihood sensitivity (α)		0.474°°°	
		(0.026)	
Degree of local thinking (δ)			0.922°°°
			(0.013)
Standard deviation of	172.056***	6.158***	0.707***
Fechner-type error (σ)	(43.745)	(1.744)	(0.076)
Number of subjects[b]	84	100	99
Number of observations		23,316	
Log Likelihood		-11527.18	
AIC		23,074.35	
BIC		23,154.92	
Share of correctly predicted choices[c]		0.745	

Subject cluster-robust standard errors are reported in parentheses. Significantly different from 0 (1) at the 1% level: *** (°°°).

[a] The relative group sizes are not tested against zero, since under the null hypothesis that a type's relative size is zero, the preference parameters are meaningless. Consequently, the test statistic would exhibit an unknown distribution.

[b] Subjects are assigned to the best-fitting model according to their ex-post probabilities of type-membership (see equation (7)).

[c] Choices are predicted by using the subjects' classification into types and by calculating the lotteries' values, $V^M(X_g, \hat{\theta}_M)$ and $V^M(Y_g, \hat{\theta}_M)$, for the type-specific parameter estimates $\hat{\theta}_M$.

5.2 Modeling Choice Set Dependence by RT

Now we investigate how the fit of our model changes if we model choice set dependence by RT instead of ST. To specify the RT-types we use a power regret function, i.e. $Q(\Delta v) = \Delta v^{\zeta}$ if $\Delta v \geq 0$ and $Q(\Delta v) = -(-\Delta v)^{\zeta}$ if $\Delta v < 0$, with $\zeta \geq 0$. Moreover, since RT does not directly provide individual values of the lotteries under consideration, we have to use a Fechner-type error instead of the random utility approach. Thus, the probability of RT-type i choosing lottery X_g in binary choice g, i.e., $C_{ig} = X$, is given by

$$\begin{aligned} Pr(C_{ig} = X; \theta_{RT}, \sigma_{RT}) &= Pr\left(\sum_{s=1}^{S} p_s\, Q[v(x_s, \beta_{RT}) - v(y_s, \beta_{RT}), \zeta] + \nu_g \geq 0\right) \\ &= \Phi\left(\frac{\sum_{s=1}^{S} p_s\, Q[v(x_s, \beta_{RT}) - v(y_s, \beta_{RT}), \zeta]}{\sigma_{RT}}\right), \end{aligned}$$

where θ_{RT} contains the preference parameters β_{RT} and ζ. In this model, RT-type i's contribution to the finite mixture model's likelihood is

$$f_{RT}(C_i; \theta_{RT}, \sigma_{RT}) = \prod_{g=1}^{G} Pr(C_{ig} = X; \theta_{RT}, \sigma_{RT})^{I(C_{ig}=X)}\, Pr(C_{ig} = Y; \theta_{RT}, \sigma_{RT})^{1-I(C_{ig}=X)},$$

which replaces $f_{ST}(C_i; \theta_{ST}, \sigma_{ST})$ in equation (6).

Online Table 7 shows the estimation results of the model replacing ST with RT when we use a Fechner-type error for all three types. Comparing these results to the model in Online Table 6 reveals the following.

1. Although the model replacing ST with RT yields a similar percentage of correctly predicted choices, it fits the data substantially worse in terms of the AIC (23,135.17 vs. 23,074.35) and BIC (23,215.74 vs. 23,154.92) and achieves a considerably lower log likelihood (-11,557.59 vs. 11,527.18).

2. The model fails to pick up any choice set dependence as the subjects classified as RT-types exhibit on average a linear regret function ($\hat{\zeta} = 1.003$). Thus, combined with their almost linear utility function, the RT-types essentially maximize the expected payoff. We suspect that the model's failure to pick up the choice set dependence behind the observed Allais Paradoxes in our data is due to the regret function's convexity which violates diminishing sensitivity.

3. When we analyze how the individual classification of subjects into types changes, the following result emerges: 99.1% of subjects originally classified as CPT-types remain in

this type. However, 88.8% of subjects originally classified as EUT-types with an almost linear utility function are now classified as RT-types, and 93.7% of subjects originally classified as ST-types with a strongly concave utility function are now classified as EUT-types.

In conclusion, we prefer the model using ST due to its superior fit and ability to pick the choice set dependence in our data – which is essential to explain the non-parametric results in Section 4 of the paper as well as the pattern in the subjects' preference reversals in Section 5.4 of the paper.

To rule out that this conclusion is driven by imposing a Fechener-type error on all types – i.e. the EUT- and CPT-types as well – we also estimated a model replacing ST with RT in which only the RT-types exhibit a Fechner-type error but the other two types follow the random utility approach. Online Table 8 shows the estimation results. When we compare these results with our baseline model in Table 2 of the paper, the conclusion prevails: the model using ST exhibits a superior fit and, in contrast to the model using RT, picks up the choice set dependence in our data.

Online Table 7: Type-Specific Parameter Estimates of the Finite Mixture Model using RT instead of ST with a Fechner-Type Error for all Types

Type-specific estimates	EUT	CPT	RT
Relative size (π)[a]	0.325	0.366	0.309
	(0.035)	(0.042)	(0.044)
Concavity of utility function (β)	0.858***	0.571***	0.098***
	(0.015)	(0.043)	(0.030)
Likelihood sensitivity (α)		0.469°°°	
		(0.025)	
Exponent of regret function (ζ)[b]			1.098
			(0.066)
Standard deviation of	0.651***	5.494***	345.392**
Fechner-type error (σ)	(0.067)	(1.368)	(167.218)
Number of subjects[c]	93	100	90
Number of observations		23,316	
Log Likelihood		-11557.59	
AIC		23,135.17	
BIC		23,215.74	
Share of correctly predicted choices[d]		0.752	

Subject cluster-robust standard errors are reported in parentheses. Significantly different from 0 (1) at the 1% level: *** (°°°).

[a] The relative group sizes are not tested against zero, since under the null hypothesis that a type's relative size is zero, the preference parameters are meaningless. Consequently, the test statistic would exhibit an unknown distribution.

[b] The specification of RT uses a power regret function, $Q(\Delta v) = \Delta v^{\zeta}$ if $\Delta v \geq 0$ and $Q(\Delta v) = -(-\Delta v)^{\zeta}$ if $\Delta v < 0$, with $\zeta \geq 0$.

[c] Subjects are assigned to the best-fitting model according to their ex-post probabilities of type-membership (see equation (7)).

[d] Choices are predicted by using the subjects' classification into types and by calculating the lotteries' values, $V^M(X_g, \hat{\theta}_M)$ and $V^M(Y_g, \hat{\theta}_M)$, for the type-specific parameter estimates $\hat{\theta}_M$.

Online Table 8: Type-Specific Parameter Estimates of the Finite Mixture Model using RT instead of ST with a Fechner-Type Error for the RT-Types and a Random Utility Approach for the EUT- and CPT-types

Type-specific estimates	EUT	CPT	RT
Relative size (π)[a]	0.315	0.427	0.259
	(0.044)	(0.056)	(0.058)
Concavity of utility function (β)	0.866***	0.582***	0.082***
	(0.018)	(0.067)	(0.052)
Likelihood sensitivity (α)		0.487°°°	
		(0.304)	
Exponent of regret function (ζ)[b]			1.003
			(0.115)
Choice sensitivity (σ)	2.938***	0.323***	
	(0.406)	(0.145)	
Standard deviation of Fechner-type error (σ)			193.298
			(168.118)
Number of subjects[c]	91	119	73
Number of observations		23,316	
Log Likelihood		-11,510.36	
AIC		23,040.72	
BIC		23,121.29	
Share of correctly predicted choices[d]		0.747	

Subject cluster-robust standard errors are reported in parentheses. Significantly different from 0 (1) at the 1% level: *** (°°°).

[a] The relative group sizes are not tested against zero, since under the null hypothesis that a type's relative size is zero, the preference parameters are meaningless. Consequently, the test statistic would exhibit an unknown distribution.

[b] The specification of RT uses a power regret function, $Q(\Delta v) = \Delta v^{\zeta}$ if $\Delta v \geq 0$ and $Q(\Delta v) = -(-\Delta v)^{\zeta}$ if $\Delta v < 0$, with $\zeta \geq 0$.

[c] Subjects are assigned to the best-fitting model according to their ex-post probabilities of type-membership (see equation (7)).

[d] Choices are predicted by using the subjects' classification into types and by calculating the lotteries' values, $V^M(X_g, \hat{\theta}_M)$ and $V^M(Y_g, \hat{\theta}_M)$, for the type-specific parameter estimates $\hat{\theta}_M$.

6 Instructions

The following pages contain translations of the instructions that were handed out to the subjects. The original instructions in French are available on request.

The subjects received printed instructions regarding the general explanations on the experiment, the main part of the experiment (Part 1), and the additional part of the experiment (Part 2). Note that the instructions of the main part of the experiment differ, depending on whether the subject was exposed to the canonical presentation or the states of the world presentation.

The instructions of the remaining Parts 3-5 were shown on screen and are available on request.

General explanations on the experiment

You are about to participate in an economic experiment. The experiment is conducted by the departement d'économetrie et économie politique (DEEP) of the university of Luasanne and funded by the Swiss National Science Foundation (SNSF). It aims at better understanding individual decision making under risk.

For your participation in the experiment you will earn a lump sum payment of 10 CHF for sure. The experiment consists of five parts in some of which you can earn points that depend on your decisions. At the end of the experiment, you get an additional payment of one CHF for every 100 points you earned during the course of the experiment. In other words, each point corresponds to one centime. **Thus, it is to your own benefit to read these explanations carefully.**

You can take your decisions at your own speed. The amount of points you earn only depends on your own decisions.

It is prohibited to communicate with the other participants during the whole course of the experiment. If you do not abide by this rule you will be excluded from the experiment and all payments. However, if you have questions you can always ask one of the experimenters by raising your hand.

You can also abort the experiment anytime you wish without giving any reasons. To do so, please raise your hand and tell the experimenter that you wish to abort the experiment. The experimenter will then guide you outside the laboratory. Note that if you abort the experiment, you are not entitled to any payments.

We will ask you about your personal information and contact address in the fifth part of the experiment. We will only use this information in an anonymized way for scientific purposes or to contact you again with respect this experiment, if necessary. **Thus, your anonymity is guaranteed.**

The backside of these explanations gives you an overview of the experiment. If you have any questions please raise your hand. Otherwise, you can now begin with the instructions of first part of the experiment.

Thank you very much for your participation!

Overview of the experiment

Part 1:
Choosing between two risky options

↓

Part 2:
Choosing between a risky option and a sure amount

↓

Part 3:
Pattern supplementation

↓

Part 4:
Personality questionnaire

↓

Part 5:
Personal Data

↓

Payment

Part 1: Choosing between two risky options [Canonical Presentation]

In this part of the experiment, you first draw a sealed envelope that contains one of 93 decision situations in which you have to choose between two risky options. The possible payoffs of the two risky options are either correlated with each other or independent of each other.

The decision situation in the sealed envelope is the only one relevant for your payoff in this part of the experiment. **However, you are not allowed to open the envelope before the end of the experiment (if you do, you will be excluded from the experiment and all payments).** Instead, you should give us instructions on the computer screen, for each of the 93 decision situations that may be in you sealed envelope, which of the two risky options you choose.

These explanations first contain two examples of the decision situations for which you have to give us instructions on the computer screen. In the first example the possible payoffs of the two risky options are correlated, while in the second example they are independent. Subsequently, the explanations illustrate how your payoff for this part of the experiment is calculated. Finally, they contain some questions that verify your understanding.

Examples of decision situations

In each of the 93 decision situations that may be in your sealed envelope you have the choice between two risky options X and Y. In 45 out of these 93 decision situations the possible payoffs of the two risky options are correlated with each other, while in the remaining 48 decision situations the possible payoffs are independent of each other.

Correlated payoffs

First, consider the following example of a decision situation in which the possible payoffs of the two risky options are correlated. There are three possible payoff states which are realized with probabilities 10.50%, 19.50%, and 70.00%, respectively. Option X pays either 0, 500, or 2400 points depending on the realized payoff state. Option Y yields either 500, 500, or 1500 points depending on the realized payoff state. Hence, the realized payoff state determines the payoff of *both* risky options. For example, if the rightmost payoff state is realized, option X yields 2400 and option Y pays 1500 points.

Probability:	10.50%	19.50%	70.00%	Your Choice
Option X	0	500	2400	❑
Option Y	500	500	1500	❑

If you indicate on the computer screen that you prefer option X and if the decision situation in this example corresponds to the one in your envelope, you get either 0 points with probability 10.50%, 500 points with probability 19.50%, or 2400 points with probability 70.00%. If you indicate that you prefer option Y instead and if the decision situation in this example corresponds to the one in your envelope, you get either 500 points with probability 10.50%, 500 points with probability

19.50%, or 1500 points with probability 70.00%.

Independent payoffs

Now, consider the following example of a decision situation in which the possible payoffs of the two risky options are independent. Option X pays either 0, 500, or 2400 points with probability 10.50%, 19.50%, or 70.00%, respectively. Option Y yields either 500 or 1500 points with probability 30.00% or 70.00%, respectively. Since the possible payoffs are independent, the payoff of one option does not determine the payoff of the other. For example, if the realized payoff of option X is 2400 points, option Y still pays either 500 points with probability 30.00% or 1500 points with probability 70.00%.

Probability:	10.50%	19.50%	70.00%		Probability:	30.00%	70.00%
Option X	0	500	2400	VS.	Option Y	500	1500
Your Choice:		❑				❑	

If you indicate on the computer screen that you prefer option X and if the decision situation in this example corresponds to the one in your envelope, you get either 0 points with probability 10.50%, 500 points with probability 19.50%, or 2400 points with probability 70.00%. If you indicate that you prefer option Y instead and if the decision situation in this example corresponds to the one in your envelope, you get either 500 points with probability 30.00%, or 1500 points with probability 70.00%.

Possible payoffs and probabilities

In each decision situation, you always have to indicate your choice between the two risky options X and Y. However, the number and the size of the possible payoffs as well as the corresponding probabilities differ across the 93 decision situations.

- The number of possible payoffs of a risky option is always between 1 and 3.
- The size of the payoffs varies between 0 and 7000 points.
- The corresponding probabilities of the payoffs range from 1% to 100%.

Calculation of your payoff

At the end of the experiment, you will hand in the sealed envelope to the experimenter who will open it together with you. For the decision situation that is inside your envelope, you will then get the option you have previously indicated on the computer screen.

Correlated payoffs

For instance, let's assume that the decision situation in your envelope is the one with the correlated payoffs from before, and you instructed us on the computer screen that you prefer option X:

Probability:	10.50%	19.50%	70.00%	Your Choice
Option X	0	500	2400	✓
Option Y	500	500	1500	❑

After opening the envelope, you will have to roll four 10-sided dice to generate a random number between 0000 and 9999. The first die indicates the first digit corresponding to thousands. The second die indicates the second digit corresponding to hundreds. The third die indicates the third digit corresponding to tens. Finally, the fourth die indicates the last digit corresponding to units. This random number determines the realized payoff state, as shown in the table below.

Random number				
between	*0000*	*1050*	*3000*	
and	*1049*	*2999*	*9999*	
Probability:	10.50%	19.50%	70.00%	Your Choice
Option X	0	500	2400	✓
Option Y	500	500	1500	❑

With probability 10.50% the random number lies between 0000 and 1049, and the first payoff state is realized. With probability 19.50%, the random number is between 1050 and 2999, and the second payoff state is realized. Finally, with probability 70.00% the random number is between 3000 and 9999, and the third payoff state is realized.

For example, assume that the random number you roll is 4276. Since 4276 is between 3000 and 9999, the third payoff state is realized, and your resulting payoff is 2400 points.

Thus, if you indicate the option you want on the computer screen, you will get the option you want. However, if you give us wrong instructions on the computer screen, you won't get the option you want.

Independent payoffs

Now, assume that the decision situation in your envelope is the one with the independent payoffs from before, and you instructed us on the computer screen that you prefer option Y:

Probability:	10.50%	19.50%	70.00%		Probability:	30.00%	70.00%
Option X	0	500	2400	VS.	Option Y	500	1500
Your Choice:	❑					✓	

After opening the envelope, you will have to roll the four 10-sided dice twice to generate two random numbers between 0000 and 9999. Since the risky options are independent, the first random number determines the payoff of option X, while the second random number determines the payoff of option Y.

First random number					*Second random number*		
between	*0000*	*1050*	*3000*		*between*	*0000*	*3000*
and	*1049*	*2999*	*9999*		*and*	*2999*	*9999*
Probability:	10.50%	19.50%	70.00%		Probability:	30.00%	70.00%
Option X	0	500	2400	VS.	Option Y	500	1500
Your Choice:	❑					✓	

With probability 30.00% the second random number lies between 0000 and 2999, and option Y pays 500 points. With probability 70.00% the second random number is between 3000 and 9999, and option Y yields 1500 points.

For instance, assume that the second random number you roll is 1387. As 1387 is between 0000 and 2999, your resulting payoff from choosing option Y is 500 points.

Again, if you indicate the option you want on the computer screen, you will get the option you want. However, if you give us wrong instructions on the computer screen, you won't get the option you want.

Questions to verify your understanding

The following questions test whether you correctly understood the explanations for the first part of the experiment.

Let's assume that at the end of the experiment your envelope contains the following decision situation:

Random number					
between	*0000*	*0525*	*1800*	*3800*	
and	*0524*	*1799*	*3799*	*9999*	
Probability:	5.25%	12.75%	20.00%	62.00%	Your Choice
Option X	0	1000	1500	3500	❑
Option Y	100	1000	2000	2500	❑

If you indicated on the computer screen that you prefer option Y, what are the possible payoffs and corresponding probabilities?

____

If you roll the number 2845, which of these payoffs will you get?

____

To how many CHF does this payoff correspond?

____

Now, assume that at the end of the experiment your envelope contains the following decision situation:

First random number					*Second random number*		
between	*0000*	*1550*	*3450*		*between*	*0000*	*3450*
and	*1549*	*3449*	*9999*		*and*	*3449*	*9999*
Probability:	15.50%	19.00%	65.50%		Probability:	34.50%	65.50%
Option X	100	1500	2400	VS.	Option Y	1500	2000
Your Choice:		❑				❑	

What is your payoff if you indicated on the computer screen that you prefer option X, and the first random number you rolled is 1201, while the second random number is 5498?

After finishing these questions, please raise your hand and wait for the experimenter to correct them. Thank you.

Part 1: Choosing between two risky options
[States of the World Presentation]

In this part of the experiment, you first draw a sealed envelope that contains one of 84 decision situations in which you have to choose between two risky options.

The decision situation in the sealed envelope is the only one relevant for your payoff in this part of the experiment. **However, you are not allowed to open the envelope before the end of the experiment (if you do, you will be excluded from the experiment and all payments).** Instead, you should give us instructions on the computer screen, for each of the 84 decision situations that may be in you sealed envelope, which of the two risky options you choose.

These explanations first contain an example of one of the decision situations for which you have to give us instructions on the computer screen. Subsequently, they illustrate how your payoff for this part of the experiment is calculated. Finally, they contain some questions to verify that you understood the explanations correctly.

Example of a decision situation

In each of the 84 decision situations that may be in your sealed envelope you have the choice between two risky options X and Y.

Consider the following example. There are three possible payoff states which are realized with probabilities 10.50%, 19.50%, and 70.00%, respectively. Option X pays either 0, 500, or 2400 points depending on the realized payoff state. Option Y yields either 500, 500, or 1500 points depending on the realized payoff state.

Probability:	10.50%	19.50%	70.00%	Your Choice
Option X	0	500	2400	❑
Option Y	500	500	1500	❑

Thus, if you indicate on the computer screen that you prefer option X and if the decision situation in this example corresponds to the one in your envelope, you get either 0 points with probability 10.50%, 500 points with probability 19.50%, or 2400 points with probability 70.00%. If you indicate that you prefer option Y instead and if the decision situation in this example corresponds to the one in your envelope, you get either 500 points with probability 10.50%, 500 points with probability 19.50%, or 1500 points with probability 70.00%.

In each of the 84 decision situation, you always have to indicate your choice between two risky options X and Y. However, the number of payoff states as well as the corresponding probabilities and sizes of the payoffs differ across the 84 decision situations.

- The number of payoff states is always either 3 or 4.
- The probabilities of the payoff states range from 0.02% to 97.02%.
- The sizes of the payoffs vary between 0 and 7000 points.

Calculation of your payoff

At the end of the experiment, you will hand in the sealed envelope to the experimenter who will open it together with you. For the decision situation that is inside your envelope, you will then get the option you have previously indicated on the computer screen.

For instance, let's assume that the decision situation in your envelope is the one from before, and you instructed us previously on the computer screen that you prefer option X:

Probability:	10.50%	19.50%	70.00%	Your Choice
Option X	0	500	2400	✓
Option Y	500	500	1500	❑

After opening the envelope, you will have to roll four 10-sided dice to generate a random number between 0000 and 9999. The first die indicates the first digit corresponding to thousands. The second die indicates the second digit corresponding to hundreds. The third die indicates the third digit corresponding to tens. Finally, the fourth die indicates the last digit corresponding to units. This random number determines the realized payoff state, as shown in the table below.

Random number				
between	*0000*	*1050*	*3000*	
and	*1049*	*2999*	*9999*	
Probability:	10.50%	19.50%	70.00%	Your Choice
Option X	0	500	2400	✓
Option Y	500	500	1500	❑

With probability 10.50% the random number lies between 0000 and 1049, and the first payoff state is realized. With probability 19.50%, the random number is between 1050 and 2999, and the second payoff state is realized. Finally, with probability 70.00% the random number is between 3000 and 9999, and the third payoff state is realized.

For example, assume that the random number you roll is 4276. Since 4276 is between 3000 and 9999, the third payoff state is realized, and your resulting payoff is 2400 points.

Thus, if you indicate the option you want on the computer screen, you will get the option you want. However, if you give us wrong instructions on the computer screen, you won't get the option you want.

Questions to verify your understanding

The following three questions test whether you correctly understood the explanations for the first part of the experiment.

Let's assume that at the end of the experiment your envelope contains the following decision situation:

Random number					
between	*0000*	*0525*	*1800*	*3800*	
and	*0524*	*1799*	*3799*	*9999*	
Probability:	5.25%	12.75%	20.00%	62.00%	Your Choice
Option X	0	1000	1500	3500	❑
Option Y	100	1000	2000	2500	❑

If you indicated on the computer screen that you prefer option Y, what are the possible payoffs and corresponding probabilities?

____

If you roll the number 2845, which of these payoffs will you get?

____

To how many CHF does this payoff correspond?

____

After finishing these questions, please raise your hand and wait for the experimenter to correct them. Thank you.

Part 2: Choosing between a risky option and a sure amount

In this part of the experiment, you first draw a sealed envelope that contains one of 180 decision situations in which you have to choose between a risky option and a sure amount.

The decision situation in the sealed envelope is the only one relevant for your payoff in this part of the experiment. **However, you are not allowed to open the envelope before the end of the experiment (if you do, you will be excluded from the experiment and all payments).** Instead, you should give us instructions on the computer screen, for each of the 180 decision situations that may be in you sealed envelope, whether you choose the risky option or the sure amount.

These explanations first contain an example of a computer screen on which you have to give us instructions about your choice. Subsequently, they illustrate how your payoff for this part of the experiment is calculated. Finally, they contain a question to verify that you understood the explanations correctly.

Example of a computer screen

There will be nine computer screens each containing 20 decision situations. In each of these decision situations, you have to chose between either a risky option A or a sure amount B.

Consider the example below of such a computer screen. The risky option remains the same across all 20 decision situations. However, the sure amount increases from the lowest possible payoff of the risky option, 0, to its highest possible payoff, 6400, in twenty equally sized steps.

	Option A	Your Choice	Option B
1	6400 with probability 10 % or 0 with probability 90%	A ❑ ❑ B	0
2		A ❑ ❑ B	320
3		A ❑ ❑ B	640
4		A ❑ ❑ B	960
5		A ❑ ❑ B	1280
6		A ❑ ❑ B	1600
7		A ❑ ❑ B	1920
8		A ❑ ❑ B	2240
9		A ❑ ❑ B	2560
10		A ❑ ❑ B	2880
11		A ❑ ❑ B	3200
12		A ❑ ❑ B	3520
13		A ❑ ❑ B	3840
14		A ❑ ❑ B	4160
15		A ❑ ❑ B	4480
16		A ❑ ❑ B	5120
17		A ❑ ❑ B	5440
18		A ❑ ❑ B	5760
19		A ❑ ❑ B	6080
20		A ❑ ❑ B	6400

For each of these 20 decision situations on the computer screen, you have to give us instructions whether you choose the risky option A or the sure amount B, if that decision is in your sealed envelope. For instance, you may start by choosing the risky option in the first decision situation where the sure amount is zero. But at some decision situations further down the list, where the sure amount is larger, you may switch to choosing the sure amount instead of the risky option.

Across the nine computer screens, the risky option differs: It always has two possible payoffs, but the probabilities and sizes of these two possible payoffs vary.

- The probabilities range from 4.00% to 96.00%.
- The lower of the two possible payoffs is always 0, while higher one varies between 400 and 6000 points.

Calculation of your payoff

At the end of the experiment, you will hand in the sealed envelope to the experimenter who will open it together with you. For the decision situation that is inside your envelope, you will then get the option you have previously chosen on the computer screen.

For example, consider you gave us the following instructions on the computer screen from before:

	Option A	Your Choice	Option B
1	6400 with probability 10 % or 0 with probability 90%	A ✓ ❑ B	0
2		A ✓ ❑ B	320
3		A ✓ ❑ B	640
4		A ✓ ❑ B	960
5		A ✓ ❑ B	1280
6		A ✓ ❑ B	1600
7		A ✓ ❑ B	1920
8		A ❑ ✓ B	2240
9		A ❑ ✓ B	2560
10		A ❑ ✓ B	2880
11		A ❑ ✓ B	3200
12		A ❑ ✓ B	3520
13		A ❑ ✓ B	3840
14		A ❑ ✓ B	4160
15		A ❑ ✓ B	4480
16		A ❑ ✓ B	5120
17		A ❑ ✓ B	5440
18		A ❑ ✓ B	5760
19		A ❑ ✓ B	6080
20		A ❑ ✓ B	6400

Moreover, assume that your envelope contains the following decision situation which corresponds to the *sixth row* in the above computer screen:

- Option A: 6400 with probability 10% (random number between 0000 and 0999), or 0 with probability 90% (random number between 1000 and 9999).
- Option B: 1600 for sure.

Since in this example, you chose the risky option A over the sure amount of 1600 in the sixth row of the computer screen, you will get the risky option A. As in the first part of the experiment, you will have to roll four 10-sided dice to generate a random number between 0000 and 9999 that will determine the realized payoff of the risky option A. If you had chosen the sure amount instead of the risky option, you would have gotten 1600 points for sure.

Thus, if you indicate the option you want on the computer screen, you will get the option you want. However, if you give us wrong instructions on the computer screen, you won't get the option you want.

Question to verify your understanding

The following question tests whether you correctly understood the explanations for the second part of the experiment.

Let's assume that the decision situation in your envelope corresponds to the *sixteenth row* of the example of the computer screen as shown on the previous page, i.e.:

- Option A: 6400 with probability 10% (random number between 0000 and 0999), or 0 with probability 90% (random number between 1000 and 9999).
- Option B: 5120 for sure.

If you gave the same instructions as in the example of the computer screen on the previous page, does your payoff depend on the random number you roll? If yes, what are the possible payoffs? If not, which payoff do you get?

After finishing these questions, please raise your hand and wait for the experimenter to correct them. Thank you.