First-order stochastic dominance, framing effects and risk preferences

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Abstract

This paper experimentally investigates whether decision-makers' violations of the first-order stochastic dominance (FSD) criterion of rational choice, as documented in previous studies, are correlated with their risk preferences. As argued in the literature, FSD violations require framing effects to affect individual's decisions: the frame of the lotteries in an individual's choice set must prevent the individual from the "inferiority" of choosing stochastically dominated lotteries. This paper moves a step ahead by investigating whether (consistent or erratic) risk averse or risk seeking attitudes towards uncertainty make individuals more or less receptive to the framing effects which can induce FSD violations. Our main finding is that consistent (and, to a minor extent, "erratic") risk seeking individuals are statistically significantly more prone to violate the FSD criterion in their choices than individuals exhibiting different risk attitudes (i.e., consistent risk averse and systematically inconsistent risk taking individuals). We finally control for the role of the framing effects in our results. Consistently with the previous literature, we find that the framing effects play a crucial role. As we re-frame lotteries in such a way to make the FSD superior prospects more easily distinguishable, any participants hardly violates the FSD criterion, irrespective of their risk preferences, gender and exerted cognitive abilities.

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

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1 Introduction

Tversky and Kahneman (1985) first show how the frame of risky options, *id est* how and which order consequences are presented, influence decision-makers choice under risk. Their famous *Asian disease* problem is one of the most significant examples that show how an individual's cognitive bias processes information differently depending on the way consequences are phrased out. Hence, decision-makers' cognitive bias to the frame of choices can be the reason for the notorious first-order stochastic dominance (FSD) criterion violations of a rational choice (Birnbaum, 2005; Levy, 2008). However, Birnbaum (2005) formally argues that people sensitivity to the framing effects in the FSD criterion violations are related to their risk-preferences. Following Birnbaum's argument, one can claim that the FSD violations can be correlated to decision-maker's risk attitude since it ultimately defines their sensitivity to the framing effects. Therefore, in this chapter, we experimentally investigate whether the FSD violations are associated with the decision-maker's risk preferences. If so, how their risk preferences impact to their sensitivity to the framing effects.

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, $u' \geq 0$, (*id est* monotonicity assumption) should prefer F over G because the chance of receiving x is higher in F than in G.

Standard decision theories in the literature, namely Expected Utility Theory (EUT), Cumulative Prospect Theory (CPT) and Salience Theory of choice under risk (ST), claim that agents with non-decreasing utility should not violate the FSD criterion under any condition. Hence, these theories consider FSD violation a random or computational error. 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 and Navarrete, 1998; Birnbaum, 2005, 2007; Levy, 2008).

Birnbaum (2005, 2007) and Levy (2008) argue that an essential trait of decision makers' preferences leading to FSD violations is the direct result of *violating coalescing*[1] property of lotteries. Coalescing property is characterised by a lottery's underlying *frame*, *id est* how and in which order outcomes and probabilities are presented; therefore violating coalescing property is also equivalently defined as being prone to the subtle frame of lotteries, or *framing effects* in short. Therefore, Birnbaum (2007) and Levy (2008) claim that the framing effects play a crucial role in explaining FSD violations. Thus, Levy (2008) claims that if the subtle frame of lotteries makes the first-order stochastic dominant (henceforth FSD superior) lottery easier to

[1] In Expected Utility paradigm, 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.

distinguish in a choice set, individuals tend to choose the FSD superior most of the time. The FSD superior lottery is easily distinguishable if a "clear" *probability monotonicity*[2] or *consequence monotonicity*[3] exists between lotteries. On the contrary, if a clear probability monotonicity or consequence monotonicity does not exist anymore, the lottery frame is getting more complex. For this reason, individuals cannot identify the FSD superior lotteries easily and therefore tend to violate the FSD criterion more often (Levy, 2008, p.765).

From a theoretical viewpoint, violating coalescing property or equivalently being prone to the framing effects is not supported by any of the standard decision theories mentioned above. However, there is a handful alternative decision theories under risk in the literature that can explain the FSD violations. The most advanced alternative decision theory in the literature– Transfer for Attention Exchange (TAX) model, formally explains FSD violations as a result of breaching coalescing property. According to the TAX model, people are sensitive to the underlying frame of lotteries but their sensitivity to the frame depends on their risk-preferences, i.e., curvature of their utility. Intuitively, the TAX model predicts a different set of FSD violations for individuals with concave utility compared to the ones with convex or linear utility. On the other hand, the TAX model also claims that given that individuals are prone to the lottery frames, FSD violations can be eliminated or induced by *framing* lotteries, i.e., presenting lottery outcomes differently.

However, recent developments in the decision theory literature, namely Cumulative Prospect Theory (CPT) and Salience Theory (ST), theoretically and empirically confirm that individuals can be *systematically inconsistent* in their risk behaviour, which means that they can be risk-averse in higher probabilities of gain state and risk-seeker in lower probabilities of gain (Tversky and Kahneman, 1992; Bordalo et al., 2012). Despite predicting systematic inconsistent behaviour in risk-taking, CPT and ST never violate the FSD criterion for any individual with non-decreasing utility. However, Dertwinkel-Kalt and Köster (2015) introduce a modified version of the Salience Theory, arguing that systematic inconsistent risk-taking behaviour can lead to the FSD violations depending on the subtle frame of lotteries 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

[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 $F = \{(12, 0.5), (5, 0.5)\}$ and $G = \{(10, 0.5), (5, 0.5)\}$, where F first-order stochastically dominates G.

ST will not predict FSD violation, either.

Following our initial research questions at the beginning, we ask 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, we experimentally investigate this link while controlling for the importance of the framing effects. Particularly, we analyse how people with different risk-taking attitudes and behaviour assess the first-order stochastic dominant choices under different frames.

To investigate our research questions, we develop a multi-stage individual decision-making game under risk. The first stage investigates participants' risk attitude and behaviour throughout their choices over mean-preserving spreads. The second stage explores how participants with different risk attitudes decide when they face complex-framed lotteries (i.e., neither clear consequence nor probability monotonicity exists). Finally, in the third stage, we examine how re-framed lotteries from the previous stage influence participants' preferences over the FSD inferior lotteries. In this stage, we re-frame lotteries in a way that clear consequence monotonicity exists between lottery pairs. After completing the three essential stages, participants face a simple cognitive reflection test and a demographic survey. At the end of the experiment, they learn their bonus payment, which is determined based on their choices during the experiment.

We find that significant FSD violations occur when the lottery frames are complex, i.e., FSD superior lottery is not easily noticeable. In that case, the mean FSD violation rate is higher across the population. However, when we look at the FSD violation rate within the risk-taking behaviour groups, we realise that consistent risk-seeking people have statistically significantly violate the FSD criterion in 5 out of 7 complex-framed choice sets, while participants with the erratic risk-taking behaviour violating the FSD criterion in 1 out of those 7 complex-framed choice sets. However, the FSD violation rate amongst other participants, namely consistent risk-averters and systematic inconsistent risk-takers, are not statistically significant. Our finding indicates that the FSD violation rate is associated with individuals' risk-taking preferences, and consistent risk-seekers are the most prone amongst the others to the framing effects. However, after re-framing complex framed lotteries into a transparent frame in the third stage the FSD violation rate significantly decreases across for each risk-taking behaviour group. Neither risk-taking behaviour group violates the FSD criterion in a statistically significantly manner in any choice set in the transparent framed lotteries.

We also run a probit regression to understand how other characteristics of participants influence on their decisions in violating the FSD criterion. We find that not only participants' risk-taking attitude, but also their gender, exerted cognitive abilities during the experiment, self-persuaded readiness taking a risk influence their FSD violations in the complex-framed lotteries. On the contrary, these explanatory variables play no prominent role if the underlying structure of lotteries makes FSD superior easier to distinguish since all participants are charmed to choose the superior FSD dominant lottery, irrespective of their background.

The next section provides a theoretical discussion regarding FSD violations, the role of risk-taking behaviour and framing effects. Based on this theoretical discussions, we develop a set of hypotheses to test in 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. *In postremo*, 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. We first review the standard theories that do not violate the FSD criterion, and then, those that can tolerate and explain FSD violations.

Expected Utility Theory (EUT) argues that people are consistent in their risk-taking behaviours, which can be risk-averse, risk-seeker, or risk-neutral, depending on the curvature of their utility. So, if individuals are confronted 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 maximising 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 decision-makers' valuation of the FSD options. If FSD violations occur, EUT consider them 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. According to the ST, an individual with risk-averse (risk-seeking) preferences can exhibit risk-seeking (risk-averse) behaviour at the extremely low (high) probabilities. Therefore, we define this kind of behaviour as systematic inconsistent risk-taking (SIR) behaviour[4], and Appendix B provides detailed explanation why and how SIR behaviour emerges in the ST[5]. Nevertheless, despite distorting objective probabilities, and therefore SIR attitudes, the ST formally argues that any systematic inconsistent risk-takers will always prefer the FSD superior[6], irrespective of the subtle frame of lotteries.

Now let us consider the decision theories under risk that can predict FSD violations. To begin with, we first consider the **Transfer for Attention Exchange** (TAX) model – a leading alternative decision theory that can predict and explain statistically significant FSD violations in the experimental studies. According to TAX model, an individual weighs 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, 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. 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 any choice set that the TAX model predicts FSD inferior as an optimal option can be re-framed by splitting up the branches

[4]Suppose an individual faces a pair 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 $x > l > 0$. In the 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 $p > 1/2$.

[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 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.

(i.e., lottery returns) in a certain way that will make the stochastically dominant lottery more attractive to the TAX agent, and therefore, under this new frame, they will over-value of the FSD superior more than the FSD superior, irrespective of their utility functions. However, a closer look at Birnbaum (2007) reveals that Birnbaum has split both lottery branches in a way that both lotteries have got the same probability distribution for each lottery in a choice set. So, following Levy (2008)'s definition of consequence monotonicity, one can claim that Birnbaum's re-framing methodology creates *consequence monotonicity* in every choice set. We, however, go a step ahead and find that when there is a "clear" consequence monotonicity, i.e., it means the order of probabilities in both lotteries is identical in a choice set, the TAX model stops predicting the FSD violation for any type of decision-makers, irrespective of their utility function.

Proposition 1. *Suppose F and G are two lotteries, where F first-order stochastically dominates G. If a clear consequence monotonicity exists between these two lotteries 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 $x_{i\backslash n} \geq y_{i\backslash n}$ 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, θ direction of attention and n number of branches. 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 consequence monotonicity frame exists, the modified ST will stop predicting FSD violation, either. However, we cannot generalise this argument 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 weighting, and therefore, treats systematic inconsistent risk-taking people no more different than the consistent risk-taking people. 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. For these reasons, the TAX model is reserved for studying the agents' behaviour with the consistent risk-taking preferences, while the modified ST for the systematic inconsistent risk-takers in FSD violations.

Hypotheses

Considering our discussions and theoretical findings above, we develop a set of hypotheses to test in this study. The first hypothesis explores whether FSD violations happen and if so how people's risk-taking behaviour influence on their FSD violated choices. According to the EUT,

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

[9] *Exempli causa*, 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.

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, it is possible that people make random mistakes and choose FSD inferior lotteries. Hence, we suggest that the chance of choosing the FSD inferior lottery in any choice set is less than 50%. If there are some naïve participants who simply randomise their choices, they should choose the FSD inferior choices at most 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 some choice sets, where the TAX model or the modified ST predicts 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 role of the subtle frame of lotteries in FSD violations. We are interested in observing whether complex or transparent framed lotteries influence on participants' choices, and if so, which risk-taking behaviour group is more prominent to the framing effects. Standard decision theories argue that the lotteries' subtle frame has no impact on FSD violations, whereas 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 lotteries improves participants' preferences over the FSD superior options. Therefore, the difference between the mean score of the FSD violation rate under two frames will not be the same for anyone, $H_A : \mu_1 \neq \mu_2$.

In summary, 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 two developed hypotheses in this paper and consists of three stages that serves three essential purposes. The first purpose is to identify individuals' risk attitudes and behaviour. The second is to test how individuals with different risk preferences assess complex-framed first-order stochastic dominant lotteries. Finally, the third is to observe how converting complex-framed lotteries into transparent-framed lotteries influence participants' preferences over the FSD choices.

The experiment is developed as an individual decision-making task in *o-Tree* (Chen et al., 2016). During the experiment, participants have faced 19 pairs of risky prospects and slightly modified version of *Cognitive Reflection Test* (CRT) by Frederick (2005) at the end. We changed numbers in Cognitive Reflection Test in order to prevent participants to search for answers in the internet.

Once the experiment has started, participants saw only one choice set in each page and must make a decision by choosing one lottery in order to move to the next page. Participants were not able to go back and look at their previous choices; therefore, it was not possible to reverse any decision once they click on their preferred option.

This experiment has received a full ethical approval from the University of Leicester Ethics Committee before launching.

Setup

Stage 1: The purpose of this stage is to identify risk preferences of participants via mean-preserving spread lotteries. 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 $P = \{0.90, 0.80, 0.25, 0.20, 0.10\}$, 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. Inversely, 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 [11] 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 inconsistent risk-takers (SIR) who switch 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 lotteries (Birnbaum, 2005, p266). In every pair, one lottery first-order stochastically dominates the other, and 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 while the TAX model and the modified ST do. Thus, the TAX model with *prior* estimated model parameters[12] predicts that a decision-maker with a convex utility function will 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, $\Delta_1 < 0.25$.[13] On the other hand, the TAX model with prior parameters predicts 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 $\Delta_1 < 0.45$. Consequently, the TAX model with prior estimated parameters predicts

[11] See Appendix for a detailed theoretical review.

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

[13] 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.

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 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 Stage 3, 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. To frame the lotteries, we have completed the following stages in order:

1. All lottery returns are diminished 20% to avoid confusion with the earlier stage;
2. the lotteries are re-framed according to Birnbaum (2007)'s methodology:
    (a) Split the upper branch of the dominant lottery to improve the number of higher outcomes in that lottery;
    (b) Split the lower branch of the dominated lottery to increase the number of lower outcomes in that lottery;
    (c) Adjust probabilities of the new branches in a way that the probability distribution in each lottery is identical;

After completing every stage from (a) to (c) in the given order, *consequence monotonicity* will emerge in that choice set. The choice sets are provided in this stage is provided in Table 13.

The 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 cognitive effort is exerted by participants 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). Therefore, 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.

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 the instructions and take a mini-quiz to ensure they have understood the instructions well. Explanations for any incorrect answers are provided in a message box, and participants 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 were paying attention during the session. Full details of instructions, CRT Tests and sample choice sets from each choice set is provided in Appendix C.

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 chosen 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 minimum 20 points and maximum of 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.

Participant's background

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

In the Cognitive Reflective Test (CRT), only 44 participants (32%) answered all three questions correctly and achieved a score of three. 42 participants (30%) scored two, while 30 participants (22%) scored one. The rest of the participants (24,18%) failed all three questions and scored zero.

4.1 Elicited risk preferences

Participants risk attitudes and behaviour were identified by screening their preferences over the mean-preserving lotteries in Stage 1. To do this, I employed the the classification defined in subsection 3 to identify each type of decision maker. Based on this classification, the majority of the participants (60, 43%) fits the *systematic inconsistent risk-taking* (SIR) behaviour group, those 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 remainder of the participants display *erratic risk-taking behaviour* (ER) (21, 15%); those 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, 22 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. However, if participants make the computational error more than once, they are then 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 readiness to take risks differ than their elicited risk preferences. Thus, 15 participants have indicated that they are “definitely” ready to take risks, while Stage 1 observations confirm that only 3 of them are CRS, while 6 are CRA. 39 subjects define themselves as “most probably” ready to rake risks, but elicited risk preferences confirm that only 10 of them are CRS, 19 are SIR, and 8 are ER. On the other hand, 53 participants identify themselves as “possible” ready for seeking risks, but only 11 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.

4.2 FSD violations and risk preferences

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

To begin with, we 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 claim 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.

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 in a statistically significant manner 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

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: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

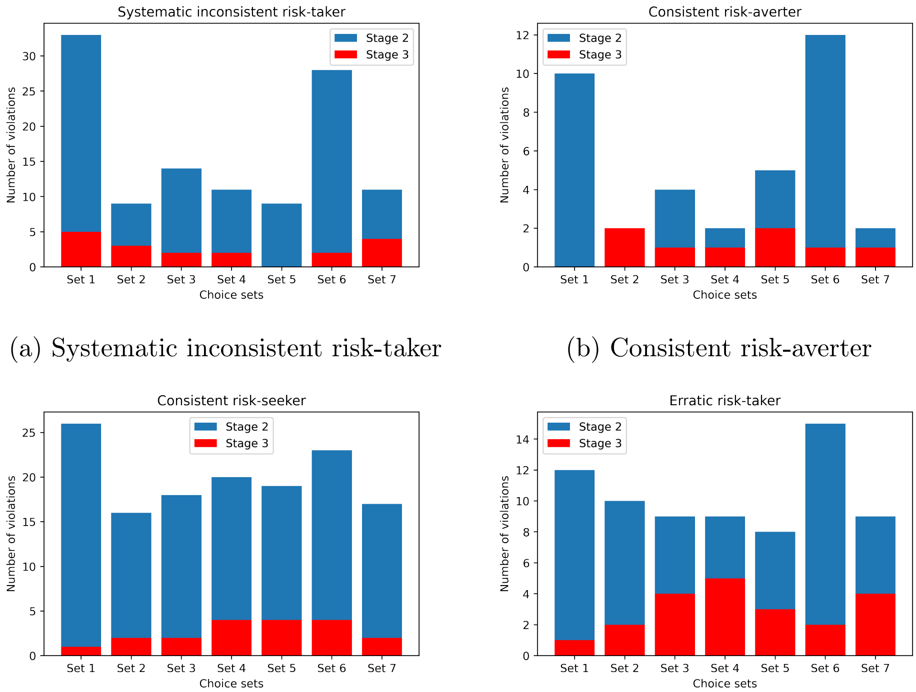
Table 3: Number of FSD violations in each choice set and the binomial statistics for Stage 2 observations

of not violating the FSD cannot be rejected for CRA and SIR.

In contrast, erratic risk-takers (ER) violate the FSD in a statistically significantly manner in 1 choice set out of 7 at a 10% confidence interval, while consistent risk-seekers (CRS) violate the FSD in 5 out of 7 choice sets, more than the TAX model predicts for the CRS.[14] 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, whereby consistent risk-seekers (CRS) are the leading risk-taking behaviour group that violate the FSD most.

In addition, pooled Stage 2 observations confirm that participants violate FSD mostly in Choice set 1 and 6, where probability difference in the upper branch of dominant and dominated lotteries, Δ_1, is equal to 0.05, which is the smallest Δ_1 amongst the other choice sets in Stage 2. Nevertheless, a binomial test confirms that FSD violation is statistically significant in only Choice

[14]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

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 has "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 set at 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.

4.3 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, we test whether the mean of FSD

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

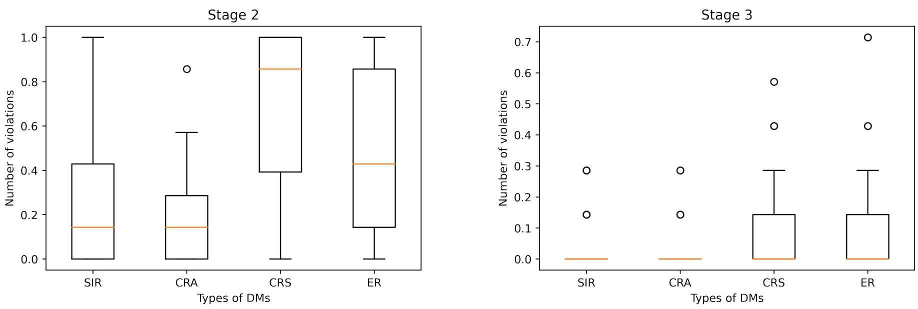
violation rate between two stages, i.e., Stage 2 and 3, is statistically different. The previous section indicates that re-framing lotteries improves the choices of those participants who violate the FSD significantly in Stage 2. In this part, I investigate the significance of the framing effects further and understand whether re-framing lotteries improve decisions of everyone, including those who do not violate the FSD criterion in the first place.

The second null hypothesis of this study argues that the re-framing of lotteries should not impact the participants' choices; therefore, the mean score of the FSD violation rate in each stage should be equal to one another. 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, implying that re-framing improves not only the choices of those who violate the FSD prominently in Stage 2, but also those who do not. A 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; this suggests that re-framed lotteries help participants with selecting the FSD superior lotteries more often. 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.

On the other hand, Welch's t-test in Table 7 and 8 confirms that the mean of the FSD

$N = 140$	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

violation rate of each risk-taking behaviour group differs in a statistically significantly manner in Stage 2 at a 5% confidence level, confirming that individuals' risk preferences develop a unique pattern in the FSD violation rate. However, we cannot observe the same results for Stage 3 observations. More precisely, Welch's t-test for Stage 3 observations, the results of which are presented in Table 8 finds that the mean of the FSD violation rate of each risk-taking behaviour group does not differ at any confidence level. Therefore, we claim that re-framing lotteries in Stage 3 nudges everyone to choose the FSD superior lotteries, such that their choices are not much different from one another.

In conclusion, we find that individuals' risk preference is a key factor in determining FSD violations in complex framed lotteries, but an irrelevant factor once lotteries have clear consequence monotonicity frames.

	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

	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

4.4 Econometric analysis

Given the nature of the experiment, participants' preferences over the lotteries in every choice set are stored as a binary variable, as we denote it y, which takes a value of 1 if FSD superior is chosen, and 0 otherwise. Considering 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, we 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. Moreover, the probit model also includes two *polychotomous* variables that are:

1. *participant's self-persuaded readiness to take a risk* takes a value between 1 and 5, where 1 indicates "definitely" ready to take risks; 2 indicates "probably"; 3 indicates "possibly"; 4 indicates "possibly not" and 5 indicates "definitely not";

2. *Cognitive Reflective Test (CRT) score* takes a value between 0 and 3, 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 in both of polychotomous variables is considered the reference group. Therefore, considering all the explanatory variables, the probit model equation is as follows:

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

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.

A probit model regression will be estimated for Stage 2 and 3 observations. Since re-framing

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

lotteries in Stage 3 decreases the FSD violation rate for all participants, it is expected that the probit model regression estimation for every stage will be different.

In Stage 2, consistent risk-seekers (CRS) significantly violate the FSD criterion in 5 out of 7 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 1 choice set out of 7, 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 the FSD easily distinguishable; therefore, participants tend to prefer the FSD superior option, irrespective of their characteristics. Therefore, we are expecting that the independent variables do not produce any statistically significant estimators for 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 does not provide sufficient observations for the probit regression to produce a 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, $\mathit{\Delta}_1$. Note that we have previously found 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 0 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 the *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, respectively.

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.

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, $\mathit{\Delta}_1$	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 $p > 0.10$

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 the 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 their reluctance to take a risk, the higher probability of choosing the FSD dominant lottery in Stage 2[15].

The 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 better intuition in identifying 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.

The upper branch probability difference between the dominant and the dominated, $\mathit{\Delta}_1$, is another critical factor in the decision-making process in Stage 2. As $\mathit{\Delta}_1$ 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 $\mathit{\Delta}_1$. 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 $\mathit{\Delta}_1 \geq 0.45$.

Nevertheless, this new probit regression model still fails to produce statistically significant estimators for Stage 3 observations. Re-framed lotteries make the FSD superior easily identifiable; therefore, participants characteristics 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 successfully rejects the second null hypothesis of this study.

[15] 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.

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 experimentally examines whether the people who prefer the FSD superior option are risk-averse. Their studies find that the majority of participants are not risk-averse but risk-seeking. 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. Furthermore, the TAX model and modified ST with their prior estimated parameters predict no FSD violation in that choice set. 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 no clear probability or consequence monotonicity exists. Furthermore, these studies confirm that the Transfer for Attention Exchange (TAX)[16] 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 our 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 contrary to Birnbaum and Navarrete (1998) and Birnbaum (2005), here we investigate how those FSD violations are associated with individuals' risk-taking behaviour.

Birnbaum (2007) and Levy (2008) are two leading studies that examine the importance of the subtle frame of lotteries in FSD violations. Birnbaum (2007) state 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. In our study, we employ the same methodology of re-framing, therefore, Stage 3 of our study replicates Birnbaum (2007) and confirms that FSD violation is not statistically significant for any type of risk-taking behaviour group once the lottery frame makes the FSD superior option obvious. However, our study differs from Birnbaum (2007) from two stances. First, Birnbaum (2007) the lottery returns were presented in a fictitious values,

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

namely "millions of USD", which had nothing to do with the participants' payment. Therefore, the incentive mechanism of the experiment was not sufficiently encouraging participants. Second, the most important factor was that Birnbaum (2007) did not observe how participants would react when lottery frames were complex.

On the other hand, Levy (2008) argues 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 the FSD superior has only a consequence or probability monotonicity frame, this new frame is sufficient for participants to be convinced to choose the FSD superior, irrespective of the frame of the FSD inferior. So, in our study, we confirm that Levy (2008) claims regarding the complexity of lottery frames are indeed correct. In addition, we also show participant's risk preferences, gender and exerted cognitive abilities define their sensitivity to the framing effects.

6 Concluding remarks

This experimental study finds that people's violations of the FSD criterion of a rational choice are correlated to their risk preferences. Meanwhile, their risk preferences define how much they are prone to the framing effects. When participants confronted complex framed choice sets, where identifying the FSD superior lottery was hard, they violated the FSD criterion more often. More specifically, participants with consistent and, to a minor extent, erratic risk-seeking attitudes violated the FSD criterion more often in a statistically significant manner than participants exhibiting consistent risk-averse and systematic inconsistent risk-taking behaviours. While investigating further the FSD criterion violations in the complex framed choice sets, we find that not only participants' risk-taking behaviour but also their gender, exerted cognitive ability during the experiment, and self-persuaded preparedness taking a risk influence their decisions in violating the FSD criterion. More interestingly, we also discover that if the probability distributions of outcomes in both lotteries in complex framed choice sets follow similar patterns, participants violate the FSD criterion more often in those choice sets. On the contrary, if the probability distributions of outcomes differ significantly between the FSD superior and inferior lotteries in any choice set, participants do not violate the FSD criterion more often, irrespective of their risk attitudes, despite the choice sets being complex framed.

In contrast, when we re-frame the complex framed choice sets into transparent frames, where distinguishing the FSD superior is easier, participants hardly violate the FSD criterion. The sharp difference between the FSD violation rates within the risk-taking behaviour groups and, in general, between the two stages suggests that people are prone to the framing effects, while their risk preferences determine their sensitivity to the framing effects.

As a concluding remark, this chapter finds that people are sensitive to the framing effects, and their risk-taking behaviour defines the magnitude of the sensitivity. Our finding here suggests that people with consistent risk-seeking preferences are the most prone to the framing effects. Intuitively, if consistent risk-seeking people are known in advance, one can exploit them by offering contracts or risky options in a complex frame[17], making sub-optimal choices more attractive to them. On the contrary, offering "transparent" framed lotteries or contracts will not confuse anyone irrespective of their risk preferences, and therefore they will choose the optiomal superior option that returns the best outcome with the highest option all the time.

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

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A Choice sets in Stage 2 and 3

A.1 Choice sets in Stage 2

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

Table 12: Stage 2 choice sets

A.2 Choice sets in Stage 3

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

A.3 Summary of explanatory variables

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., Δ_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.[18] 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.

Salience 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 eye-catching 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

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

[18] C second-order stochastically dominates R.

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.

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[19]

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

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

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 $\delta \in (0,1)$.[20]. On the other hand, systematic inconsistent risk-takers with a convex utility function prefer the risky option if δ satisfies condition (13). Otherwise, if condition (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.

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 evaluates 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

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

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 model 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).

D Experiment design

D.1 Info Page

Thank you for considering participating in this research project. This page explains what the work is about and what your participation would involve, to enable you to make an informed choice.

The purpose of this study is to examine the individual decision-making under uncertainty. Should you choose to participate, you will be asked to complete an individual decision-making task which will take approximately 15 minutes to complete. In this task, you will be presented with a series of choices, each of which contains two possible options to pick from. Each option will be associated with some numerical rewards (points) and the probability with which each of those rewards will be realised. You will be asked to indicate your favoured choice by clicking the corresponding button. During the task, you will also be asked some random questions to check your attention. Finally, at the end of the task, you will answer a brief demographics survey.

Participation in this study is absolutely voluntary. There is no obligation to participate, and should you choose to do so, you can refuse to answer specific questions, or decide to withdraw from the study. All information you provide will be confidential, and your anonymity will be protected throughout the study. All the data you provided will be stored on an encrypted and secure server as per General Data Protection Regulation (GDPR).

You will be paid £1.50 in case you decide to participate in this task. On top of the participation fee, you can win an average £3 bonus. The bonus amount is determined randomly as per your choices during the task. More detailed information about the bonus will be provided in Instructions page.

This study has obtained ethical approval from the University of Leicester School of Business Ethics Committee.

If you have any queries about this research, you can contact me at my email address mi156@le.ac.uk.

If you agree to take part in this study, please go to the next page and complete the consent form.

D.2 Instructions

This study is about decision making under uncertainty. Your participation in this study can help scientists learn more about how people make choices when they face uncertainty.

Game description

This task has two parts. In the first part of the task, you will see several different pairs of choices and will be required to choose your preferred option by clicking the corresponding button on the screen. Once you have selected your preferred choice, you will see a new pair of options.

Your choices are important here. One of the options you have chosen in this part will be selected randomly and be played by the computer, and its outcome will determine the prize you receive on top of your participation fee.

The task currency is in *points*. You can win up to 100 points, so please choose carefully. The conversion rate between the points and the real currency, GBP (British Pound), is 1:20; 20 points are equivalent to 1 GBP (20 points = 1 GBP). For instance, if you win 100 points you will receive 5 GBP; 80 points will receive 4 GBP; 30 points will receive 1.5 GBP and so on.

You must pay attention to the task. During the task, you will be asked to answer simple random questions to verify that you pay attention to the task. You can check your progress in the task via the progress bar at the end of each page.

In the second part of the task, you will answer some questions and a brief demographic survey about you. Once you complete the second part, you will finish your tasks and learn how much bonus you have won.

To facilitate your understanding of the first part of the task, please consider the example on the next page.

We refer to the choices in a pair as an *Urn*. Each urn in every pair contains 100 identical marbles. The marbles can be in different colours. The colour of the marbles defines the prize

Urn A	Urn B
50 red marbles to win 100 points	50 blue marbles to win 35 points
50 white marbles to win 0 points	50 green marbles to win 25 points

Table 15: Example choice set in the experiment

that you can win. The number of each colour and the value assigned each colour may differ in every new pair. The maximum amount each colour can yield is 100 points.

In this example, Urn A has 50 red marbles and 50 white marbles; if a marble drawn randomly from urn A is red, you win 100 points. If a white marble drawn is drawn you win 0 points. So, the probability to draw a red marble and win 100 points is $50/100 = 0.50$, whereas the probability to draw a white marble and win 0 points is $50/100 = 0.50$. If someone reaches in urn A and draws a random marble from urn A with the closed eye, half the time they draw red and win 100 points and half the time they draw white and win 0 points. However, in this study, you only get to play a gamble once, so the prize will be either 0 or 100 points.

Urn B has also 100 marbles. 50 of them are blue winning 35 points, and 50 of them are green and win 25 points. Urn B thus guarantees at least 25 points, but the most you can win is 35 points. Some will prefer A and others will prefer B. Once you click on your preferred choice, you will see a new set of urns. You cannot reverse your decision by going back to the previous page.

The name of the urns will be randomised during the experiment.

Before starting the experiment you will answer three brief questions in the next page to ensure you have understood the instructions.

Please answer the following questions:

Urn K	Urn M
35 red marbles to win 100 points	20 blue marbles to win 75 points
40 white marbles to win 50 points	45 green marbles to win 50 points
25 yellow marbles to win 10 points	35 pink marbles to win 20 points

Table 16: Choice set in the trial round of the experiment

1. What is the probability of winning 50 points in Urn K?
    - 0.40
    - 0.35
    - 0.25

2. What is the probability of winning 75 points in Urn M?
   - 0.25
   - 0.35
   - 0.20
3. The total number of marbles in each urn is always equal to 100?
   - True
   - False

NB: When the participant choose the wrong answer an error message popped-up on the screen explaining correct answer.

Attention! The experiment starts in the next page.

D.3 Sample choice sets from each main stage

Question: Which one of the urns below would you prefer?

Urn K	Urn N
100 blue marbles to win 50 points	20 blue marbles to win 90 points
	80 white marbles to win 40 points

Table 17: Stage 1: Sample mean-preserving lotteries

Urn C	Urn D
90 red marbles to win 95 points	85 red marbles to win 95 points
5 blue marbles to win 15 points	5 blue marbles to win 90 points
5 white marbles to win 10 points	10 white marbles to win 10 points

Table 18: Stage 2: Sample complex-framed FSD lotteries

Cognitive Reflection Test

Please answer the following questions

1. A bat and a ball cost 17 dollars in total. The bat costs 5 dollars more than the ball. How many dollars does the ball cost?
   [ ]

Urn A	Urn B
85 red marbles to win 76 points	85 red marbles to win 76 points
5 red marbles to win 76 points	5 blue marbles to win 72 points
5 blue marbles to win 12 points	5 white marbles to win 8 points
5 white marbles to win 8 points	5 white marbles to win 8 points

Table 19: Stage 3: Sample transparent-framed FSD lotteries, which is re-framed version of the lottery above, while its outcomes decreased by 20%.

2. If it takes 3 machines 3 minutes to make 3 widgets how many minutes would it take 30 machines to make 30 widgets?

   [ ]

3. In a lake there is a patch of lily pads. Every day the patch doubles in size. If it takes 25 days for the patch to cover the entire lake how many days would it take for the patch to cover half of the lake?

   [ ]