Avoiding Risk in the Lab: An Experiment on Set-Dependent Risk Aversion*

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Abstract

We study how risk preferences may be subject to context effect specific to the risk domain—the amount of avoidable risk at any given time. Avoidable risk is captured by the riskiness of the safest option in a choice set, which induces set-dependent risk preferences. In a laboratory experiment, we find that adding safer options systematically increases risk aversion, even when the added options are not themselves chosen. By contrast, adding riskier options does not result in detectable change in risk attitude. Our finding suggests that context effect specialized to the risk domain may overwhelm those that are generally applicable in all types of choice domains (such as the compromise effect) when it comes to studying context-dependent risk preferences.

1 Introduction

Understanding risk attitudes is paramount to a wide range of economic models and applications. To this end, varying risk attitudes at the population level (e.g., as affected by wealth, age, gender) and across different choice domains (e.g., financial, health, ethical) have invited extensive studies and surveys.[1] By contrast, less is known about how the very structure of

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[1] Impossible to list all, a few examples are: Weber et al. (2002); Eckel and Grossman (2008); Nicholson et al. (2005); Choi et al. (2007); Einav et al. (2012); Dohmen et al. (2011).

every choice problem involving uncertainty—such as the avoidability of risk—directly affects risk aversion. For instance, even when wealth levels are fixed, an agent may choose a riskier investment over a safer one but reverses her decision when the same two options appear alongside a risk-free option, leading to a case of set-dependent preferences specialized to risk preferences.

This paper focuses on a specific kind of *set-dependent risk preferences*: those affected by the amount of risk that an agent can avoid at the time of decision making. We hypothesize that when the safest option in a choice set becomes even safer, the agent becomes more risk averse. To illustrate, consider a group of investors who must decide between investing in a composite index or a high-risk commodity. Each of these options is sensible and depends on the risk preference of the investor. However, imagine a corporate bond becomes available and some investors who originally chose the high-risk commodity switch to investing in the composite index. This behavior is inconsistent with any set-independent risk preferences. Lim (2021) characterizes this behavior with a model in which the very same agent would use a more concave utility function when safer options are added to a choice set. The intuition is straightforward—risk is psychologically more bearable when it is unavoidable.

In a laboratory setting, we test for changes in risk attitude when a third option is added to a choice set, which originally contains two alternatives of intermediate riskiness. The added option is either extremely risky or extremely safe and expands the choice set by increasing the amount of risk an agent can take or avoid. All lotteries take the form "a 50% chance of x (low prize) and a 50% chance of y (high prize)", and a lottery is deemed safer when x and y gets closer to each other.

We find that subjects displayed increased risk aversion when a safe option was added to a choice set, which contradicts standard theory in which risk aversion is set-independent. On the contrary, there is no detectable change in risk attitude when a risky option was added. Together, our finding is in line with the Avoidable Risk Expected Utility model by Lim (2021), which proposes greater risk aversion when risk is avoidable than when it is not, and draws a difference to models like the *compromise effect* which abstract from risk preferences and in so doing indiscriminately predicts an effect even when a riskier option is added.[2] Therefore, our evidence suggests that certain set-dependent preferences are specific to the risk domain, and adds to the literature that studies set-dependent and context-dependent preferences more broadly.

Our finding that risk aversion increases with avoidable risk is consistent with suggestive

[2]The compromise effect broadly characterizes the behavior of choosing the *intermediate* options. When adding a very safe (risky) option to a binary choice set, the safer (riskier) of the original two becomes the intermediate option, which increases the likelihood of being chosen.

evidence already in the literature. The Allais (1953)'s paradox is one example: In two binary choice problems, in which one contains a sure prize and the other does not, subjects overwhelmingly choose the sure prize even when it is in violation of expected utility's predictions.[3] In Wakker and Deneffe (1996), a novel method of eliciting risk aversion without involving a sure prize was introduced, and they found that risk aversion in general decreased. Herne (1999), using lotteries of the form "probability p on prize x" to study set effect on choices, also found that the availability of safer option (greater probability of a lower prize) increases risk aversion, although they experiment was not designed to disentangle the effect of a riskier option.

Although existing evidence leans in our direction, the idea that adding a riskier lottery can also affect risk aversion is not without support. For example in Kroll and Vogt (2012), the addition of a riskier lottery decreased risk aversion, which contradicts our finding. However, since they rely on the use of certainty equivalence to measure risk aversion, they did not test for changes in risk aversion when, instead, a safer lottery was added (since a sure prize is always present).

Similar in spirit to Lim (2021), Bleichrodt and Schmidt (2002) proposes a model that restricts attention to binary comparisons, in which a decision maker uses a different utility function when a sure prize is present than when it is not. Since our design is one in which a total of three options may be present at the same time, we primarily refer to Lim (2021)'s Avoidable Risk Expected Utility as our model of interest.

The rest of the paper is organized as follows. Section 2 presents our main hypotheses and the underlying intuitions. Section 3 describes the methodology, experimental design, and the dataset, whereas the findings are reported in Section 4. Section 5 analyzes the the consistency of our data with competing models. Section 6 concludes.

2 Hypotheses

Increase in risk aversion upon introduction of a very safe option is a phenomenon predicted by Lim (2021)'s Avoidable Risk Expected Utility model. Their model assumes that agents use the safest available alternative as reference, which in turn determines a utility function that is more concave when the reference is safer. Therefore, the composition of a choice set affects risk aversion in the aforementioned direction. The model describes an agent who finds risk less bearable/acceptable when it is avoidable than when it is not. On the contrary, since

[3] Lim (2021) shows that as long as the support of the prize space has size three, which is the case for the majority of Allais-type experiments, a violation of the Independence axiom in the standard direction (where the safe prize is chosen whenever available) implies a more concave utility function for the choice set that contains a safe prize.

the introduction of a very risky option does not change the amount of avoidable risk, it also does not change risk aversion.

Specialized to risk preferences, the Avoidable Risk Expected Utility model makes starkly different predictions when compared to models of set-dependent preferences that applies broadly to all multi-attributes alternatives. For instance, Simonson (1989)'s *compromise effect* suggests that the introduction of an extreme option would render some of the existing alternatives as a compromise, resulting in their increased likelihood of being chosen. In our setting, starting from a choice between a safer and a riskier options, adding a very safe option renders the safer option a compromise; on the other hand, and adding a very risky option renders the riskier option a compromise. As result, compromise effect predicts that the safer and riskier options would both experience increased likelihood of being chosen, depending on what is added. The opposite prediction is given by the *repulsion effect* Frederick et al. (2014), where the addition of an option reduces the likelihood of choosing its nearby options.

In summary, the effects of adding a very safe lottery and very risky lottery are summarized in Table 1.

Table 1: Changes in risk attitude upon addition of extreme options

	Addition of very safe options	Addition of very risky options
Standard Expected Utility	No change	No change
Avoidable Risk Expected Utility	Increased	No change
Compromise effect	Increased	Decreased
Repulsion effect	Decreased	Increased

In this paper we focus on *50/50 lotteries*, each taking the form "a 50% chance of x (low prize) and a 50% chance of y (high prize)". For example, a *safer lottery* (S) yields \$250 and \$200 each with 50% chance and a *riskier lottery* (R) yields \$500 and \$50 each with 50% chance. Similarly, a safest lottery (SS) and a riskiest lottery (RR) are related by less and more spread out prizes. For each set of S, R, SS, RR, we study the resulting behavior when subjects face the choice sets $\{S, R\}$, $\{SS, S, R\}$, and $\{S, R, RR\}$.

Our behavior of interest is when subjects choose R from $\{S, R\}$ but S from $\{SS, S, R\}$, reflecting increased risk aversion upon the introduction of a very safe option. Moreover, if subjects choose R from $\{S, R\}$ but SS from $\{SS, S, R\}$, although this behavior is consistent with expected utility when arbitrary utility functions are used, we can still conclude that subjects display increased risk aversion beyond what is allowed by any CARA / CRRA utility functions (for which we consider as the benchmark). Taken together, we say that subjects display *increased risk aversion* upon introduction of SS if they choose R from $\{S, R\}$ but S or SS from $\{SS, S, R\}$, and *decreased risk aversion* upon introduction of SS if they choose S from $\{S, R\}$ but R from $\{SS, S, R\}$. Changes in risk aversion is defined similarly when RR is introduced. Subsection 5.1 formalizes our method of classifying changes in risk aversion.

Hypothesis 1 The addition of a very safe option SS leads to more-risk-averse choices.

Hypothesis 2 The addition of a very risky option RR does *not* lead to more-risk-loving choices.

Hypothesis 3 The effect of adding a very safe option SS is robust to different types of SS: degenerate vs non-degenerate and more-appealing vs less-appealing.

3 Experimental Design

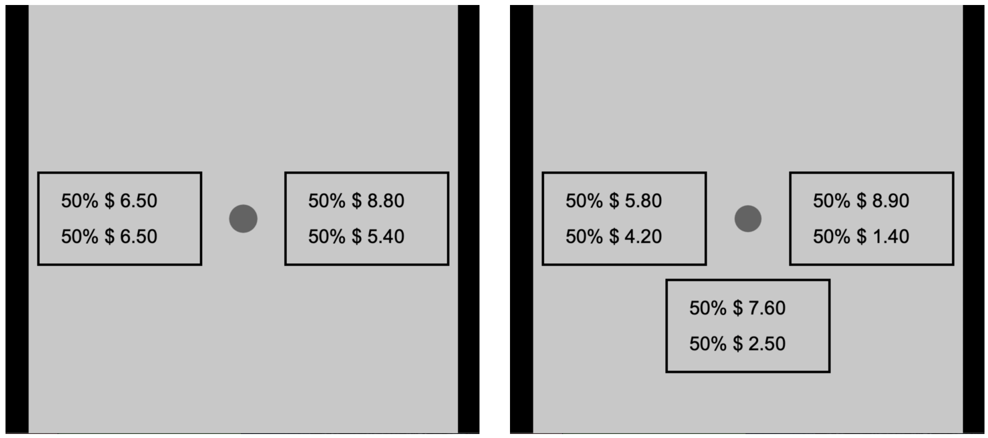
3.1 Task

The experiment involves a series of choices between lotteries. In each round, subjects choose one lottery between the two or three options available, as displayed in Figure 3.1. Each lottery is expressed as a pair of outcomes (dollar amounts), each with 50% chance of realization. Subjects have no time limit to make the choice, and no feedback is provided upon choice. The whole task includes 120 rounds, with the possibility to take short breaks every 30 rounds. All subjects faces the same list of choice sets. The order of presentation of the rounds is randomized at the subject level; the on-screen locations of the lotteries and the positions of the two outcomes (high and low prize) is randomized at the subject-round level. One of the chosen lotteries is randomly selected at the end of the session and implemented for the bonus payment. See Appendix A for additional details on the task.

3.2 Dataset

Each subject faces 120 choice sets, divided into 90 *target rounds* and 30 *control rounds*. Target rounds are designed specifically to test the main hypotheses of the study (details below). Control rounds are designed to detect possible heuristics in choices under uncertainty.

The target rounds are grouped into *conditions*, following the paradigm typically used to study decoy effect (Soltani et al. (2012); Pettibone (2012); Dumbalska et al. (2020)). Each condition is comprised of 6 rounds that always include two target lotteries, and sometimes

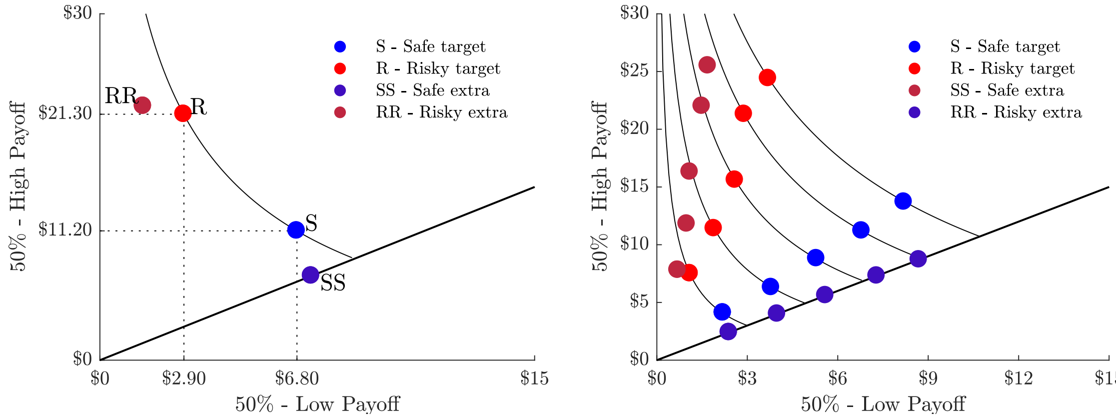


(a) Binary choice (b) Trinary choice

Figure 3.1: Example of choice between two or three lotteries.

include a third option. The set of rounds in the same condition are used to test how the third option affects the choice between the two target lotteries. For the rest of the paper, we will call the two *target lotteries* S (safe) and R (risky), and the *third options* SS (safest) and RR (riskiest). SS, S, R, RR are ordered by increasing spread of prizes, i.e., the lower prize of SS is greater than the lower prize of S, the higher prize of SS is less than the higher prize of S, and so on. In every choice set, no two lotteries are related by first-order stochastic dominance. This is the main difference with the typical decoy effect design, in which the third option is stochastically dominated by one of the targets. Figure 3.2 illustrates the relationship between these lotteries in various conditions used in the study. In addition to the safest option SS, we also used other types of safe lotteries as third option (thereafter called $SS2$, $SS3$, and $SS4$) to test the robustness of the results across different levels of certainty and attractiveness. Lotteries SS and $SS3$ are degenerate lotteries, $SS2$ and $SS4$ are non-degenerate lotteries. $SS3$ and $SS4$ have lower payoffs compared to their counterpart SS and $SS2$. See Appendix A for additional details on the the procedure used to generate the lotteries.

The control rounds are designed to detect heuristics (e.g., maximizing the downside, minimizing the upside), and are not part of the main analyses. Like the target rounds, control rounds include binary and trinary choice sets, and within each round there are no first-order stochastically dominated options. These choice sets contain options with large positive (resp. negative) risk premia, for which we expect choices in favor of the riskier (resp. safer) options. Systematically failing to do so would suggest extreme risk preferences (a possible confounding factor for our test) or decision processes that follow simple heuristics, such as maximizing the lowest (resp. highest) payoffs or minimizing (resp. maximizing)



(a) Lotteries in one condition (fixed (d, α)). (b) Lotteries used in different conditions

Figure 3.2: Example of groups of lotteries used in the study. (a) Target lotteries S (safe) and R (risky). They lie in the same indifference curve according to a CRRA utility function (fixing a value α for the relative risk coefficient and a degenerate lottery d). The third options SS (safest) and RR (riskiest) lie below the indifference curve. (b) The parameters d and α were varied to obtain different conditions.

variance.

3.3 Procedure

The experiment was conducted in CELSS (Columbia Experimental Laboratory of Social Sciences, Columbia University, New York, USA) between August and September 2019. It was coded in MATLAB (Release 2018b) using Psychotoolbox 3 (Psychophysics Toolbox Version 3). 55 paid volunteers were recruited using the platform ORSEE (Online Recruitment System for Economic Experiments) Greiner (2015)and were naive to the main purpose of the study. All subjects provided written, informed consent. The experiment took on average 45 minutes, including instructions, payment, and another set of questions not analyzed in the present paper.

Upon completion, subjects received payment in cash that depended on the choices they had made. One trial was randomly selected for implementation, for which the chosen lottery was played and the outcome was paid. Each subject also received a $10 show-up fee. The average payment was $16.70.

Instructions were provided both (i) on the computer screen as slides that can be browsed by each subject at the desired pace and (ii) as a paper printout that is available to the subject throughout the experiment. The two versions of the instructions contained the same information verbatim. At the beginning of the experiment, subjects were informed of the payment structure, the no-deception policy of the laboratory, and that their decisions would not affect the questions they would face in other rounds.

4 Descriptive Results

We present the results of the experiment in two sections. First, we present the model-free results on choice probability and WARP violations. In the next section, we analyze how the results can be reconciled with various families of choice models (Expected Utility, Prospect Theory, Random Utility).

4.1 Treatment Effect

We analyze the frequency of choosing a safer option (either S or SS) in the binary and trinary choice. In the binary choice trials, participants chose the safe lottery S 63.4% of the times. The frequency of choosing one of the safe options in trinary choices trials with SS is significantly higher (**H1**, 73.3%, p<0.0001, Wilcoxon signed-rank test with data clustered at the subject level), whereas it is not significantly different when RR was added (**H2**, 60.4%, p=0.149, Wilcoxon signed-rank test). The frequencies and confidence intervals are shown in Figure 4.1. Both results are consistent with the hypotheses previously discussed. Subjects choose safer options more often when a very safe option SS is introduced, but the choice probability is not significantly different when a very risky third option RR is added. Subsection 5.1 shows that this pattern can me modeled as increased risk aversion when SS is added and no change in risk aversion when RR is added.

4.2 Robustness Across Safe Options

One immediate question is whether this result relies on the characteristics of the safest option introduced in the choice set. SS is a degenerate lottery with expected value much lower than lottery S, and both of these characteristics could be necessary in order to observe the phenomenon described above. In order to answer this question, we use different versions of SS that differ in two dimensions: level of certainty and attractiveness.

We collect data for a series of trinary choices that include S, R, and a third safest option (therefore called $SS2$, $SS3$, $SS4$). Lotteries $SS2$ and $SS4$ are non-degenerate lotteries. Lotteries $SS3$ and $SS4$ are more attractive safest lotteries (more similar to target lottery S) as they have higher payoffs than SS and $SS2$.

Figure 4.2 and Table 2 show that the behavior observed for SS is qualitatively and quantitatively analogous to the one observed for the three robustness conditions. Consistent

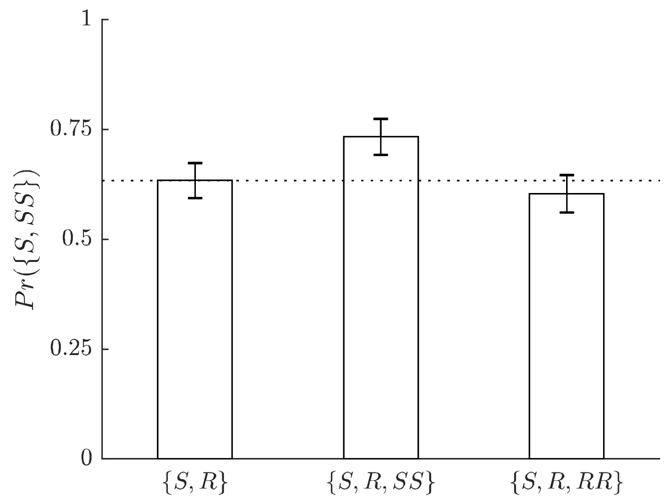


Figure 4.1: Frequency of Safe Choices. Probabilities and 95% Confidence Intervals for *safe group* choices (S or SS) across conditions.

with the third hypothesis, we have a larger probability of choosing a safe option ($p < 0.0001$ Wilcoxon signed-rank test).

Figure C.1 reports the panel data on the direction of risk aversion switches across $SS - SS4$. Table 2 provides further details on choice probabilities. The p-values for the Wilcoxon signed-rank test are calculated within subject with respect to the null hypothesis $\Pr(\text{safe group}|\{S, R, Z\}) = \Pr(\text{safe group}|\{S, R\})$, where $Z = SS, SS2, SS3, SS4, RR$, safe group contains $S, SS - SS4$, and risky group contains R and RR.

	$\{S, R\}$	$\{S, R, SS\}$	$\{S, R, SS2\}$	$\{S, R, SS3\}$	$\{S, R, SS4\}$	$\{S, R, RR\}$
S	63.39%	62.42%	62.91%	57.21%	56.00%	60.36%
R	36.61%	26.67%	25.82%	26.06%	24.24%	32.48%
Z		10.91%	11.27%	16.73%	19.76%	7.15%
Safe group	63.39%	73.33%	74.18%	73.94%	75.76%	60.36%
Risky group	36.61%	26.67%	25.82%	26.06%	24.24%	39.64%
Wilcoxon SRT		<0.0001	<0.0001	<0.0001	<0.0001	0.1489

Table 2: Safe and risky choices across choice sets.

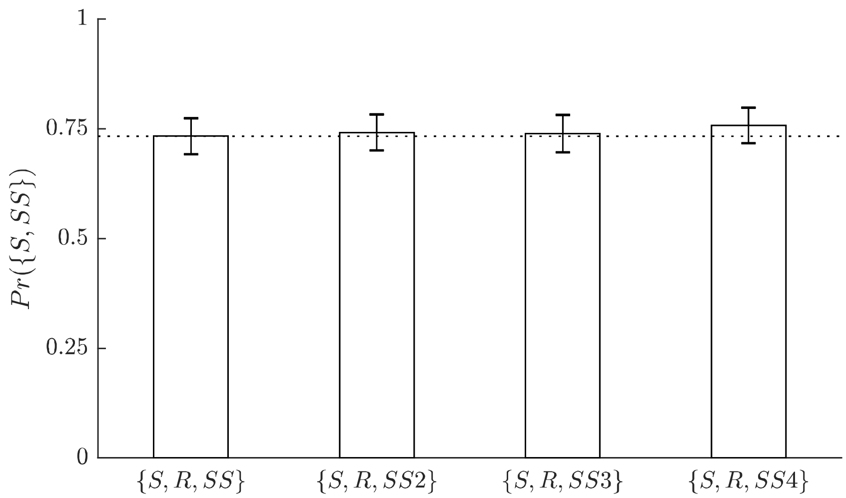


Figure 4.2: Robustness of the results for lotteries with different level of Certainty and Attractiveness. Choice probabilities and 95% confidence intervals.

4.3 WARP Violations

So far we have tested the hypothesis at the aggregate level, by considering a pair of observations (choice probabilities in different types of choice sets) for each participant. Another formal way to look at the respondents behavior is to investigate inconsistencies in the choice pattern within each subject. We do this by looking at the number and direction of Weak Axioms of Revealed Preferences (WARP) violations for each participant. Given an observed choice a in a choice set $\{a, b\}$, we observe a WARP violation if, after introducing a new option c to the choice set, the subject chooses b—reversing her choice of a over b.

Table 3 displays the results for different types of trials. WARP violations are overwhelmingly in the direction of switching from R to S when $SS - SS4$ was added, reflecting increased risk aversion, but equally likely in either direction when RR was added, reflecting inconclusive change in risk aversion.

This table reports the frequency of WARP violations between $\{S, R\}$ and $\{S, R, Z\}$, where $Z = SS, SS2, SS3, SS4, RR$. The upper part of the table reports WARP-compliance due to selecting the third option (first row) or the same option as in the binary choice (second row). WARP violations (third row) are separated into the two possible directions. The presence of both $S \to R$ and $R \to S$ switches in all conditions will be discussed further in Subsection 5.3, when we analyze the data using Random Utility. Assuming that subjects sometimes choose randomly (with "mistake" probabilities depending on the utility difference between options), a symmetric distribution of the switch directions (switch probability conditional on WARP violation) as we observe in RR trials is consistent with the no-effect hypothesis when a very risk option is introduced. On the other hand, the skewed behavior in the SS trials is consistent with our hypothesis that introducing a very safe options makes subjects more risk averse.

$Z =$	SS	$SS2$	$SS3$	$SS4$	RR
WARP (Z)	11%	11%	17%	20%	7%
WARP (not Z)	68%	71%	65%	62%	70%
WARP Violation	20%	18%	18%	18%	23%
Conditional on WARP violations:					
$R \to S$	71%	74%	69%	75%	50%
$S \to R$	29%	26%	31%	25%	50%

Table 3: Choice probabilities and types of WARP violations.

More details on choice probabilities and transition probabilities between binary and trinary trials can be found in Appendix C.

5 Models

In this section, we consider three families of models of choice under risk. For each model, we introduce how they provide a framework for the analysis of choices, we illustrate how they relate to the main hypotheses of interest, and we compare these hypotheses with the data collected. In the first part, we consider expected utility with a risk aversion coefficient that may vary across conditions. In the second part, we show the relationship between Lim (2021)'s Avoidable Risk Expected Utility (AREU) and Kahneman and Tversky (1979)'s Prospect Theory. In the third part, we investigate the compatibility of our dataset with models of random utility, and argues that they are in general incompatible.

5.1 Expected Utility and Avoidable Risk

5.1.1 Framework

Consider a stochastic expected utility (EU) model (Blavatskyy (2007)) in which the (true) utility of a 50/50 lottery p is given by the pair of equally likely outcomes (x_1, x_2) and a CRRA coefficient α,

$$U_\alpha(p) = \mathbb{E}_p u(x) = \sum_{i=1}^{2} \frac{1}{2} \frac{(x_i)^{1-\alpha} - 1}{1-\alpha},$$

Higher values of α reflect greater risk aversion. We consider stochasticity in choice by introducing noise, $\hat{U}_\alpha(p) = U_\alpha(p) + \frac{\epsilon}{\lambda}$, where ϵ is a Type 1 Extreme Value error (T1EV, or logit error) and λ is a scalar. Equivalently, given the true utility and an accuracy parameter λ, the probability of choosing lottery p_i from choice set $A = \{p_1, p_2, ..., p_J\}$ is characterized by

$$\Pr(p_i, A) = \frac{e^{\lambda U_\alpha(p_i)}}{\sum_j e^{\lambda U_\alpha(p_j)}},$$

where higher values of λ results in fewer deviations from the deterministic behavior of an agent who maximizes $U_\alpha(p)$.

5.1.2 Mechanism: Change in Risk Aversion

Our analysis deems "chooses S over R" as more risk averse than "chooses R over S". In addition to being intuitive, this approach is backed by a formal definition of *more risk averse*, which we now introduce.

Suppose we restrict attention to the class of utility functions defined by constant relative risk aversion (CRRA), commonly used across economics and finance research for their intuitive properties. Then, variation in the Arrow-Pratt risk aversion coefficients agree with our notion of changes in risk aversion. The same is true if, instead, we restrict attention to the constant absolute risk aversion (CARA) class.

Let p and q be two 50/50 lotteries where the high prize of lottery p is h_p and its low prize is l_p. Then, restricting attention to CRRA utility functions, there exists an Arrow-Pratt coefficient $\bar{\alpha}$ such that $EU_\alpha(q) \geq EU_\alpha(p)$ if and only if $\alpha \geq \bar{\alpha}$. The existence of $\bar{\alpha}$ is guaranteed as long as one lottery does not first-order stochastically dominate the other. In other words, we can formalize the statement "an agent who chooses q over p is *more risk averse* than an agent who chooses p over q" using CRRA utilities: this behavior implies a higher risk aversion coefficient. [4]

Formally, where $U_\alpha(L)$ is the expected utility of L under a CRRA utility function with coefficient α:

Fact. *Let SS, S, R, RR be four 50/50 lotteries sorted by increasing spread of low and high*

[4] A similar argument can also be made when we restrict attention to CARA utilities instead, although $\bar{\alpha}$ will be different. This is because of the "single coefficient" nature of CARA and CRRA, that a single observation is sufficient to pin down the range of α that explains an underlying behavior. The same comparative statics cannot be done with DARA, etc.

prizes. There exists a unique CRRA coefficient $\bar{\alpha}$ such that

1. $U_\alpha(S) > U_\alpha(R)$ *if and only if* $\alpha > \bar{\alpha}$,
2. $\min\{U_\alpha(SS), U_\alpha(S)\} > U_\alpha(R)$ *if and only if* $\alpha > \bar{\alpha}$,
3. $\min\{U_\alpha(R), U_\alpha(RR)\} > U_\alpha(S)$ *if and only if* $\alpha < \bar{\alpha}$.

5.1.3 Hypotheses

We use this fact to develop and test our hypotheses, and then conclude that risk aversion has increased from choice set A to choice set B if subject's choices imply a greater risk aversion coefficient in B than in A. Specifically, each choice from a choice set is consistent with a (deterministic) range of CRRA coefficients. We compare the implied ranges to conclude changes in risk aversion.

We can categorize changes in risk attitude as follows: (1) If a subject chooses R from $\{S, R\}$ and SS or S from $\{S, R, SS\}$, her behavior is inconsistent with a persistent CRRA coefficient in the direction of becoming more risk averse in the presence of SS. (2) If a subject chooses S in $\{S, R\}$ and R in $\{S, R, SS\}$, then she has become more risk seeking in the presence of SS. (3) Any other choice combinations from $\{S, R\}$ and $\{S, R, SS\}$ is consistent with a single CRRA coefficient.

By fitting a EU using the Maximum Likelihood method we can estimate the risk aversion coefficient for different groups of trials (binary choices, trinary with SS, trinary with RR). The null hypothesis is that the estimated coefficient is the same across types of trials. The alternative (AREU) hypothesis is that the estimated coefficient for the trinary choices with SS is significantly larger than the one estimated for the full dataset, but that the coefficient for the trinary choices with RR is not.

Although our method of classifying changes in risk aversion is formalized with CRRA, it is also consistent with basic intuitions. When a subject switches from choosing R, a higher spread lottery, to S, a lower spread lottery, we believe it is natural to interpret it as increased risk aversion. Similarly, the opposite behavior corresponds to decreased risk aversion. Moreover, choosing R in $\{S, R\}$ but SS in $\{S, R, SS\}$ means, despite having chosen a high spread lottery (R) over a low spread one (S), she now prefers the lowest spread lottery above all else. Again, this suggests that her risk aversion is greater in the latter choice problem.

To simplify notation, it suffices to categorize choices into the *safe group* when S or SS is chosen, and the *risky group* when R or RR is chosen. For $Z = SS, RR$, when we observe a risky group choice from $\{S, R\}$ but a safe group choice from $\{S, R, Z\}$, we say that the addition of Z increases risk aversion; likewise, a safe group choice from $\{S, R\}$ but a risky group choice from $\{S, R, Z\}$ suggests that the addition of Z decreases risk aversion. Any other combination of choices between $\{S, R\}$ and $\{S, R, Z\}$ is consistent with a single CRRA coefficient.

5.1.4 Tests and Results

To fit the EU model, we allow α to differ across binary choice sets, when SS was added, when RR was added, etc. This allows for the same participant to display different risk preferences when third options are added to the choice set.[5] Consistently with the predictions

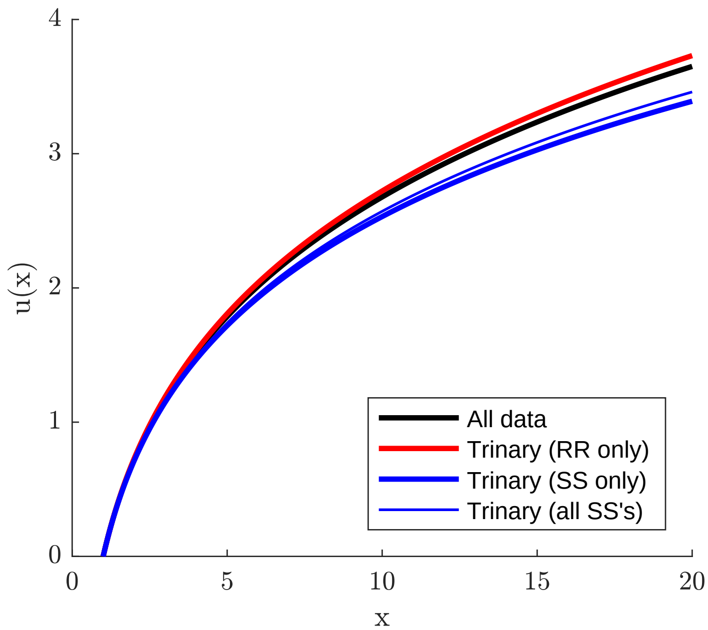


Figure 5.1: Model Fitting: Expected Utility Under Different Risk Aversion Coefficients

of AREU, estimated parameters for risk aversion differed across choice sets systematically. The estimated risk aversion coefficient α is 0.87 when all choice sets are pooled together. For $\{S, R, SS\}$ (and variations of SS described in Appendix A), we observe increased risk aversion: the estimated parameters for α are 0.92 for SS trials and 0.91 when we pool together all $SS - SS4$ (statistically different from 0.87, p-value< 0.01 using bootstrap standard errors).

[5]For "All data", we used all trials, including control trials. We consider the logit model described in the paragraph with a lower bound in the choice probability. Subjects that always choose the safest alternatives or (less frequently) always choose the riskiest alternatives provide a poor fit for the data. A parsimonious way to discount their weight in the dataset is to introduce a 5% lower bound in the choice probabilities, regardless of the lottery. The results are robust to the adoption of different values between 1% and 10%.

On the contrary, the estimated α for RR trials is 0.86, not significantly different from 0.86). These findings are in line with AREU, which suggests increased risk aversion when the safest alternative become safer (but not when the riskiest alternative changes).

5.2 Prospect Theory

5.2.1 Framework

In prospect theory Kahneman and Tversky (1979), lotteries are evaluated with respect to a reference point, which in turn determines gains and losses. When losses loom larger than gains, a decision maker suffers from *loss aversion*, and this prominent phenomenon had been used to explain various anomalies in economics including the endowment effect and the equity premium puzzle.[6][7]

A well-known issue with prospect theory is the formation of the reference point. By considering reference formation using a max-min criterion we can bring the intuition basal to AREU in the framework of prospect theory.

In our exercise, we define as reference point the "highest minimum outcome guaranteed" from the available lotteries. This is the outcome that *can be guaranteed* if the subject simply chooses the safest alternative in the current choice set. Adding a safer option raises the reference point whilst adding a riskier option leaves it unchanged.[8]

Deploying a commonly-used functional form of prospect theory, we define the value of payoff x given reference point x_{RP} as

$$v_\alpha(x, x_{RP}) = \begin{cases} (x - x_{RP})^{\alpha} & \text{if } x \geq x_{RP} \\ -\beta (x_{RP} - x)^{\alpha} & \text{if } x < x_{RP} \end{cases},$$

We can use the entire dataset to estimate a stochastic choice model with three parameters:

[6]For example, Knetsch (1989); Kahneman et al. (1990) for endowment effect and Benartzi and Thaler (1995) for the equity premium puzzle.

[7]In our experiment we do not use stochastically dominated lotteries, so we do not need to make assumptions about whether all the lotteries are used to determine the reference point. Traditional prospect theory includes an editing phase in which the decision maker removes from the choice set all the FOSD lotteries before proceeding with their evaluation. The Avoidable Risk - Prospect Theory formulation that incorporates this assumption would predict that the effect holds for lotteries like the ones we used in the study, but not for decoys that are asymmetrically dominated by the safe lottery. We are not able to test this conjecture with the data available.

[8]If the new lottery is riskier (larger spread of values, and not stochastically dominant), its lower outcome cannot be the highest one, and the reference point is unchanged. This means that risk preferences should also be unchanged by adding a risky lottery. Instead, if the new lottery is safer (smaller spread of values), its lowest outcome becomes the new reference point, higher than the previous one. Moving the reference point has two effects: on the concavity of the curve above and below the reference point, and on the range of values that are perceived as losses, and therefore discounted further in the evaluation process.

α (risk aversion), β (loss aversion), and λ (accuracy in the choice stage, as described in the EU model).

5.2.2 Hypotheses

The key hypothesis is that a change in the reference point, due to the introduction of safer option, generates change in the evaluation of payoffs due to loss aversion. We observe loss aversion when the parameter $\beta > 1$. The experimental literature provides extensive evidence supporting loss aversion, typically using with lotteries that involve both positive and negative payoffs (with a reference point of zero dollars). In our design all the payoffs are positive and the presence of loss aversion can be tested only by assuming that subjects use a different reference point across choice sets.

5.2.3 Tests and Results

The estimates obtained using the Maximum Likelihood method confirm the hypothesis, and the estimated value function shown in Figure 5.2 appears with the typical S-shape that captures risk aversion ($\hat{\alpha} = 0.80 < 1$) and loss aversion ($\hat{\beta} = 1.85 > 1$).

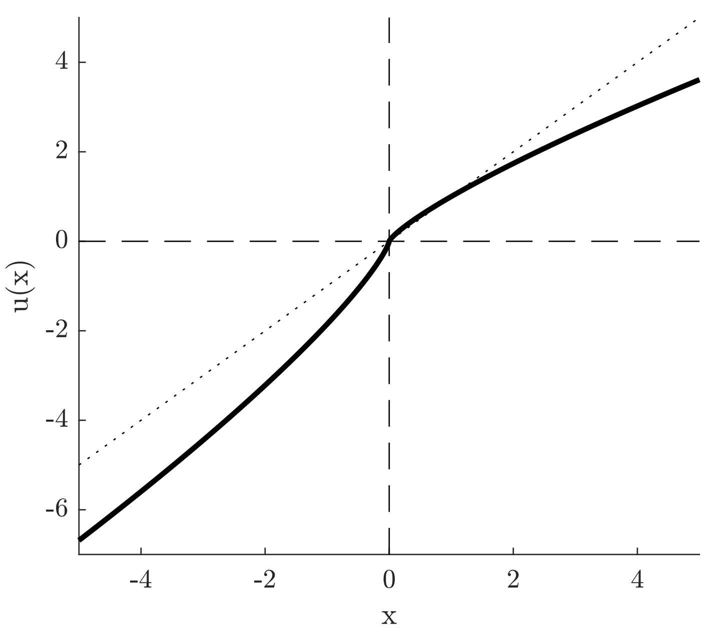


Figure 5.2: Model Fitting: Prospect Theory

The high degree of loss aversion—where the reference point is the max-min outcome of a choice set—is consistent with the observed shift towards safer options when very safe options are available.

5.3 Random Utility

5.3.1 Framework

We also investigate the compatibility of our results with random utility models (RUM).[9] Each lottery p has a utility value $U(p)$ that is subjected to mean-zero noise ϵ_p. Facing a choice set A, the agent chooses p from A to maximize $U(p) + \epsilon_p$, resulting in stochastic choice

$$\Pr(p, A) = \Pr\left[U(p) + \epsilon_p \geq U(q) + \epsilon_q \,\forall q \in A\right].$$

Under the most general setup, RUM is characterized by a set of probabilities, one for each alternative in each choice set, $\Pr(p, A)$. In our case, $p = SS, S, R, RR$ and $A = \{S, R\}, \{S, R, SS\}, \{S, R, RR\}$. Moreover, it is typically assumed that $\Pr(p, A) \geq \Pr(p, B)$ if $A \subset B$.

5.3.2 Tests and Results

According to RUM, the probability of each choice from $\{S, R, SS\}$ is independent of whether a subject has chosen S from $\{S, R\}$ or R from $\{S, R\}$, under the assumption of a representative decision maker. In our dataset, panel data rule this prediction: Figure C.1 shows that for the conditions in which participants chose S from $\{S, R\}$, the vast majority (76%) chose S from $\{S, R, SS\}$, and very few (9%) chose R from $\{S, R, SS\}$. On the contrary, among those who have chosen R from $\{S, R\}$, only 40% chose S from $\{S, R, SS\}$ and as many as 57% chose R from $\{S, R, SS\}$.

Our dataset could be reconciled with RUM if we were to consider multiple populations of representative agents. For example, suppose we have two population of agents, and each population has their own RUM parameters, then with the right calibrations our dataset can be obtained as a result of over-fitting (7 parameters for 5 equations).[10]

Another property of RUM is stochastic monotonicity,

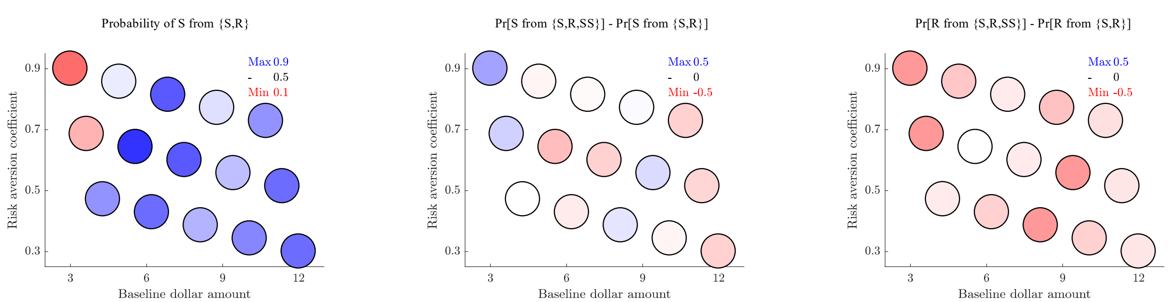
$$\Pr(p, A) \geq \Pr(p, B) \text{ if } A \subset B,$$

[9]For an overview of RUM, see Manski (1977); Walker and Ben-Akiva (2002).

[10]The 7 parameters are $\Pr(S, \{S, R\})$, $\Pr(S, \{S, R, SS\})$ and $\Pr(R, \{S, R, SS\})$ for each of the two types of agents and the weight of each type. The 5 equations are the equations for, on the dataset, $\Pr(S, \{S, R\})$, $\Pr(S, \{S, R, SS\} | S, \{S, R\})$, $\Pr(R, \{S, R, SS\} | S, \{S, R\})$, $\Pr(S, \{S, R, SS\} | S, \{S, R\})$ and $\Pr(R, \{S, R, SS\} | R, \{S, R\})$.

which simply says that an alternative p is not chosen more often when more options are available. Our dataset does not display stochastic monotonicity violation with the aggregate data, where all trials are clustered together. However, this is partly due to fact that in most trials, subjects choose S in $\{S, R\}$ overwhelming (in aggregate, this happens 63% of the time). This makes it harder for the frequency of S to increase further. We can partially address this issue by considering the different conditions used in the study. We use pairs of target lotteries that vary in their risk premium, and in 2 of the 15 conditions the risky lottery is chosen more often than the safe one. When we restrict the analysis to these conditions, we observe stochastic monotonicity violations. The presence of multiple tests requires us to be careful about the interpretation of this result, that should be considered only as suggestive evidence supporting the avoidable risk hypothesis and against RUMs.

As illustrated in Figure 5.3, for trials where S is chosen from $\{S, R\}$ less than half of the time (low baseline amount and high risk premium), stochastic monotonicity is violated in that S is chosen more often in $\{S, R, SS\}$ than in $\{S, R\}$. On the contrary, stochastic monotonicity holds for R throughout. That is, for all trials—even the ones where R is chosen from $\{S, R\}$ less than half of the time—R is chosen even less often in $\{S, R, SS\}$ than in $\{S, R\}$, again suggesting that introducing SS increases risk aversion.



(a) (b) (c)

Figure 5.3: Choices by condition. Each circle is a *condition*, it characterizes a set of $\{S, R, SS\}$ as described in Section 3. Figure (a) reports the frequency of S from $\{S, R\}$ from each condition. Figure (b) reports the increase in frequency of S from $\{S, R\}$ to $\{S, R, SS\}$. Figure (c) reports the increase in frequency of R from $\{S, R\}$ to $\{S, R, SS\}$.

6 Conclusion

We study a specific kind of context-dependent preferences specialized to the risk domain, where avoidable risk—captured by the presence of a safe option—increases risk aversion.

Our experiment finds evidence of this behavior, which is in line with the prediction of Lim (2021)'s Avoidable Risk Expected Utility model.

Using a within-subject design, we find that adding a very safe option to a choice set changes risk aversion by increasing it. The change can be so drastic that WARP violations occur, where a subject who originally chooses a safer option over a riskier one switches her decision when a very safe option becomes available. On the contrary, the introduction of a very risky option does not result in systematic changes in risk aversion.

The asymmetry between adding a very safe option and adding a very risk option suggests that context-dependent preferences that apply more generally to multi-attributes alternatives may not capture all context effects, especially those that are driven by the very nature of the choice problem, in this case decisions under uncertainty. Although the compromise effect correctly predicts that adding a very safe option leads to more risk averse choices, it also predicts that adding a very risky option leads to more risk loving choices, which is not observed. By capturing a unidirectional change in risk aversion that occurs only when a very safe option is added, our experiment adds to the intuition that some context effects observed in the risk domain may be inherent in risk preferences.

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A Appendix - Experimental Design

Task The lotteries appear on the screen in four possible locations (top, right, bottom, left) equally distant from the fixation point placed at the center of the screen, as shown in Figure 3.1. Each round starts with only the fixation point on the screen. After 500 ms, two (three) empty boxes appear at random locations. At this point subjects know the number of available options and their positions on the screen, but not their values. After another 500 ms, the values appear on the screen. No action is allowed for the first 3 seconds, after which the subject may select one option using the keyboard (arrow keys to select, spacebar to confirm). There is no time limit for the action phase. Upon confirmation, no feedback is provided and a new round begins.

Dataset The target rounds are grouped into 15 *conditions*, with 6 rounds per condition. Each condition is characterized by two parameters: a baseline dollar amount $d \in [\$3, \$12]$ and a CRRA coefficient $\alpha \in [0.3, 0.7]$.[11] A procedural algorithm takes a pair (d, α) and generates two *target options*—S (safer) and R (riskier)—and two *third options*—SS (safest) and RR (riskiest). SS, S, R, RR are ordered by increasing spread of prizes, i.e., the lower prize of SS is greater than the lower prize of S, the higher prize of SS is less than the higher prize of S, and so on. In every choice set, no two lotteries are related by first-order stochastic dominance.

Figure 3.2 illustrates the relationship between these lotteries. The target options, S and R, lie on the same indifference curve under CRRA utility and risk aversion coefficient α. The third options, SS and RR, are designed to be less appealing; they lie below the indifference curve connecting S and R under the same utility function. Therefore, extremely risk averse (resp. risk seeking) subjects will choose SS (resp. RR) over S and R.

In addition to SS, we also used other types of safe lotteries ($SS2$, $SS3$, and $SS4$) to test whether absolute certainty and attractiveness affect our finding.

Each $SS2$ lottery is obtained from the corresponding SS lottery by adding 10 cents to the high payoff and removing 10 cents from the low payoff. $SS3$ (degenerate) and $SS4$ (non-degenerate) are analogous to SS (degenerate) and $SS2$ (non-degenerate), but with a *smaller* penalization in expected value (about 20% of the expected value instead of 50%). SS was penalized so that subjects' choices concentrate at the target options, S and R. In order to reduce similarity between trials, we use a procedural algorithm that penalizes SS

[11] The range of parameters for α was calibrated based on estimated risk preferences in other lab experiments (Harrison and Rutström (2008)), as well as a pilot study we conducted in the Summer 2019. This range allows to implement the within-subject analysis of the data despite the large heterogeneity in risk preferences across participants.

by a random percentage between 45% and 55%. The risky options RR are generated in a similar way, by reducing the lowest value of R by 40-60% and increasing the higher value of R by a smaller fraction (30-60% of the subtracted value). This allows us to test whether the effect on risk aversion depends on the attractiveness of the added safe options.

B Appendix - Heterogeneity Analysis

How robust is the main effect across subjects? We calculate the choice probabilities and run the tests at the subject level. The result is robust when we look at the distribution of choices across participants: 69% of the participants appear more risk averse when SS is introduced (22% unchanged, 9% less risk averse), and only 26% appear more risk averse when RR was added (27% unchanged, 47% less). The pair of scatter plots displayed in Figure B.1 show the distribution of safe and risky choices across participants and how they vary after the introduction of the third lottery.

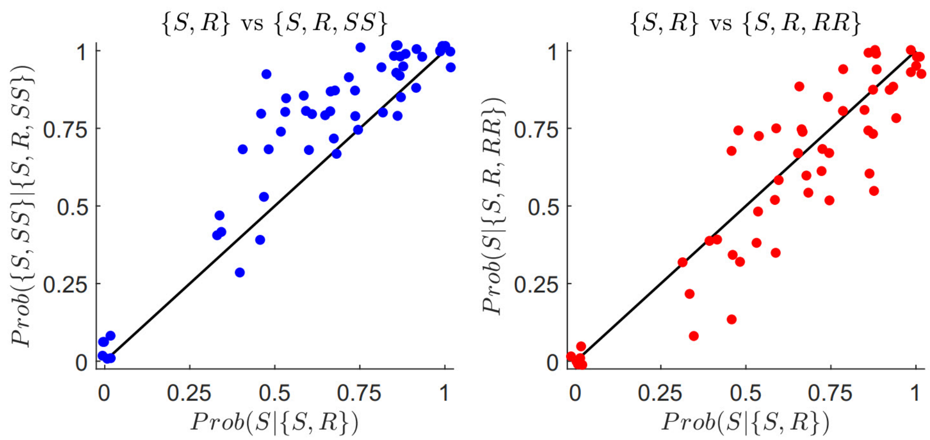
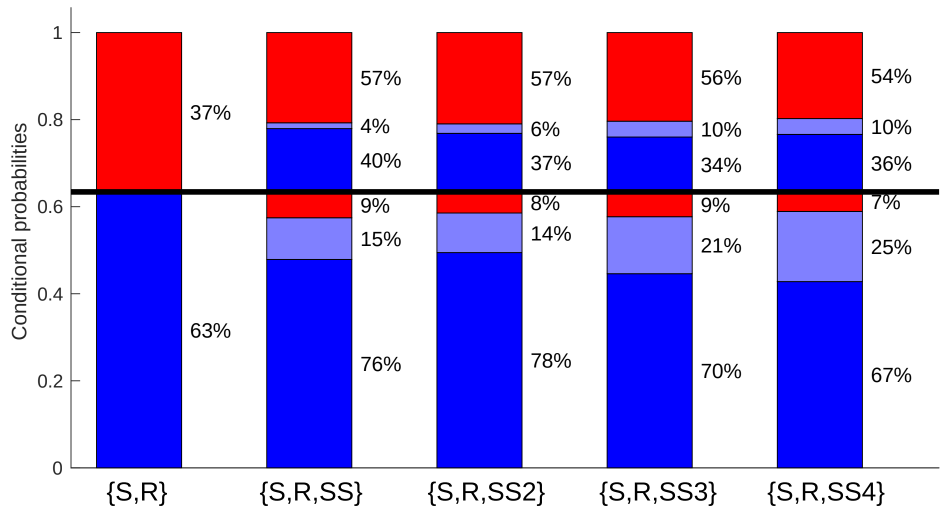


Figure B.1: Proportion of *safe group* choices (S or SS) for different types of trials: binary choices (x-axis) and trinary choices (y-axis), based on which third option is added. On the left, the third option is SS. On the right, the third option is RR.

C Appendix - Conditional Choice Probabilities

The figure and table reports panel data on changes in risk aversion. The leftest bar reports the probability that S was chosen (from $\{S, R\}$) in Blue, and R in Red. The second bar reports that, conditional on choosing R from $\{S, R\}$, 57% chose R from $\{S, R, SS\}$, 4% chose SS, and 40% chose S. Similarly, conditional on choosing S from $\{S, R\}$, 9% chose R from $\{S, R, SS\}$, 15% chose SS, and 76% chose S. The third, fourth, and rightest bars report the same information but for $\{S, R, SS2\}$, $\{S, R, SS3\}$, and $\{S, R, SS4\}$.



Unconditional probabilities [after excluding decoy]

Other	0	0.11	0.11	0.17	0.2
Risky R	0.37 [0.37]	0.27 [0.3]	0.26 [0.29]	0.26 [0.31]	0.24 [0.3]
Safe S	0.63 [0.63]	0.62 [0.7]	0.63 [0.71]	0.57 [0.69]	0.56 [0.7]

Figure C.1: Panel Data on Changes in Risk Aversion

D Appendix - Results Across Conditions

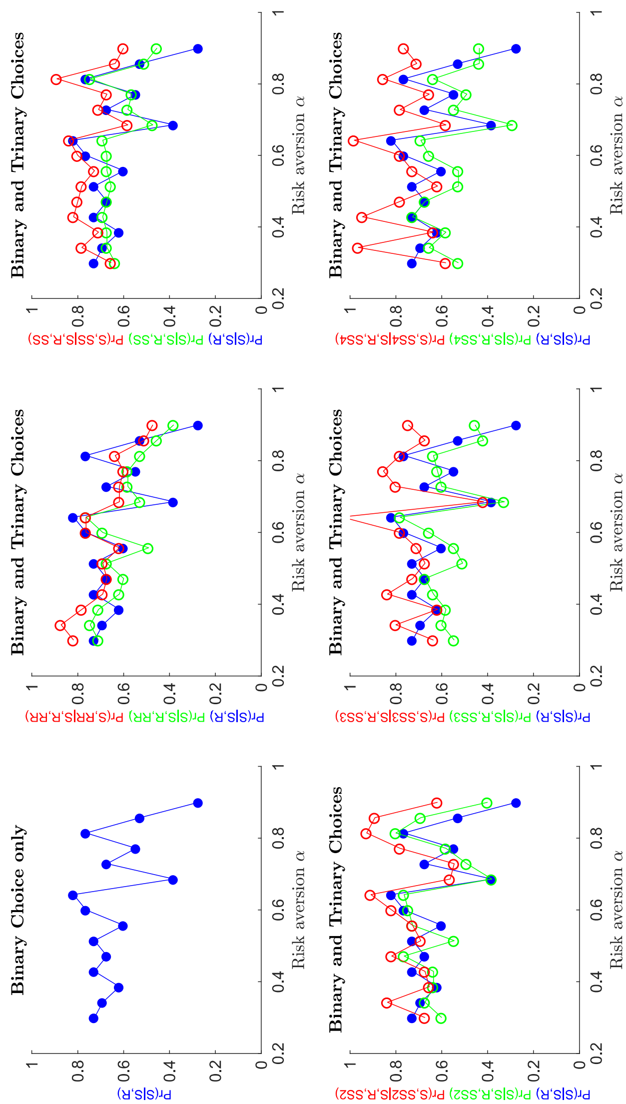
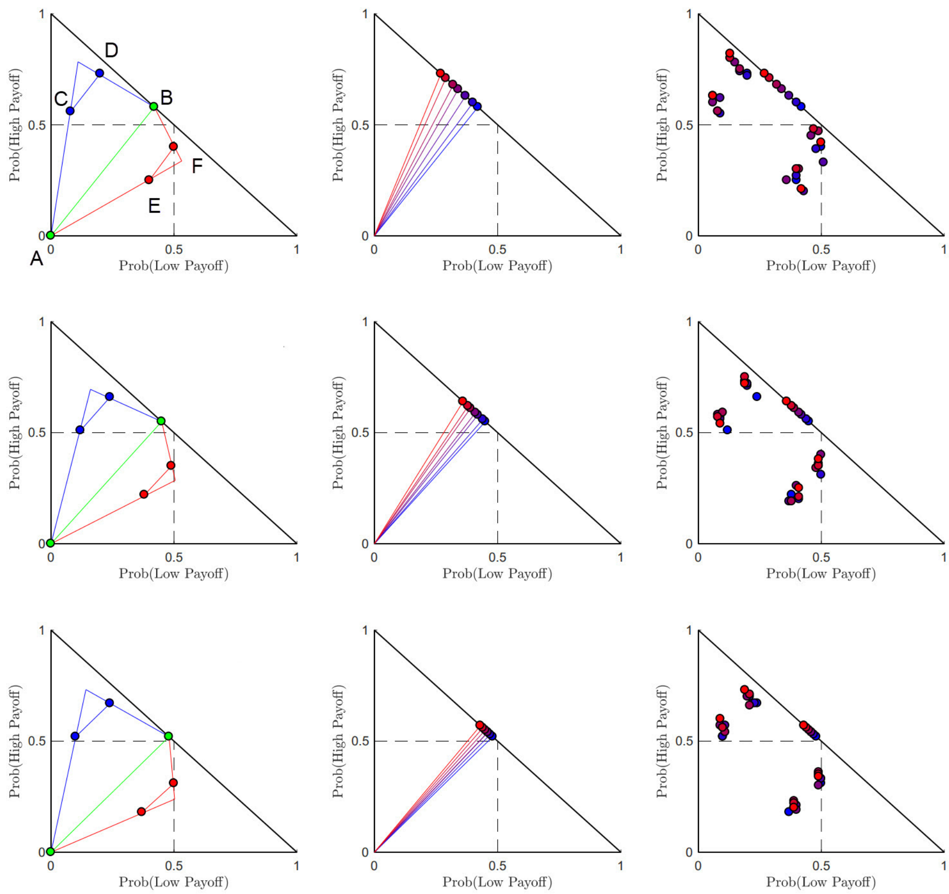


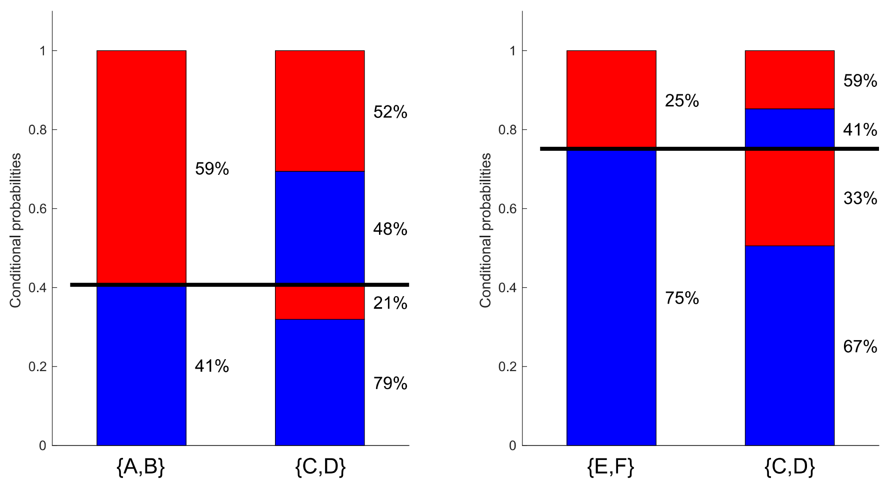
Figure D.1: Choice Frequencies Across Trials Generated with Different CRRA Coefficients

E Appendix - Allais Task



Subjects in our experiment took an Allais Task at the end of the experiment. In this task, they faced multiple choice sets containing lotteries of the same color on the leftest figures. The Green choice set contains degenerate lottery, and no other choice sets do. Blue and Red choice sets are related to the Green choice set by common ratios.

Figure E.1: Trials Generating Process for Allais Task



These figures report the outcome of our Allais Task. C, D correspond to the Green lotteries in Figure E.1, where C is the degenerate lottery. If a subject chooses B from $\{A, B\}$ but C from $\{C, D\}$, the subject committed the Allais paradox, which is a violation of expected utility maximization. In the bars, Blue corresponds to A, C, E and Red corresponds to B, D, F. The left figure, for example, reports that 59 of the choices from $\{A, B\}$ are B, and conditional on choosing B from $\{A, B\}$, 52% chose D from $\{C, D\}$ and 48% chose C.

Figure E.2: Data from Allais Task