First-order stochastic dominance, framing effects and risk preferences

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Abstract

This paper experimentally investigates the importance of framing effects in first-order stochastic dominance (FSD) criterion violations and finds that individuals violate the FSD criterion, depending on the underlying frame of lotteries. Thus, if the underlying frame makes the FSD superior lottery hard to identify, participants tend to violate the FSD criterion significantly. In this case, participants' sensitivity to the framing effects is related to their risk preferences that play an essential role in identifying which type of them prominently violate the FSD criterion. On the contrary, if the subtle frame of lotteries makes the FSD superior lottery easy to identify, participants hardly violate the FSD criterion. Therefore, the role of risk preferences becomes negligible.

Keywords— first-order stochastic dominance, framing effects, risk preferences

1 Introduction

Let F and G be two risky independent prospects that return a positive outcome x with some probabilities. F first-order stochastically dominates G if $\Pr[F \geq x] \geq \Pr[G \geq x]$ for all x and $\Pr[F > x] > \Pr[G > x]$ for some x. The first-order stochastic dominance (FSD) violation occurs if G is preferred over F. Under rational expectations, any decision-maker with non-decreasing utility in income, i.e., monotonicity assumption, $u' \geq 0$, should prefer F over G because the chance of receiving x is higher in F. Since standard decision theories in the literature, i.e., Expected Utility Theory (EUT), Cumulative Prospect Theory (CPT) and Salience Theory of choice under risk (ST), assume agents have non-decreasing utility, these theories consider FSD violations random or computational errors. However, experimental evidence has documented FSD violations as non-sporadic phenomena, proving that people can deliberately prefer first-order stochastically dominated (henceforth FSD inferior) lotteries, such that their violation of the FSD criterion can be statistically significant.

Birnbaum (2005), Birnbaum (2007) and Levy (2008) argue that an essential trait of decision makers' preferences leading to FSD violations is to be prone to *framing effects* or equivalently *violating coalescing*[1] property of lotteries. In other words, FSD violations depend on the subtle frame of lotteries in a given choice

[1]Coalescing is that if a lottery has more than one branch that returns identical outcomes with different probabilities, combining those branches by adding their corresponding probabilities should not affect individuals preferences. Similarly, reversing coalescing by splitting up a lottery branch into sub-branches should not impact their decisions, either.

set. Thus, Levy (2008) claims that if the subtle frame of lotteries makes the first-order stochastic dominant (henceforth FSD superior) lottery easy to distinguish in a choice set, individuals tend to choose the FSD superior most of the time. The FSD superior prospect is easily notable if a "clear" *probability monotonicity* [2] or *consequence monotonicity*[3] exists between lotteries. However, as the lotteries are getting more complex, such that a clear probability monotonicity or consequence monotonicity does not exist anymore, individuals tend to make mistakes and choose the FSD inferior options, which causes FSD violations (Levy, 2008, p.765).

The most advanced decision theory in the literature explaining the FSD violations – the Transfer for Attention Exchange (TAX) model also explains FSD violations as a result of violating coalescing property. Therefore, the TAX model predicts FSD violations depending on the underlying frame of lotteries, but the sensitivity to the framing effects depends on the curvature of utility functions. Thus, individuals risk-taking behaviour and attitudes develop distinctive patterns predicting FSD deviations. According to the TAX model, people distort objective probabilities and transfer attention to the lottery outcomes, but the curvature of their utility function determines the direction of attention. So, an individual with a concave utility function evaluates a lottery differently than another with a convex utility. Hence, the TAX model can predict more or less FSD deviations for one type of risk-taking behaviour group than others, depending on their probability weighting and utility functions.

Recent developments in the decision theory under risk, namely CPT and ST, have proven that individuals can have systematically inconsistent risk-taking behaviour[4] rather than consistent when confronted with a safe and risky option. In CPT and ST, individuals distort objective probabilities; therefore, people can switch their risk preferences between settings depending on the context. Despite the distorted objective probabilities, CPT and ST models predict no FSD violation for individuals with monotonic utility. However, Dertwinkel-Kalt and Köster (2015) introduce a modified version of the ST, arguing that systematic inconsistent risk-taking behaviour can lead to the FSD violations depending on the subtle frame of lotteris since this modified version of the ST violates coalescing property. Similar to the TAX model, the modified ST predicts FSD violation depending on the underlying frame of lotteries. If the frame of lotteries is changed in a certain way, the modified ST will not predict FSD violation, either.

One natural question is whether the framing effects leading to violations of FSD may or may not be significantly associated with different risk-taking attitudes and behaviour. In this chapter, I experimentally investigate this link while controlling for the importance of the framing effects. Particularly, I analyse how people with different risk-taking attitudes and behaviour assess the first-order stochastic dominant choices under different frames.

This experiment first screens subjects risk-taking attitudes and behaviour throughout their observed choices over mean-preserving spread alternatives. Next, I elicit their choices over first-order stochastic dominance ranked

[2]Clear probability monotonicity exists if two lotteries in a choice set have the same set of returns, and the probabilities of receiving the highest outcomes are higher in one lottery than the other. An example of the probability monotonocity is $F = \{(10, 0.5), (5, 0.5)\}$ and $G = \{(10, 0.4), (5, 0.6)\}$, where F first-order stochastically dominates G.

[3]Clear consequence monotonocity exists if two lotteries in a choice set has the same probability distribution but one lottery has higher outcome. An example of the consequence monotonocity is $F = \{(10, 0.5), (5, 0.5)\}$ and $G = \{(12, 0.5), (5, 0.5)\}$, where F first-order stochastically dominates G.

[4]The systematic inconsistent behaviour can also arise in the TAX model due to probability weighting, which will be discussed in more details in the next section.

lotteries presented under alternative frames and evaluate their choices launching various inferential statistics tests and the probit model regression analysis at the end.

This study finds that individuals risk-taking behaviour is associated with FSD violations. Significant FSD violations occur when the FSD superior lottery is not easily distinguishable in a choice set, and the consistent risk-seeking behaviour groups are the leading group that violates the FSD substantially in this case. However, if re-framed lotteries make the FSD superior option easily identifiable, all participants, including the consistent risk-taking behaviour group, hardly violate the FSD criterion, suggesting people are prone to the subtle frame of lotteries. Furthermore, besides participants risk-taking behaviour, their gender, cognitive abilities and self-persuaded preparedness to take a risk are related to FSD violations when lottery frames are complex, i.e., FSD superior is not easy to identify. On the contrary, these explanatory variables play no prominent role if the underlying structure of lotteries make FSD superior easy to distinguish since all participants are charmed to choose the dominant option, irrespective of their background.

The next section discusses different theories that can and cannot explain FSD violations while justifying the role of risk-taking behaviour and framing effects. Based on the theoretical discussions, a set of hypotheses is developed to test this study. Section 3 describes experiment setup and design for each stage. This section provides full details of choice sets in every stage and reports theoretical predictions of every model employed in this study regarding choice sets. Section 4 reports experiment results, including descriptive and inferential statistics and econometric analysis. Section 5 discusses the related literature and presents our contributions to the literature. Finally, Section 6 summarises the findings of this paper.

2 Theoretical background and hypotheses

This section analyses the theoretical models employed in this study from the viewpoint of FSD violations while exposing the role of risk attitudes and the framing effects in these models. So, I first consider theories that do not violate the FSD criterion and later the ones that can accommodate FSD violations.

Expected Utility Theory (EUT) argues that people are consistent in their risk taking behaviours, that can be risk averse, risk seeker, or risk neutral, depending on the curvature of their utility. So, if individuals confront with safe and risky alternatives, they will consistently choose either risky or safe alternatives, subject to their utility. However, if they face FSD superior and inferior lotteries, the FSD superior is always a utility maximiser choice for everyone, irrespective of their risk preferences. In other words, EUT predicts no FSD deviation for any individual with a non-decreasing utility function (i.e., $u' \geq 0$). Moreover, the EUT never violates coalescing property, suggesting that the subtle frame of lotteries does not alter the decision-makers valuation of the options. If FSD violations occur, EUT consider them as a random or computational error.

Salience Theory of choice under risk (ST) claims that some lottery states are more eye-catching than others; therefore, the individuals who concentrate more on these eye-catching states distort objective probabilities and actual choices. Distorted objective probabilities cause switching risk-preferences between two settings, depending on the context, defined as systematic inconsistent risk-taking (SIR) behaviour[5]. Thus, suppose an individual face a pair of the mean-preserving lotteries: a safe prospect $C = \{(x, 1)\}$ that pays an amount x for

[5]Note that the systematic inconsistent risk-taking behaviour can also arise in the Cumulative Prospect Theory (CPT). The reason for employing the ST as a leading model explaining the systematic inconsistent risk-taking behaviour is that the alternative competing theory that predicts FSD violations for this risk-taking behaviour group is developed based

sure, and a risky prospect $R = \{(x+g, p); (x-l, 1-p)\}$ which returns an amount $x+g$ with probability p and an amount $x-l$ with probability $1-p$, where $g = \frac{(1-p)l}{p}$ and $x > l > 0$. In ST, the state of gain $(x+g, x)$ becomes more (less) salient than the state of loss $(x-l, x)$ for any $p < 1/2$ $(p > 1/2)$. Hence, the ST suggests that a systematic inconsistent risk-taker with concave or linear utility switches from the safe to the risky option at $p < 1/2$, while a systematic inconsistent risk-taker with convex utility will switch from the risky to the safe option at $p > 1/2$. Nevertheless, irrespective of their utility function and switching points, the ST argues that the systematic inconsistent risk-takers will always prefer the FSD superior [6]. In addition, the ST does not violate coalescing, therefore, the underlying frame of lotteries does not alter valuation of FSD lotteries.

Now let us consider decision theories under risk that can predict FSD violations. To begin with, I first consider the **Transfer for Attention Exchange** (TAX) model – a leading alternative decision theory that can predict statistically significant FSD violations in the experimental studies. In the TAX model, an individual weights objective probabilities and transfers attention across lottery branches. However, the direction of attention that determines which branches the individual transfers more attention to is determined by the curvature of their utility function. Thus, an individual with concave or linear (convex) utility transfers a specific and constant ratio of weighted probabilities of the upper (lower) branches to the lower (upper) branches, which distorts objective probabilities even further[7]. Distorted objective probabilities can value the FSD inferior lotteries higher than FSD superiors, which is subject to the underlying frame of lotteries. This implies that the subtle frame of lotteries impacts an individual's valuation of lotteries. Intuitively, if the TAX model predicts FSD violation under one frame, changing the existing frame of these lotteries can halt the prediction of the FSD deviations in the TAX model. And, as a matter of fact, Birnbaum (2007) provides a "re-framing" methodology and experimentally proves that his re-framing methodology reverses preferences of those who violate the FSD criterion in the TAX model. Birnbaum's re-framing methodology suggests that for any choice set that the TAX model predicts FSD inferior as an optimal option can be framed by splitting up the upper branch of the dominant and the lower branch of the dominated lotteries. This new structure of lotteries will value the FSD superior higher than the FSD inferior for anyone, irrespective of their utility functions. As a result, the TAX model predicts FSD superior as an optimal choice.

More interestingly, a closer look at Birnbaum (2007) reveals that Birnbaum has split both lottery branches in a way that both lotteries have got the same probabilities in a choice set. So, following Levy (2008)'s definition of consequence monotonicity, one can claim that Birnbaum (2007)'s re-framing develops a new frame with a clear *consequence monotonicity*, such that both lotteries have the same probabilities, while FSD superior lottery has at least one higher return than the other.

Proposition 1. *If a clear consequence monotonicity exists, such that probabilities in both lotteries are the same, the TAX model never predicts FSD violation for anyone with a non-decreasing utility function.*

Proof. Consider two lotteries $F = \{(x_i, p_i)\}$ and $G = \{(y_i, p_i)\}$, where $\sum_{i=1}^{n} p_i = 1$, $x_i > y_i$ for some i and

on the ST.

[6]For the detailed proof and discussion regarding FSD and Salience theory, please see Online Appendix of Bordalo et al. (2012).

[7]This statement is true if lottery returns are given in descending order, i.e., $x_1 > x_2 > \cdots > x_n > 0$. Otherwise, if lottery returns are given in ascending order, i.e., $0 < x_n < \cdots < x_2 < x_1$, an individual with concave or linear (convex) utility transfers a specific ratio of weighted probabilities of the lower (upper) branches to the upper (lower) branches.

$x_{i\backslash n} \geq y_{i\backslash n}$ for $i\backslash n$. In this setting, the choice set has clear *consequence monotonicity* frame and F first-order stochastically dominates G. Supposing the order of outcomes in both lotteries are given in descending order, i.e., $x_1 > x_2 > \cdots > x_n > 0$ and $y_1 > y_2 > \cdots > y_n > 0$, an individual in the TAX model evaluates F and G as follows:

$$V(F) = \frac{\sum_{i=1}^{n} u(x_i) \left[t(p_i) - \frac{\theta}{n+1} \sum_{j=i+1}^{n} t(p_i) + \frac{\theta}{n+1} \sum_{j=1}^{i-1} t(p_i) \right]}{\sum_{i=1}^{n} t(p_i)} \tag{1}$$

$$V(G) = \frac{\sum_{i=1}^{n} u(y_i) \left[t(p_i) - \frac{\theta}{n+1} \sum_{j=i+1}^{n} t(p_i) + \frac{\theta}{n+1} \sum_{j=1}^{i-1} t(p_i) \right]}{\sum_{i=1}^{n} t(p_i)} \tag{2}$$

where $t(p_i)$ denotes probability weighting function and θ direction of attention. The individual prefer F over G iff $V(F) > V(G)$ or

$$\frac{\sum_{i=1}^{n} (u(x_i) - u(y_i)) \left[t(p_i) - \frac{\theta}{n+1} \sum_{j=i+1}^{n} t(p_i) + \frac{\theta}{n+1} \sum_{j=1}^{i-1} t(p_i) \right]}{\sum_{i=1}^{n} t(p_i)} > 0 \tag{3}$$

which is true for $x_i > y_i$ for some i and $x_{i\backslash n} \geq y_{i\backslash n}$ for $i\backslash n$. □

This proposition suggests that if a clear consequence monotonicity frame exists, the TAX model never predicts FSD violation for anyone with monotonic utility.

The **modified version of the Salience theory** by Dertwinkel-Kalt and Köster (2015) suggests that systematic inconsistent risk-takers do not consider lotteries state by state as the original ST suggests[8], but attribute-wise, where attributes are the lottery outcomes with the same branch index number. Considering lotteries attribute-wise requires less effort than state by state, which is more natural and heuristic. However, evaluating lotteries attribute-wise violates coalescing property, leading to preferences that violate the FSD criterion. On the other hand, attribute-wise consideration makes individuals even more sensitive to the framing effects. Thus, without changing the subtle frame of the lotteries, if the order of returns or probabilities is shuffled even in one lottery, the valuation of the lotteries will be different[9]. So, the modified ST suggests that not only the underlying frame of lotteries but also the order of returns and probabilities impact the valuation of lotteries. Nevertheless, Dertwinkel-Kalt and Köster (2015) formally argue that if lotteries are framed based on Birnbaum (2007)'s methodology, such that a clear probability monotonicity frame exists, the modified ST will stop predicting FSD violation. However, we cannot generalise this arguement and conclude that if the TAX model does not predict FSD violation in one frame, the modified ST will not predict FSD violation under this frame, since the modified ST is more sensitive to the structure of lotteries.

In addition, systematic inconsistent risk-taking behaviour (SIR) can arise in the TAX model due to distorted objective probabilities[10]. However, the TAX model considers SIR behaviour as a side effect of probability

[8]Note that the modified ST relies on the original ST to identify the systematic consistent risk-takers via the mean-preserving lotteries.

[9]For instance, in the modified ST, the preference between $F = \{(5, p), (3, 1-p)\}$ and $G = \{(4, q), (3, 1-q)\}$ is not same with $F = \{(3, 1-p), (5, p)\}$ and $G = \{(4, q), (3, 1-q)\}$. So, changing the order of returns in F causes different valuation.

[10]Suppose agents confront a safe and a risk alternative of C and R described above, where R is a mean preserving spread of C. Thus, the TAX model can predict risk-averse (risk-seeking) behaviour for risk-seekers (risk-averters) at higher (lower) values of p depending on the probability weighting function, and the pattern of switching in the risk-attitude in the TAX model is similar to ST.

weighting, therefore, treats them no more different than the others. In addition, the TAX model cannot provide a clear switching point for changes in risk preferences as the ST does because of the complex structure of the model. Hence, the TAX model is reserved for studying the agents' behaviour with the consistent risk-taking preferences and the modified ST for the systematic inconsistent risk-takers in FSD violations.

2.1 Hypotheses

In the light of this theoretical discussion and findings, a set of hypotheses are developed to test in this study. The first hypothesis tests how people's risk-taking behaviour and attitude are associated with their FSD violation rate by asking whether people violate the FSD? According to the EUT, ST and CPT, any individual, irrespective of their risk preferences, should not violate the FSD; therefore, the probability of choosing the FSD inferior is 0%. However, if people make random mistakes and go for FSD inferior choices, the chance of choosing the FSD inferior is less than 50%, and completely naïve people who simply randomise should choose the FSD inferior choices 50% of the time. On the contrary, if people behave according to the TAX and the modified ST theories, the chance of choosing the FSD inferior lottery will be more than 50% in those choice sets, where these theories predict FSD violations. Hence, the first null hypothesis is:

Hypothesis 1. ***(H1:)*** *The probability of choosing the FSD inferior lottery is less than or equal to 50%; $H_0 : q \leq 50\%$, where q is the probability of choosing the FSD inferior.*

In comparison, the alternative hypothesis proposes that the chance of choosing the FSD inferior is greater than 50% in those choice sets where the TAX and the modified ST predicts FSD violations, $H_A : q > 50\%$.

The second part of this study investigates the importance of the subtle frame of lotteries in FSD violations. Although the standard decisions claim that lotteries' subtle frame has no impact on FSD violations, the TAX model and the modified ST argue otherwise. Thus, if the frame of lotteries is *complex*, i.e., lacking clear consequence monotonicity, people tend to violate the FSD criterion under this frame more often. Otherwise, if the underlying frame of lotteries has consequence monotonicity, the frequency of the FSD violation will be less. Considering two competing views on the importance of framing effects, the second null hypothesis is:

Hypothesis 2. ***(H2:)*** *The mean of FSD violation frequency will be the same irrespective of the frame of lotteries, $H_0 : \mu_1 = \mu_2$, where μ_1 and μ_2 are the mean of the FSD violation frequency under two different frames, respectively.*

Intuitively, the alternative hypothesis suggests that re-framing improves the FSD choices. Therefore, the difference between the mean score of the FSD violation rate under two frames will not be the same for anyone, $H_A : \mu_1 \neq \mu_2$.

So, the first part of this experiment tests whether people violate the FSD criterion. If so, how the violation rate differs across different risk-taking behaviour groups, discovering the potential links between risk-taking behaviour and the FSD violation rate. On the other hand, the second part of this experiment will investigate whether the underlying frame of lotteries influences the FSD violation rate. If so, which risk-taking behaviour group is more prone to the framing effects.

3 Experiment design & setup

This experiment is designed to test the developed hypotheses in this chapter and consists of three stages that serves three essential purposes. The first purpose is to screen out individuals' risk attitudes and behaviour. The second is to test how individuals with different risk preferences assess the first-order stochastic dominant lotteries. Finally, the third is to observe how re-framing lotteries influence each individual's preferences over the FSD choices.

The experiment is developed as an individual decision-making task in *o-Tree* (Chen et al., 2016) in which participants face 19 pairs of risky prospects (i.e., lotteries) and the modified version of *Cognitive Reflection Test* (CRT) by Frederick (2005) at the end. Participants face one pair of lotteries on each page and must choose one lottery to move to the next pair during the task. The order of lotteries is the same for everyone. Participants cannot reverse their decisions once they click on their preferred option [11].

3.1 Setup

Stage 1: The purpose of this stage is elicit risk preferences of participants via mean-preserving spread alternatives. Thus, participants face five pairs of the mean-preserving lotteries: a safe prospect $C = \{(x, 1)\}$ that pays an amount x for sure, and a risky prospect $R = \{(x + g, p); (x - l, 1 - p)\}$ which returns an amount $x + g$ with probability p and an amount $x - l$ with probability $1 - p$, where $g = \frac{(1-p)l}{p}$ and $x > l > 0$. The set of values for p receives is $P = \{0.9, 0.8, 0.25, 0.2, 0.1\}$, where $p \in P$. Values for x and l vary differently, ensuring that the state of gain does not return more than 100 points at lower values of p due to the study budget.

Individuals who are consistent risk-averse or risk-seeking will prefer either the safe option C or the risk prospect R accordingly. But, most importantly, their choices will be consistent in all five choice sets in this stage. On the contrary, systematic inconsistent risk-taking people will switch their risk attitudes at one point in this stage. Thus, the Salience Theory of choice under risk (ST) predicts [12] that a systematic inconsistent risk-taker with concave or linear utility switches from the safe to the risky option at $p < 1/2$, while a systematic inconsistent risk-taker with convex utility will switch from the risky to the safe option at $p > 1/2$. So, in this stage, p starts at 0.90 and descends in the given order of P. So, by definition, a systematic inconsistent risk-taker will shift risk attitude from a risk-averse to risk-seeking at one of the mean-preserving lottery choice sets. According to the participants' preferences over the mean-preserving lotteries $C = \{(x, 1)\}$ and $R = \{(x + g, p); (x - l, 1 - p)\}$, any $p \in P$, they can be categorised as:

- consistent risk-averters (CRA) who always prefers the sure prospect C;
- consistent risk-seekers (CRS) who always prefers the risky prospect R;
- systematic inconsisntent risk-taker (SIR) who switches their risk attitudes from risk-averse to risk-seeking at one point;
- erratic risk-takers (ER) whose choices are random, such that cannot be explained by the theoretical models employed in this study.

Stage 2: After completing Stage 1, participants move to Stage 2, where they face seven pairs of lotteries. The pair of lotteries are developed based on Birnbaum's receipt of creating first-order stochastic dominant

[11] This experiment received full ethical approval from the University of Leicester Ethics Committee before launching.

[12] See Appendix for a detailed theoretical review.

lotteries (Birnbaum, 2005, p266). In every pair, one lottery first-order stochastically dominates the other. In addition, the underlying frame of lotteries in this stage are *complex*, such that there is no clear probability or consequence monotonicity. The choice sets are presented in this stage is provided in Table 12.

EUT, CPT and ST do not predict any FSD violation in this stage. On the contrary, the TAX model and the modified ST predict FSD violations. Thus, the TAX model with *prior* estimated model parameters[13] predicts that a decision-maker with a convex utility function violate FSD in Choice set 1, 4 and 6, or equivalently, in choice sets, where the upper branch probability difference between the dominant and the dominated lottery, that is denoted as Δ_1, is less than 0.25, $\Delta_1 < 0.25$.[14] On the other hand, the TAX model with prior parameters forecasts that an individual with concave or linear utility will violate the FSD in Choice set 1, 3, 4, 5 and 6, or equivalently, in choice sets where $\Delta_1 < 0.45$. In comparison, the TAX model with prior estimated parameters predicts that an individual with concave or linear utility will violate the FSD in more choice sets than an individual with convex utility.

The modified ST also predicts FSD violations in this stage, depending on the value of δ, which captures how much an individual departs from rationality and takes value between 0 and 1, where 1 indicates full rationality. The modified ST suggests that as Δ_1 increases in a choice set, a systematic inconsistent risk-taking behaviour will prefer the FSD inferior at lower values of δ, suggesting that people should depart from the rationality substantially to prefer the FSD inferior at higher values of Δ_1. The previous experimental studies, namely Bordalo et al. (2012); Königsheim et al. (2019), estimate a value for the rationality parameter, which happens to be around 0.7. If $\delta = 0.7$, the modified ST suggests that a systematic inconsistent risk-taking people will violate the FSD in Choice set 1 and 6.

Stage 3: After completing Stage 2, participants move to this stage, where they face seven different pairs of lotteries, where one lottery first-order stochastically dominates the other. The new pairs are "re-framed" versions of Stage 2 choice sets. First, all lottery returns are diminished 20% to avoid confusion with the earlier stage. Later, the lotteries are re-framed according to Birnbaum (2007)'s methodology – splitting the upper branch of the dominant and the lower branch of the dominated lotteries in all choice sets. Likewise Birnbaum (2007), branches of the complex framed lotteries are split in a way that probabilities in both lotteries are the same to give a rise *consequence monotonicity* naturally. Therefore, as per Proposition 1, the TAX model does not predict any FSD violation in this stage for anyone. In addition, the modified version of ST with its prior estimated parameter predicts does not predict the FSD violation, either.

Cognitive Reflection Test (CRT) by Frederick (2005) is presented at the end of the main task, which is a practical methodology to measure how much participants exert cognitive effort during the task. Previous studies show a correlation between the achieved score in CRT and the risk preference of participants (Frederick, 2005; Königsheim et al., 2019). So, this study will also test how exerted cognitive effort during the experiment is associated with the FSD violations.

After finalising the main experiment, participants complete a questionnaire regarding their demographics (e.g., age, sex, education, ethnicity) and learn the bonus payment they earned on the following page.

[13] The parameters that Birnbaum estimated using their experimental study.

[14] I have developed a web-based calculator based on Birnbaum's exicting calculator, where you can calculate and compare a pair of lotteries returns simultaneously according to TAX, CPT and EUT models; link to the calculator.

3.1.1 Controls and incentives

Before starting the task, participants are informed about the purpose of the research and data management protocols. Then, upon agreeing and giving full consent of using their data for scientific research, participants read instructions and take a mini-quiz to ensure they have understood the instructions well. Upon their incorrect answers, the explanations are provided in a message box, and they are asked to retake the mini-quiz to ensure they are ready to start the task. The experiment also consists of some additional questions to check whether the participants pay attention during the session.

Upon completing the task successfully, participants receive a fixed participation fee of 1.50 GBP and bonus payment determined by their choices during the experiment. Thus, one of the lotteries they selected during the task was picked up and based on its probability distribution, the software plays the lottery and determines the amount of bonus payment.

The experiment currency is *point* basis, and each participant can win up to 100 points. The conversion rate between the experiment currency and the actual currency – GBP, is 20:1 (i.e., 20 points are equivalent to 1 GBP). Hence, the bonus payment is in a range between 1 GBP and 5 GBP.

4 Results

The experiment was run in four different sessions with 140 participants in the Prolific platform. Participants received an average total payment of 4.10 GBP (5.60 USD) and completed the task in an average of 15 minutes.

4.1 Characteristics of participants

In the sample, the ratio of female participants (85, 61%) is more significant than male. In addition, most participants identify themselves as white (113, 81%). In terms of age, the youth between ages 18 to 24 is the largest group (45, 32%). Subjects in their late 20s (32, 23%) and early 30s (22, 16%) are the sample's second and third most prominent populated age groups, respectively. Interestingly, participants older than 45 are the fourth biggest age group with 17 (12%) subjects, suggesting that age groups are well-diversed. With regard to educational background, most participants highest achieved educational qualification is a non-university degree (61, 43%), while participants with a bachelor's degree are the second most populous group in the sample (46, 33%). The number of participants who holds a master's degree is 28 (20%), and a doctoral degree is 5 (4%).

In the Cognitive Reflective Test (CRT), only 44 participants (32%) have answered all three questions correctly and scored three. Fourty-two participants (30%) have scored two, while thirty participants (22%) have scored one. The rest (24,18%) have failed in all questions and scored zero.

4.2 Stage 1: elicited risk preferences

Participants risk attitudes and behaviour were elicited by screening their preferences over the mean-preserving lotteries in Stage 1. To do this, I employ the the classification defined in sub-section 3.1 to identify each type of decision maker. Based on this classification, the single largest group of participants (60, 43%) fits the *systematic inconsistent risk-taking* (SIR) behaviour group who switches their risk attitude from risk-averse to risk-seeking at one point in Stage 1. The second-largest group of participants is the *consistent risk-averters* (CRA) (31, 22%), while the third-largest group is *consistent risk-seekers* (CRS) (28, 20%). The rest of the participants are classified into *erratic risk-taking behaviour* (ER) category (21, 15%) who switch their risk attitudes more than once or randomly, which cannot be explained by any of the theories employed in this study.

In Stage 1, twenty-two subjects switch their risk attitude at one choice set, and in the following choice set, they switch their risk attitudes back again. If this kind of subsequent switch in the risk attitude occurs just once, it is considered a *computational error*. Participants who have made a computational error just once are still considered consistent risk-taking people. They are classified as either consistent risk-averter or risk-seeker depending on their preferences before and after the computational error in Stage 1. Nevertheless, if participants make the computational error more than once, they are also considered an erratic risk-taker (ER).

Type	Freq.	Percent	Cum.
Systematic inconsistent risk-taker (SIR)	60	43%	43%
Consistent risk-averter (CRA)	31	22%	65%
Consistent risk-seeker (CRS)	28	20%	85%
Erratic risk-taker (ER)	21	15%	100%
Total	140	100%	

Table 1: Risk-taking behaviour groups and their relative size in the sample

At the end of the experiment, participants answered how prepared they are to take risks, and their answers are provided in Table 2. The results show that participants persuaded readiness to take risks differ than their elicited risk preferences. Thus, fifteen participants have indicated that they are "definitely" ready to take risks, while Stage 1 observations confirm that only three of them are CRS, while six are CRA. Thirty-nine subjects define themselves as "most probably" ready to rake risks, but elicited risk preferences confirm that only ten of them are CRS, nineteen are SIR, and eight are ER. On the other hand, fifty-three participants identify themselves as "possible" ready for seeking risks, but only eleven of them consistently prefer the safe option in Stage 1, while majority of them are SIR.

	1-Definitely	2-Probably	3-Possibly	4-Probably Not	5-Definitely Not
CRA	6	2	11	10	2
CRS	3	10	12	3	0
SIR	4	19	22	14	1
ER	2	8	8	2	1
Total	15	39	53	29	4

Table 2: Readiness to take risk and elicited risk preferences

Let us now examine how participants assess the first-order stochastic dominant lotteries in Stage 2 and 3.

4.3 FSD violations and risk preferences

Considering the first null hypothesis of the study, I first test whether the FSD violations are statistically significant in Stage 2 and 3. If so, how participants risk-taking behaviour is associated with FSD violations.

To begin with, I first consider participants choices in Stage 2, where the lotteries are presented in *complex* frame, i.e., neither clear probability nor consequence monotonicity exists. EUT, CPT and ST argue that no individual should prefer the FSD inferior option unless it is chosen accidentally. On the contrary, the TAX model and the modified ST predict the FSD violation in some choice sets in Stage 2. More precisely, the TAX model with prior estimated parameters predicts that a consistent risk-averse individual will violate the FSD in Choice Sets 1, 3, 4, 5 and 6, while a consistent risk-seeking individual in Choice set 1, 4 and 6. On the other hand, the modified ST with prior estimated rationality parameter δ predicts that a systematic inconsistent risk-taker will violate the FSD in Choice set 1 and 6.

Sets	All N=140	*excld* CRS N=112	SIR N=60	CRA N=31	CRS N= 28	ER N=21
Set 1	81 (0.0378)**	55 (0.6115)	33 (0.2595)	10 (0.9853)	26 (0.000)***	12 (0.3318)
Set 2	36 (1.000)	20 (1.000)	9 (1.000)	1 (1.000)	16 (0.2858)	10 (0.6682)
Set 3	45 (1.000)	27 (1.000)	14 (1.000)	4 (1.000)	18 (0.0925)*	9 (0.8083)
Set 4	42 (1.000)	22 (1.000)	11 (1.000)	2 (1.000)	20 (0.0178)**	9 0.8083
Set 5	41 (1.000)	22 (1.000)	9 (1.000)	5 (1.000)	19 (0.0436)**	8 (0.9054)
Set 6	78 (0.1023)	55 (0.6115)	28 (0.7405)	12 (0.9252)	23 (0.005)***	15 (0.0392)**
Set 7	39 (1.000)	22 (1.000)	11 (1.000)	2 (1.000)	17 (0.1725)	9 (0.8083)

N represents the sample size. p-values in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

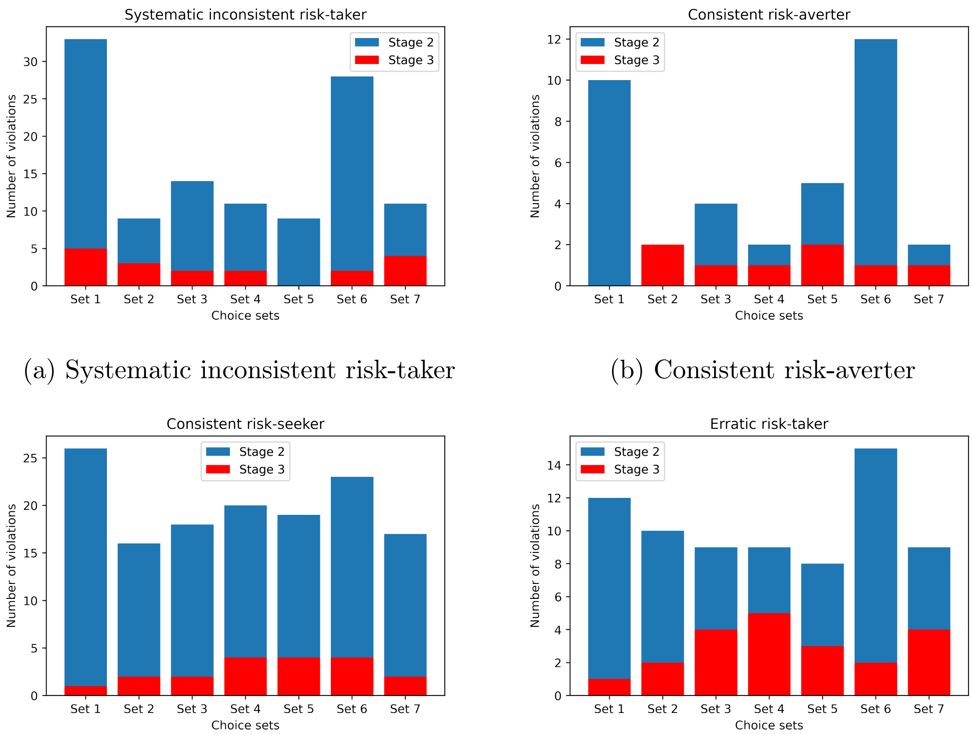
Table 3: Number of FSD violations in each choice set and the binomial statistics for Stage 2 observations

The summary of the FSD violations in Stage 2 is presented in Table 3. A binomial test confirms that the systematic inconsistent risk-takers (SIR) and the consistent risk-averters (CRA) do not violate the FSD statistically significant in any choice set in Stage 2, suggesting that the FSD violation of both these groups is a random error. Hence, the first null hypothesis of not violating the FSD cannot be rejected for CRA and SIR.

In contrast, erratic risk-takers (ER) violate the FSD statistically significantly in one choice set out of seven at a 10% confidence interval, while consistent risk-seekers (CRS) in five, more than the TAX model predicts for the CRS.[15] For this reason, the first null hypothesis can be rejected for ER and CRS in those choice sets where they violate the FSD statistically significantly. As a result, Stage 2 observations confirm that FSD violations are associated with participants risk-taking behaviour, while consistent risk-seekers (CRS) are the leading risk-taking behaviour group that violate the FSD most.

Also, pooled Stage 2 observations confirm that participants violate FSD mostly in Choice set 1 and 6, where the upper branch probability difference between dominant and dominated lotteries, $\mathit{\Delta}_1$, is equal to 0.05, the smallest $\mathit{\Delta}_1$ amongst the other choice sets in Stage 2. Nevertheless, a binomial test confirms that FSD

[15]This finding implies that prior estimated parameters for the TAX model are short of predicting the FSD violations in this sample



(a) Systematic inconsistent risk-taker

(b) Consistent risk-averter

(c) Consistent risk-seeker

(d) Erratic risk-taker

Figure 1: FSD violations in Stage 2 and 3

violation is statistically significant in only Choice set 1 at a 10% confidence level. However, excluding CRS observations from the pooled data confirms that no statistically prominent FSD violations exist, implying that CRSs' preferences for the FSD inferior lotteries in Stage 2 causes "population" wide prominent FSD violations.

In Stage 3, participants face *re-framed* version of Stage 2 lotteries, where the frame of lotteries "consequence monotonicity". Both standard and alternative decision theories predict no FSD violation in this stage. Hence, it is expected that the CRS and other risk-taking behaviour groups will not violate the FSD criterion. Consequently, a binomial test confirms that neither risk-taking behaviour type violates the FSD criterion significantly in any choice in this stage. So, the first null hypothesis of not violating FSD in any choice set cannot be rejected at any confidence level here. In addition, we can confirm that Proposition 1 prediction is valid for CRSs since they are the only group that the TAX model can predict their behaviour in the previous stage.

4.4 Re-framing effects

This section investigates the importance of the framing effects by identifying the sensitivity of each risk-taking behaviour group to it. EUT, ST and CPT argue that re-framing lotteries should not impact preferences, whereas the TAX model and the modified version ST claim otherwise. So, considering the second-null hypothesis of this study, I test whether the mean of FSD violation rate between two stages, i.e., Stage 2 and 3, is statistically different. The previous section indicates that re-framing lotteries improve participants choices who violate the FSD significantly in Stage 2. In this part, I investigate the significance of the framing effects further and understand whether re-framing lotteries improve decisions of everyone, including those who do not violate the FSD criterion in the first place.

Sets	All N=140	*excld* CRS N=112	SIR N=60	CRA N=31	CRS N= 28	ER N=21
Set 1	7 (1.000)	6 (1.000)	5 (1.000)	0 (1.000)	1 (1.000)	1 (1.000)
Set 2	9 (1.000)	7 (1.000)	3 (1.000)	2 (1.000)	2 (1.000)	2 (1.000)
Set 3	9 (1.000)	7 (1.000)	2 (1.000)	1 (1.000)	2 (1.000)	4 (1.000)
Set 4	12 (1.000)	8 (1.000)	2 (1.000)	1 (1.000)	4 (1.000)	5 (1.000)
Set 5	9 (1.000)	5 (1.000)	0 (1.000)	2 (1.000)	4 (1.000)	3 (1.000)
Set 6	9 (1.000)	5 (1.000)	2 (1.000)	1 (1.000)	4 (1.000)	2 (1.000)
Set 7	11 (1.000)	9 (1.000)	4 (1.000)	1 (1.000)	2 (1.000)	4 (1.000)

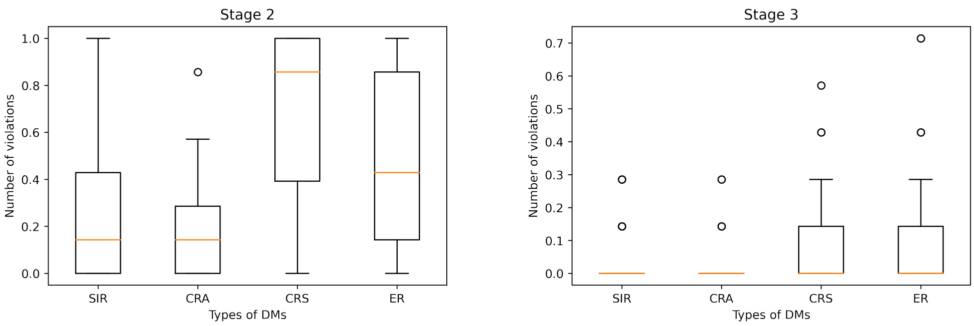
p-values in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Number of FSD violations in each choice set and the binomial statistics for Stage 3 observations

The second null hypothesis of this study argues that the re-framing of lotteries should not impact the participant's choices; therefore, the mean score of the FSD violation rate in each stage should be equal to each other. However, descriptive statistics suggest that the mean of the FSD violation rate for each risk-taking behaviour in Stage 3 is lower than Stage 2, suggesting that re-framing does not only improve choices of those who violate the FSD prominently in Stage 2 but also those who do not. So, paired t-test confirms that the difference in the mean of the FSD violation rates between the two stages is statistically significant at a 1% confidence level, suggesting that re-framed lotteries improve participants preferences leading to FSD superior options. In addition, the lower frequency of the FSD violation rates suggests that Levy (2008)'s formal argument regarding frames is correct. Thus, clear consequence monotonicity in lottery structure leads to fewer FSD violations, while complex structured lotteries lead to more FSD violations.

$N = 140$	Stages	Mean	St dev	Min	Max
All	Stage 2	0.3693	0.3549	0.0000	1.0000
	Stage 3	0.0673	0.1386	0.0000	1.0000
SIR	Stage 2	0.2738	0.2955	0.0000	1.0000
	Stage 3	0.0428	0.0884	0.0000	0.2857
CRA	Stage 2	0.1659	0.1989	0.0000	0.8571
	Stage 3	0.0368	0.0822	0.0000	0.2857
CRS	Stage 2	0.7091	0.3466	0.0000	1.0000
	Stage 3	0.0969	0.1605	0.0000	0.5714
ER	Stage 2	0.4898	0.3573	0.0000	1.0000
	Stage 3	0.1428	0.2347	0.0000	0.7143

Table 5: Descriptive statistics of FSD violation rate in Stage 2 and 3



(a) Stage 2 (b) Stage 3

Figure 2: FSD violation rate across two different stages

	All	SIR	CRA	CRS	ER
paired t-test	$t(139) = 11.04$	$t(59) = 6.60$	$t(30) = 3.23$	$t(27) = 9.97$	$t(20) = 5.10$
p-value	$(0.000)^{***}$	$(0.000)^{***}$	$(0.003)^{***}$	$(0.000)^{***}$	$(0.000)^{***}$

p-values in parentheses: *** $p < 0.01$

Table 6: Paired t-test comparing the mean score of FSD violation rate of every risk-taking behaviour group between two stages

Finally, Welch's t-test in Table 7 and 8 confirms that the mean of the FSD violation rate of each risk-taking behaviour group differs statistically significantly in Stage 2 at a 5% confidence level, confirming that individuals' risk preferences develop a unique pattern in the FSD violation rate. In contrast, Welch's t-test finds that the mean of the FSD violation rate for some risk-taking behaviour groups is not statistically different in Stage 3, that are presented in Table 8. This test result suggests that re-framing lotteries nudge everyone to choose the FSD superior lotteries, such that their choices are not much different from one another. As a result, Welch's t-test outcome for Stage 2 and 3 observations suggests that the FSD violations are related to individuals' risk preferences, and the subtle frame of lotteries is essential for the FSD violations.

	CRS	ER	CRA
SIR	$t(82.73) = 2.06$ $(0.0421)^{**}$	$t(30.15) = -2.49$ $(0.0186)^{**}$	$t(46) = -5.75$ $(0.0000)^{***}$
CRA	$t(42.10) = -7.28$ $(0.0000)^{***}$	$t(28.45) = -3.77$ $(0.0001)^{***}$	
ER	$t(42.50) = 2.15$ $(0.0369)^{**}$		

p-values in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Welch's t-test outcomes for Stage 2 observations

4.5 Econometric analysis

Given the nature of the experiment, participants preferences over the lotteries in every choice set are stored as a binary variable y, which takes a value of one if FSD superior is chosen, zero otherwise. Taking into account

	CRS	ER	CRA
SIR	$t(34.86) = -1.67$ (0.1042)	$t(22.01) = -1.90$ $(0.0698)^{*}$	$t(64.80) = 0.32$ (0.7492)
CRA	$t(39.32) = -1.78$ $(0.0827)^{*}$	$t(23.35) = -1.99$ $(0.0586)^{*}$	
ER	$t(33.44) = -0.77$ (0.4459)		

p-values in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Welch's t-test outcomes for Stage 3 observations

the binary nature of the dependent variable, a probit regression has been launched to profoundly investigate the role of risk-taking behaviour groups on the FSD violation rate under two different frames.

To begin with, I pooled participants choices over the FSD lotteries in each stage. Later, dummy variables are generated for participants risk-taking behaviour group, gender, age group, educational background and race. In addition, a set of dummy variables are produced to represent seven choice sets in each stage. Besides the dummy variables, the probit model also includes two polychotomous variables that are:

1. *participant's self-persuaded readiness to take a risk* takes a value between one and five, where one indicates "definitely" ready to take risks, two "probably", three "possibly", four "possibly not" and five "definitely not";
2. *Cognitive Reflective Test (CRT) score* takes a value between zero and three, indicating the number of correct answers to the three CRT questions in the experiment.

Treating these polychotomous variables as a *factor* variable enables the inclusion of all their levels in the probit model without creating dummy variables. In this case, the first level is considered reference group. So, considering all the explanatory variables, the probit model equation is

$$\Pr(y = 1|\mathbf{X}) = \mathbf{\Phi}(\beta_0 + \beta_1 CRA + \beta_2 SIR + \beta_3 ER + \mathbf{x}\delta) \tag{4}$$

where $\mathbf{\Phi}(\cdot)$ is the cumulative distribution, β_0 is the constant that represents the reference groups, CRA is a dummy variable representing consistent risk-averters, SIR is a dummy variable for the systematic inconsistent risk-takers, ER is a dummy variable for the erratic risk-takers and $\mathbf{x}\delta$ is shorthand for other explanatory variables that are given in Table 9. The constant term β_0 represents a participant with the following characteristics:

- elicited risk-preference: *consistent risk-seeker*;
- gender: *male*;
- age: *46 or above*;
- race: *non-white*;
- highest achieved education level: *undergraduate degree*;
- self-persuaded preparedness to take risks: *1 – Definitely*;
- CRT score: *0 – no correct answers*;
- choice set: *Set 1.*

The summary of all the explanatory variables is presented in Table 14.

Gender:	female	=1 for female, 0 otherwise
Race:	white	= 1 for white, 0 otherwise
Age group:	18 to 24	=1 for age between 18 and 24, 0 otherwise
	25 to 30	=1 for age between 25 and 30, 0 otherwise
	31 to 35	=1 for age between 31 and 35, 0 otherwise
	36 to 40	=1 for age between 36 and 40, 0 otherwise
	41 to 45	=1 for age between 41 and 45, 0 otherwise
Education:	no formal	=1 for no formal education[a], 0 otherwise
	hSchool	=1 for high school education, 0 otherwise
	master	=1 for master's degree, 0 otherwise
	doctoral	=1 for doctoral degree, 0 otherwise
CRT score:	1	for 1 correct answer, 0 otherwise
	2	for 2 correct answers, 0 otherwise
	3	for 3 correct answers, 0 otherwise
Preparedness to take risk:	2	"Probably", 0 otherwise
	3	"Possibly", 0 otherwise
	4	"Probably not", 0 otherwise
	5	"Definitely not", 0 otherwise
Choice sets:	Set 2	=1 for choice set 2, 0 otherwise
	Set 3	=1 for choice set 3, 0 otherwise
	Set 4	=1 for choice set 4, 0 otherwise
	Set 5	=1 for choice set 5, 0 otherwise
	Set 6	=1 for choice set 6, 0 otherwise
	Set 7	=1 for choice set 7, 0 otherwise

Table 9: Variable Descriptions

[a] highest achieved level of education

A probit model regression will be estimated for Stage 2 and 3 observations. Considering re-framing lotteries in Stage 3 improves the FSD violation for all participants, it is expected that the probit model regression estimation for each of these stages will be different.

In Stage 2, consistent risk-seekers (CRS) significantly violate the FSD criterion in five out of seven choice sets; therefore, it is expected that being a CRS type will negatively influence the probability of choosing the FSD lottery, ceteris paribus. Also, Erratic risk-takers (ER) violate the FSD criterion in only one choice set out of seven, suggesting that being an ER type will have either negative or incrementally positive impact choosing the FSD superior option in this stage. On the contrary, being either a consistent risk-averse (CRA) or a systematic inconsistent risk-taker (SIR) type will positively influence on the probability choosing the FSD superior, since both violate the FSD insignificantly in Stage 2.

In Stage 3, re-framed lotteries make FSD easily distinguishable; therefore, participants tend to prefer the FSD superior option, irrespective of their characteristics. Hence, one can expect that all the explanatory variables positively influence choosing the FSD superior; but this may not be the case. Thus, everyone is cajoled into choosing the FSD superior; therefore, the role of explanatory variables will may be obsolete, such that they may not produce statistically significant estimators for the Stage 3 observations.

	Stage 2		Stage 3	
Variables	**Coef.**	***p*-value**	**Coef.**	***p*-value**
female	-0.2377	0.023	-0.0023	0.988
CRA	1.4542	0.000	0.3288	0.153
SIR	1.0021	0.000	0.1016	0.576
ER	0.5924	0.000	0.3764	0.116
CRT Score				
1	0.3345	0.028	0.1178	0.613
2	0.5779	0.000	0.0027	0.990
3	0.8964	0.000	-0.1231	0.572
Self persuaded preparedness to take risk				
2	0.5262	0.005	-0.3967	0.241
3	0.3918	0.027	-0.6300	0.054
4	0.7297	0.000	-0.5049	0.139
5	0.0803	0.800	-1.0082	0.036
White	-0.1201	0.356	-0.1723	0.384
doctoral	0.3350	0.257	-0.3668	0.315
hSchool	0.2261	0.043	-0.3919	0.010
master	0.3365	0.020	0.0618	0.776
noformal	-0.1101	0.870	-0.5897	0.357
age18_to24	-0.0244	0.860	0.1302	0.509
age25_to29	0.0117	0.938	0.0433	0.837
age30_to35	-0.0317	0.845	-0.0076	0.973
age41_to45	-0.3259	0.113	0.3290	0.321
cset1	-1.0165	0.000	0.1799	0.435
cset2	0.0901	0.621	-0.0051	0.981
cset3	-0.1661	0.351	0.2675	0.260
cset4	-0.0874	0.624	0.4085	0.103
cset5	-0.0652	0.715	0.1795	0.434
cset6	-0.9416	0.000	0.1755	0.444
constant	-0.9526	0.001	1.9423	0.000
Number of obs.	980		980	
Log likelihood	-479.480		-226.818	
LR $\chi^2(26)$	331.95		29.04	
Pr $> \chi^2$	0.000		0.2702	
Pseudo R^2	0.2571		0.0619	

Table 10: Probit model regression results for Stage 2 and 3 observations

The probit model regression estimation for Stage 2 and 3 observations are presented in Table 10. The results suggest the probit regression explains Stage 2 observations better than Stage 3; thus, most explanatory variables do not produce statistically significant estimators, and the likelihood ratio is statistically insignificant for Stage 3 observations. The reason for the poor performance of the probit regression for Stage 3 observations is that re-framed lotteries make the FSD superior easily distinguishable; therefore, participants are induced to choose the FSD dominant lotteries, irrespective of their characteristics. Therefore, participants' characteristics play no role in determining the probability of choosing the FSD superior in this stage. Moreover, from a technical viewpoint, the total number of FSD violations in the pooled data is less than 7%, which do not provide sufficient observations for the probit regression to produce statistically significant log-likelihood ratio.

Although the probit model generates a significant likelihood ratio for Stage 2 observations, some explanatory variables, namely the educational background, race, and age groups, do not produce statistically prominent estimators, such that p-values of these estimators are higher than a 10% confidence level. In addition, most of the dummy variables that represent choice sets do not produce statistically significant estimators either. Therefore, I launch a new probit regression model for Stage 2 observations by dropping the explanatory variables with p-values higher than 10% and replacing choice set dummy variables with a new single variable representing the upper branch probability difference between the dominant and the dominated lotteries in every choice set, $\mathit{\Delta}_1$. Remember that participants tend to violate the FSD criterion in the choice sets where the upper branch probability difference parameter $\mathit{\Delta}_1$ is low in Stage 2. Therefore, it is expected that as $\mathit{\Delta}_1$ increases, the chance of choosing the FSD superior will improve in Stage 2 in this new probit model. However, $\mathit{\Delta}_1$ is equal to zero in Stage 3 since the new frame produces the exact probabilities in each choice set to deliver clear consequence monotonicity. So, the equation that represents the new probit model is:

$$\begin{aligned}\Pr(y=1|\mathbf{X}) = \mathbf{\Phi}(\beta_0 + \beta_1\text{CRA} + \beta_2\text{SIR} + \beta_3\text{ER} + \beta_4\text{Female} + \beta_5\text{CRT\_score} \\ + \beta_6\text{Risk\_percep.} + \beta_7\mathit{\Delta}_1).\end{aligned} \tag{5}$$

The summary of the new probit model estimation for Stage 2 and 3 observations is Table 11, where dy/dx denotes *average marginal effects* (AME) of each independent variable, determining how each regressor impacts the probability of choosing the FSD dominant option in Stage 2 and 3, accordingly.

In this new probit regression estimation, the constant term represents a male and consistent risk-seeker with a self-persuaded risk-perception of 1 (i.e., "Definitely" ready to take risks) and the CRT score of 0 (i.e., no correct answer to the CRT). So, the constant term suggests that belonging to a consistent risk-seeker group negatively influences the probability of choosing the FSD dominant lottery in Stage 2. However, if a participant belongs to other types of risk-taking behaviour groups, the probability of preferring the FSD superior option increases in Stage 2. Interestingly, average marginal effect estimation suggests that consistent risk-averter (CRA) has the most decisive influence on the probability of choosing the FSD dominant lottery in Stage 2. In contrast, the erratic risk-taker type (ER) has the lowest impact, ceteris paribus. As a result, the probit model estimation confirms our findings in inferential statistics. Thus, consistent risk-seekers are the leading risk-taking behaviour group violating the FSD more often and statistically significantly in Stage 2. In contrast, consistent risk-averters and systematic inconsistent risk-takers prefer the FSD dominant lottery most of the time. This confirms that the FSD violations are associated with participants risk-taking behaviour.

Besides participants elicited risk preferences, their self-persuaded preparedness to take a risk also significantly impacts choosing the FSD dominant lottery in Stage 2. The higher reluctance to take a risk, the higher probability of choosing the FSD dominant lottery in Stage 2 [16].

Cognitive Reflective Test (CRT) scores reveal another interesting story regarding the FSD violations, implying that exerting more cognitive effort in the experiment increases the probability of choosing the FSD superior prospect in Stage 2, ceteris paribus. In other words, the participants who have exerted more cognitive effort also have a better intuition to identify the FSD superior lotteries in Stage 2, where the lotteries are presented in a complex frame, positively influencing the probability of choosing the FSD superior lottery. The higher the score is, the higher probability of preferring the FSD superior lottery in Stage 2, as seen in average marginal effects.

[16] Note that only four people have identified themselves as "definitely not ready" to take risks by choosing option 5 in risk perception; therefore, option five does not yield a statistically significant coefficient.

Variables	Stage 2		Stage 3	
	Probit	dy/dx	Probit	dy/dx
Female	-0.1938	-0.0562	0.0469	0.0060
	$(0.047)^{**}$	(0.047)	(0.725)	(0.725)
CRA	1.3781	0.3996	0.2788	0.0354
	$(0.000)^{***}$	(0.000)	(0.191)	(0.192)
SIR	1.0022	0.2906	0.1331	0.0169
	$(0.000)^{***}$	(0.000)	(0.431)	(0.431)
ER	0.6045	0.1753	0.3773	0.0479
	$(0.000)^{***}$	(0.000)	(0.102)	(0.104)
Preparedness to take				
2	0.4102	0.1246	-0.5085	-0.0388
	$(0.017)^{**}$	0.0180	(0.112)	$(0.049)^{**}$
3	0.2970	0.0913	-0.7130	-0.0660
	$(0.068)^{*}$	(0.070)	$(0.02)^{**}$	$(0.001)^{***}$
4	0.6136	0.1812	-0.5769	-0.0470
	$(0.001)^{***}$	(0.001)	$(0.077)^{*}$	$(0.036)^{**}$
5	0.0499	0.0156	-0.9591	-0.1105
	(0.303)	(0.869)	$(0.030)^{**}$	(0.112)
CRT score				
1	0.4111	0.1381	0.0551	0.0061
	$(0.005)^{***}$	(0.004)	(0.801)	(0.802)
2	0.6678	0.2202	-0.0251	-0.0029
	$(0.000)^{***}$	(0.000)	(0.901)	(0.900)
3	0.9571	0.3038	-0.1903	-0.0255
	$(0.000)^{***}$	(0.000)	(0.351)	(0.332)
Prob. Diff, Δ_1	1.6048	0.4654		
	$(0.000)^{***}$	(0.000)		
Constant	-1.6937		1.953	
	$(0.000)^{***}$		$(0.000)^{***}$	
Number of obs	980		980	
Log likelihood	-504.805		-234.926	
LR $\chi^2(12)$	281.3		13.72	
Prob $>\chi^2$	0.0000		0.2487	
Pseudo R^2	0.2179		0.0284	

p-values in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 11: New probit regression for Stage 2 and 3 observations after dropping independent variables with $p > 0.10$

The upper branch probability difference between the dominant and the dominated, Δ_1, is another critical factor in the decision-making process in Stage 2. As Δ_1 increases by 1%, the chance of choosing the FSD dominant lottery increases in Stage 2, ceteris paribus, which is consistent with the theoretical findings of the TAX and the modified ST models. Thus, participants cannot easily distinguish the superior option between the dominant and dominated lotteries at the lower values of Δ_1. For this reason, participants tend to violate the FSD more often in the choice sets, where the upper branch probability difference is more negligible, e.g., Choice set 1 and 6. In contrast, as the upper branch probability difference increases, participants can identify the dominant and the dominated lotteries better in Stage 2, which increases the chance of choosing the FSD superior lottery, e.g., Choice sets 5 and 7, where $\Delta_1 \geq 0.45$.

Nevertheless, this new probit regression model still fails to produce statistically significant estimators for Stage 3 observations. Re-framed lotteries make FSD superior easily identifiable; therefore, participants characteristics and the environmental factor such as the upper probability difference play no prominent role in identifying the FSD superior option in this stage. The contrast difference in the constant term between Stage 2 and 3 probit regression estimation is solid empirical proof confirming that the subtle frame of lotteries matters and participants risk-taking behaviour determines how sensitive they are, which rejects the second null hypothesis of this study successfully.

5 Related literature

This study contributes to the literature by examining the relationship between risk preferences and FSD violations while controlling the frame of the FSD lotteries. The most closely related research that investigates the risk preferences and the FSD violations is Levy and Levy (2001), which examines experimentally whether the people who prefer the FSD superior option are risk-averse. Their studies find that majority of participants are not risk-averse but risk-seeker. Despite the difference in risk preferences, both types do not violate the FSD criterion in their studies. However, this result is not surprising because the only choice set in their studies that observe FSD violation has a clear probability monotonicity frame. And the TAX model and modified ST with their prior estimated parameters predict no FSD violation there. So, considering the frame of lotteries, Stage 3 of my study replicates Levy and Levy (2001) with more than one choice set that has a consequence monotonicity frame and confirms their findings, such that all participants prefer the FSD superior most of the time in Stage 3, irrespective of their risk-taking behaviour.

Birnbaum and Navarrete (1998) and Birnbaum (2005) are the two most fundamental experimental studies that find statistically significant FSD violations in choice sets, where lottery frames are complex, such that there is no clear probability or consequence monotonicity exists. Furthermore, these studies confirm that the Transfer for Attention Exchange (TAX)[17] model is the best alternative decision theory that explains the FSD violations when lottery frames are complex. So, considering the subtle structure of lotteries, Stage 2 of this study replicates Birnbaum and Navarrete (1998) and Birnbaum (2005) in a sense that participants confront the same type of complex framed lotteries. Stage 2 observations also find significant FSD violations, but in contrast to Birnbaum and Navarrete (1998) and Birnbaum (2005), I analyse the FSD violations from participants risk-taking behaviour perspective and find that only the consistent risk-seeking behaviour type causes population wide FSD violations.

Birnbaum (2007) and Levy (2008) are two leading studies that examine the importance of the subtle frame of lotteries in FSD violations. Thus, Birnbaum (2007) find that if complex framed lotteries are re-framed by splitting up the upper branch of the dominant and the lower branch of the dominated lotteries, the TAX model does not predict FSD violations, which is confirmed by their experimental study. Since I employ the same methodology to re-frame complex lotteries, Stage 3 of my study replicates Birnbaum (2007) and confirms that

[17]Previous works refer to the TAX model as the Configural Weight model.

FSD violation is not statistically significant for any type of risk-taking behaviour group. However, Birnbaum (2007) differs from my study from two stances. First, Birnbaum does not differentiate participants according to their risk preferences. Second, the lottery returns are given in "millions of USD", which has nothing to do with the participants' payment at the end of the experiment. On the other hand, Levy (2008) argue that if consequence or probability monotonicity exists between FSD lotteries, participants tend to violate the FSD criterion less, otherwise more. Levy (2008) confirms experimentally that if FSD superior has only a consequence or probability monotonicity frame, this new frame is sufficient for participants to be induced to choose the FSD superior, irrespective of the frame of the FSD inferior.

6 Conclusion

This study investigates the effects of risk-preferences and the subtle frames of lotteries in FSD violations. In line with EUT, CPT and ST, I argue whether FSD violations can be statistically significant for any type of risk-taking behaviour group. If so, how the underlying frame of lotteries impact individuals' preferences that lead to FSD violations.

This experimental study shows that when participants confront complex framed FSD lotteries, i.e., neither probability nor consequence monotonicity exists, their risk-taking behaviour type is associated with FSD violations. Thus, all participants get confused with identifying FSD superior lottery in this setting. However, the consistent risk-seeking behaviour type is the most confused since they significantly violate the FSD criterion in five out of seven choice sets, followed by the erratic risk-takers (ER) who violate the FSD in only one choice set. The other two risk-taking behaviour types, i.e., consistent risk-averters (CRA) and systematic inconsistent risk-takers (SIR), do not violate the FSD criterion in any choice set. So, based on my findings here, I can reject the first null hypothesis, $H1$ for the CRS and the ER but fail to reject it for the CRA and the ER.

Econometric analysis confirms that not only participants' risk-taking behaviour but also their gender, cognitive ability, and self-persuaded preparedness to take a risk influence their decision to choose the FSD superior option in complex framed lotteries. In addition, the econometric analysis discovers that if probabilities in a complex framed FSD choice set are close to one another, the chance of selecting the FSD superior option is getting smaller. One simply may explain this phenomenon suggesting that closer probabilities in complex framed FSD choice sets confuse people that causes randomisation in the decision-making. However, prominent FSD violations by CRS suggests that their FSD violations were not a simple randomisation problem but a deliberate choice. Nevertheless, the difference in probabilities in complex framed choice sets still plays a crucial role for the CRS, since the CRS do not violate the FSD criterion in the choice sets where the probability difference between lotteries is higher compared to other choice sets. The behaviour of CRS cannot be explained by any standard decisions employed in this study but only the TAX model. However, the TAX model with prior estimated parameters predicts that the CRS would violate the FSD criterion in only three choice sets rather than five.

In contrast, when lotteries are re-framed, the new underlying structure establishes consequence monotonicity. People, including those who violate the FSD criterion significantly previously, reverse their decisions and choose the FSD superior most of the time. In other words, the FSD violation is not an issue for anyone at this stage. Therefore, I fail to reject the $H1$ in this stage but can reject $H2$ since the mean of the FSD violation rate before and after re-framing is not the same, suggesting that re-framing lotteries improves participants' choices over the FSD superior lottery.

As a concluding remark, this paper finds that people are prone to the framing effects, and their risk-taking behaviour defines the magnitude of the sensitivity. Intuitively, if individuals' risk-taking behaviour type is known in advance, one can take advantage of the situation by offering complex framed lotteries or contracts[18] to those who are the most prone to framing effects that are consistent risk-seeking and erratic risk-taker types in this study. However, suppose contracts are more transparent such that the utility maximising option is easy to distinguish. In that case, the individuals' risk-taking behaviour plays no prominent role since the underlying structure of the choices per se nudges everyone to choose the utility maximising contract, irrespective of individuals risk preferences.

References

Birnbaum, M. H. (2005). A comparison of five models that predict violations of first-order stochastic dominance in risky decision making. *Journal of Risk and Uncertainty*, 31(3):263–287.

Birnbaum, M. H. (2007). Tests of branch splitting and branch-splitting independence in Allais paradoxes with positive and mixed consequences. *Organizational Behavior and Human Decision Processes*, 102(2):154–173.

Birnbaum, M. H. and Navarrete, J. B. (1998). Testing Descriptive Utility Theories: Violations of Stochastic Dominance and Cumulative Independence. *Journal of Risk and Uncertainty*, 17(1):49–79.

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

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

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

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

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

Levy, H. (2008). First degree stochastic dominance violations: Decision weights and bounded rationality. *Economic Journal*, 118(528):759–774.

Levy, M. and Levy, H. (2001). Testing for risk aversion: A stochastic dominance approach. *Economics Letters*, 71(2):233–240.

[18] As complex lotteries, we can think of different types of contracts that include hidden interest rates, commission fees, and other payments.

A Choice sets presented in Stage 2 and 3

Sets	Lottery 1	Lottery 2
Set 1	90 red marbles to win 95 points 5 blue marbles to win 15 points 5 white marbles to win 10 points	85 red marbles to win 95 points 5 blue marbles to win 90 points 10 white marbles to win 10 points
Set 2	55 red marbles to win 100 points 5 blue marbles to win 90 points 40 white marbles to win 10 points	90 black marbles to win 95 points 5 yellow marbles to win 15 points 5 purple marbles to win 10 points
Set 3	90 red marbles to win 95 points 5 blue marbles to win 15 points 5 white marbles to win 10 points	65 red marbles to win 95 points 5 blue marbles to win 90 points 30 white marbles to win 10 points
Set 4	75 red marbles to win 100 points 5 blue marbles to win 90 points 20 white marbles to win 10 points	90 black marbles to win 95 points 5 yellow marbles to win 15 points 5 purple marbles to win 10 points
Set 5	90 red marbles to win 95 points 5 blue marbles to win 15 points 5 white marbles to win 10 points	45 red marbles to win 95 points 5 blue marbles to win 90 points 50 white marbles to win 10 points
Set 6	85 red marbles to win 100 points 5 blue marbles to win 90 points 10 white marbles to win 10 points	90 black marbles to win 95 points 5 yellow marbles to win 15 points 5 purple marbles to win 10 points
Set 7	90 red marbles to win 95 points 5 blue marbles to win 15 points 5 white marbles to win 10 points	25 red marbles to win 95 points 5 blue marbles to win 90 points 70 white marbles to win 10 points

Table 12: Stage 2 choice sets

Sets	Lottery 1	Lottery 2
Set 1	85 red marbles to win 76 points 5 red marbles to win 76 points 5 blue marbles to win 12 points 5 white marbles to win 8 points	85 red marbles to win 76 points 5 blue marbles to win 72 points 5 white marbles to win 8 points 5 white marbles to win 8 points
Set 2	55 red marbles to win 80 points 5 blue marbles to win 72 points 5 white marbles to win 8 points 35 white marbles to win 8 points	55 black marbles to win 80 points 35 black marbles to win 80 points 5 yellow marbles to win 12 points 5 purple marbles to win 8 points
Set 3	65 red marbles to win 76 points 25 red marbles to win 76 points 5 blue marbles to win 12 points 5 white marbles to win 8 points	65 red marbles to win 76 points 5 blue marbles to win 72 points 25 white marbles to win 8 points 5 white marbles to win 8 points
Set 4	75 red marbles to win 80 points 5 blue marbles to win 72 points 15 white marbles to win 8 points 5 white marbles to win 8 points	75 black marbles to win 80 points 15 black marbles to win 80 points 5 yellow marbles to win 12 points 5 purple marbles to win 8 points
Set 5	45 red marbles to win 76 points 45 red marbles to win 76 points 5 blue marbles to win 12 points 5 white marbles to win 8 points	45 red marbles to win 76 points 45 white marbles to win 8 points 5 black marbles to win 72 points 5 white marbles to win 8 points
Set 6	85 red marbles to win 80 points 5 blue marbles to win 72 points 5 white marbles to win 8 points 5 white marbles to win 8 points	85 black marbles to win 80 points 5 black marbles to win 80 points 5 yellow marbles to win 12 points 5 purple marbles to win 8 points
Set 7	25 red marbles to win 76 points 65 red marbles to win 76 points 5 blue marbles to win 12 points 5 white marbles to win 8 points	25 red marbles to win 76 points 5 blue marbles to win 72 points 5 black marbles to win 72 points 65 white marbles to win 8 points

Table 13: Stage 3 choice sets

Variable	**Mean**	**Std Dev**	**Min**	**Max**
Female	0.6071	0.4901	0	1
White	0.8071	0.3960	0	1
Age				
18 to 24	0.3214	0.4687	0	1
25 to 29	0.2286	0.4214	0	1
30 to 35	0.1571	0.3652	0	1
36 to 40	0.0929	0.2913	0	1
41 to 45	0.0786	0.2700	0	1
46 $>$	0.1214	0.3278	0	1
Education				
College	0.1000	0.3011	0	1
Doctoral	0.0357	0.1862	0	1
High school	0.3286	0.4714	0	1
Master	0.2000	0.4014	0	1
No formal	0.0071	0.0845	0	1
Undergrad	0.3286	0.4714	0	1
Elicited risk preferences				
CRA	0.2214	0.4167	0	1
CRS	0.2000	0.4014	0	1
ER	0.1500	0.3584	0	1
SIR	0.4286	0.4966	0	1
CRT score performance				
0	0.1714	0.3782	0	1
1	0.2143	0.4118	0	1
2	0.3000	0.4599	0	1
3	0.3143	0.4659	0	1
Self-persuaded preparedness to take risks				
1	0.1071	0.3104	0	1
2	0.2786	0.4499	0	1
3	0.3786	0.4868	0	1
4	0.2071	0.4067	0	1
5	0.0286	0.1672	0	1
Probability diff., $\mathit{\Delta}_1$	0.2786	0.2051	0.05	0.65

Table 14: Statistical summary of explanatory variables

B Systematic inconsistent risk-taking behaviour

Consider a safe prospect $C = \{(x, 1)\}$ that pays an amount x for sure, and a risky prospect $R = \{(x+g, p); (x-l, 1-p)\}$ which returns an amount $x + g$ with probability p and an amount $x - l$ with probability $1 - p$, where $x > l > 0$ and $g = \frac{(1-p)l}{p}$. R is a mean-preserving spread of C.[19] In this setting, there are two different states of nature: state of gain $s_g = (x + g, x)$ which returns $x + g$ with probability p, while the safe return is x, and state of loss $s_l = (x - l, x)$ which is defined in the same way. Hence, the state space is defined as $S = \{s_g, s_l\} = \{(x + g, x), (x - l, x)\}$. In expected utility theory (EUT), a decision maker with a vNM utility function $v(\cdot)$ maximises their probability weighted utility in different states of nature, and their expected utility V from a lottery L_j is:

$$V(L_j) = \sum_i p_i v(x_i^j), \tag{6}$$

where x_i^j is lottery L_j's return in state i. The decision maker prefers prospect R to S if and only if $V(R) > V(S)$.

The curvature of the decision makers' utility function determines their attitudes towards risk. Considering $v(\cdot)$ is at least twice differentiable, a concave utility function ($v' > 0$ and $v'' < 0$) implies risk-aversion, while a convex utility function ($v' > 0$ and $v'' > 0$) risk-seeking. An agent with a concave (convex) utility behaves in a risk-averse (risk-seeking) way in any setting. Importantly, their decisions are *consistent* across all choices.

Salince theory of choice under risk by Bordalo et al. (2012) (ST), on the other hand, assumes that, depending on the context, some lottery returns are more eyecatching to decision-makers than others. The decision-makers overweight the probability of the more salient states and value lottery (s) based on the distorted probabilities. Distorting objective probabilities results in switches in risk attitudes in different settings, whom I refer to as a *systematic inconsistent risk-taker* (SIR).

In ST, the SIR firstly ranks all possible states of nature according to their salience value. Later, in the second step, the SIR distorts objective probabilities of these states according to the ranking; thus, the most salient states which have the highest salience value receives the first rank ($k^i = 1$), the second most salient state receives second rank ($k^i = 2$) and so on. If both states have the same salience value, they receive the same rank. The salience value is calculated via a salience function of

$$\sigma(x_1^i, x_2^i) = \frac{|x_1^i - x_2^i|}{|x_1^i| + |x_2^i| + \theta}, \tag{7}$$

where $\theta \geq 0$. A systematic inconsistent risk-taker then distorts probabilities of the states using parameter $\delta \in (0, 1)$ which captures how much the LT departs from rationality. The distorted objective probability of state is

$$\omega_i = p_i \cdot \frac{\delta^{k_i}}{\sum_j \delta^{k_j} p_j} \tag{8}$$

where δ^{k_i} is parameter δ to the power of state i's salience ranking k^i. Note that $\delta = 1$ implies full rationality and the model converges to EUT (Bordalo et al., 2012). A SIR's valuation of a lottery L_j is

$$V_{SIR}(L_j) = \sum_i \omega_i v(x_i^j), \tag{9}$$

where v is at least twice differentiable vNM utility function.

[19] C second-order stochastically dominates R.

For the lotteries $C = \{(x, 1)\}$ and $R = \{(x + g, p); (x - l, 1 - p)\}$, a SIR concentrates on the state of gain more than the state of loss if and only if the salience value of s_g is more than s_l or

$$\sigma(x + g, x) > \sigma(x - l, x) \tag{10}$$

Given that $g = \frac{(1-p)l}{p}$, condition (10) can be defined as

$$\sigma(x + \frac{(1-p)l}{p}, x) > \sigma(x - l, x) \tag{11}$$

This new condition defines that as p gets closer to zero, the state of gain, s_g, becomes more salient, therefore, more attractive for the SIR. On the contrary, as p gets closer to one, $p \to 1$, the state of loss, s_l, becomes more salient, therefore, more appealing for the SIR. Moreover, $p = 1/2$ reveals that each state's salient value is the same, and the SIR is indifferent between these two states. Hence, $p^\star = 1/2$ is a threshold point deciding which state is more salient for the SIR in the mean-preserving lotteries.

Suppose $p > p^\star$ in the mean-preserving lotteries. The state of loss s_l is more salient than other state s_g. A SIR with at least twice differentiable utility function $v(\cdot)$ evaluates lottery the risky prospect R as

$$V_{SIR}(R) = \frac{p\delta v(x + g) + (1 - p)v(x - l)}{p\delta + (1 - p)}, \tag{12}$$

and the safe option C as

$$V_{SIR}(C) = v(x).$$

The SIR prefers the risky option R to C if and only if $V_{SIR}(R) > V_{SIR}(C)$ or

$$\delta > \frac{v(x) - v(x - l)}{v(x + g) - v(x)} \cdot \frac{1 - p}{p} \equiv \frac{\Delta s_l}{\Delta s_g}. \tag{13}$$

Salience theory considers $\delta \in (0, 1)$, therefore, the right hand side (RHS) of condition (13) cannot be greater than 1 or[20]

$$p(v(x + g) - v(x)) > (1 - p)(v(x) - v(x - l)) \Rightarrow \underbrace{pv(x + g) + (1 - p)v(x - l)}_{E(R)} > \underbrace{v(x)}_{E(C)}.$$

This new condition suggests that the necessary condition for (13) is $E(R) > E(C)$, which is valid for any convex utility function but false for any linear or concave utility function. Intuitively, agents with a concave or a linear utility function never prefer the risky option R but the safe option C for any value of $\delta \in (0, 1)$.[21]. On the other hand, systematic inconsistent risk-takers with a convex utility function prefer the risky option if δ satisfies (13). Otherwise, if (13) is reversed, systematic inconsistent risk-takers with a convex utility function will prefer the safe option, which is a switch in risk attitude from risk-seeking to risk-averse. As a result, if the state of loss s_l is more salient than state s_g, a systematic inconsistent risk-taker with a concave or a linear utility function never switches their risk attitudes but consistently prefers the safe option. In contrast, a SIR with a convex utility function switches their risk attitude from risk-seeking to risk-averse at some values of δ, subject to the lottery returns and their underlying probability distribution. In other words, if an agent with a convex utility function departs from rationality significantly, then the convexity can predict a risk-averse behaviour in the ST.

[20] Salience theory cannot explain the situation where $\delta > 1$

[21] Agents with a concave or a linear utility function prefers the safe option if $\delta > 1$

Now suppose $p < p^{\star}$. In this case, the state of gain s_g is more salient than other state s_l. The SIR now evalutes lottery R as

$$V_{SIR}(R) = \frac{pv(x+g) + (1-p)\delta v(x-l)}{p + (1-p)\delta}. \tag{14}$$

The LT prefers C to R if and only if $V_{SIR}(R) < V_{SIR}(C)$ or

$$\delta > \frac{v(x+g) - v(x)}{v(x) - v(x-l)} \cdot \frac{p}{1-p} \equiv \frac{\Delta s_g}{\Delta s_l}. \tag{15}$$

Again, considering $\delta \in (0, 1)$, the RHS of condition (15) cannot be greater than 1 or

$$p(v(x+g) - v(x)) < (1-p)(v(x) - v(x-l)) \Rightarrow \underbrace{pv(x+g) + (1-p)v(x-l)}_{E(R)} < \underbrace{v(x)}_{E(C)}.$$

This new condition suggests that the necessary condition for (15) is $E(R) < E(C)$ which is valid for any concave (or linear utility function if $\leq$) but false for any convex utility function. Intuitively, agents with a convex utility function never choose the safe option C but the risky option R for any value $\delta \in (0, 1)$. On the other hand, systematic inconsistent risk-takers with a concave (or linear) utility function select the safe option if δ is substantially great. Otherwise, if (15) is reversed, systematic inconsistent risk-takers with a concave (or a linear) utility function will select the risky option R, which is a clear switch in risk attitude from risk-averse to risk-seeking. Consequently, if the state of gain s_g is more salient than state s_l, a systematic inconsistent risk-taker with a convex utility function never switches their risk attitude but consistently choose the risky prospect. In contrast, a systematic inconsistent risk-taker with a concave or a linear utility function can switch their risk attitude by preferring the risky prospect depending on the value of δ.

C Receipt for creating FSD lotteries

Consider a simple binary prospect $L = (x, p; y, 1-p)$, where $x > x' > \tilde{y} > y > 0$. Split the upper branch of L (i.e., (x, p)) into $(x, p-r)$ and (x, r), and reduce the return in the new branch slightly to x' creating a new lottery $L^- = (x, p-r; x', r; y, 1-p)$. Now, split the lower branch of L (i.e., $(y, 1-p)$), and increase the return in the new branch slightly to $\tilde{y}$ creating a new lottery $L^+ = (x, p; \tilde{y}, q; y, 1-p-q)$. The TAX and the modified ST violate coalescing, therefore, splitting the upper branch of L to create L^- improves it, while splitting lower branch to create L^+ aggravates it (Birnbaum, 2005, p266).