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Decision Making with Risky, Rival Outcomes: Theory and Evidence

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Abstract

Little is known about how individuals make decisions when they must choose several options from a set of options when the outcomes are risky and the payoffs are rival. When researchers model these decisions, they assume people maximize their expected utility. We design an experiment in which subjects face either rival or independent payoffs. While theory predicts different behavior, subjects behave nearly identically under these payoff schemes. This suggests individuals are not maximizing expected utility. Additional treatments demonstrate that this behavior is likely driven by a heuristic used to simplify a complex math problem, rather than a preference for lotteries with the highest independent expected utilities. Our results suggest that using expected utility as peoples' objective function in these types of environments will lead to biased predictions.

JEL classification: C90, D01, D81

Keywords: Decision Making; Risk; Rival; Online Experiment

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1 Introduction

Individuals are often faced with decisions in which they have to select several options from a larger set despite winning at most one of the selected options. Examples of these types of decisions include selecting which colleges to apply to, which jobs to apply to, and which job candidates to fly out for an in-person interview. What makes this environment unique is that the decision maker is selecting options that are risky *and* have rival outcomes. The options are risky in that the they follow known probabilities.[1] The options are rival in that the decision maker's realized outcome is the single most favorable of all options. Little is known about how individuals make decisions in such settings. In applications where researchers have analyzed behavior, expected utility maximization is often assumed (Chade et al., 2013; Fu, 2014). We test this assumption experimentally. We find significant evidence of behavior inconsistent with expected utility maximization. This result is important as it improves our understanding of decision making and has many policy implications.

The type of decision making environment we are exploring is common and relates to many matching markets. A common example for economists is a stylized version of the demand side of the economics job market. For the unfamiliar, after interviewing job candidates at the centralized meetings, hiring committees must choose which candidates to invite for a campus visit while knowing that: (A) their payoff is the value added of the best candidate who accepts the offer and (B) they usually can only invite a small number of the candidates to visit. The school's decision problem is which candidates to invite? Some candidates are likely to add a lot of value but are less likely to accept an offer on account of receiving better offers. Other candidates are likely to add less value but would be more likely to accept an offer.

To solve this problem and others like it, we demonstrate theoretically how expected utility is maximized in environments where options are rival and independent (i.e., one

[1] We abstract from the fact that in many actual decisions the probabilities will depend on the behavior of other individuals.

option is randomly selected and payoffs are dependent on the outcome of the randomly selected option). We show that in either case, when an agent is allowed to select one option, out of many, the agent will select the option that maximizes her expected utility. When agents are allowed to select more than one option from the same set, the optimal selection (i.e., portfolio of options) depends on whether or not the outcomes of these options are rival. When outcomes are not rival, agents will select the options with the highest independent expected utilities. When outcomes are rival, agents will select only options that are weakly riskier than their initial option (lotteries in our experiment and hereafter).

We next test whether or not subjects in an incentivized experiment choose differently when outcomes are rival compared to when they are independent. In our experiment there are two payment schemes. In one scheme, outcomes are rival and subjects are paid on the basis of the most favorable outcome from the lotteries selected. In the other scheme, outcomes are independent and subjects are paid based on the outcome of a randomly chosen lottery from the set of selected lotteries. We also alter the number of lotteries subjects are able to choose. If subjects are maximizing expected utility the two payment rules predict different behavior as the number of lotteries the subject is allowed to choose increases. Simulations and theory demonstrate that when the lotteries are rival, subjects should not pick any lottery safer than the lottery they would pick when they are allowed to only select one lottery. When lotteries are not rival however, the optimal portfolio of lotteries is made up of lotteries that are riskier and safer than her lottery selection when she is only allowed to pick one. We find that subjects in both cases pick safer lotteries as the number of choices increases. As we will demonstrate, this is strong evidence that subjects are not maximizing expected utility when outcomes are rival and suggests the common assumption of expected utility maximization often held by applied microeconomists in this particular environment is questionable.

Our experiments show that when people are faced with a single choice many, if not most, maximize expected utility. However, when faced with more than one *rival* choice, few subjects make selections that maximize expected utility. Rather, subjects tend to make selections that offer the highest *independent* payoffs. This type of decision making is consistent with a "picking favorites" heuristic which does not require any complex calculations - only knowledge of the independent expected value of each lottery. In a follow-up experiment, we test whether this behavior is a preference or a heuristic by informing subjects of the exact bundle of lotteries that maximizes the expected value. We find a plurality of subjects select the expected value maximizing bundle. Moreover, the fraction of subjects who select this bundle is not statistically different from the fraction of subjects who selected the expected value maximizing bundle when they are only allowed to select one lottery from the set.

We show that risk aversion is not an explanation, as all but the most risk loving agents will make riskier selections as the number of choices increases. While we do find some evidence inconsistent with the hypothesis that subjects are making decisions as if the outcomes are independent, we demonstrate this deviation is likely due to a diversification bias (e.g., Read and Loewenstein, 1995; Benartzi and Thaler, 2001; Fox et al., 2005; Fernandes, 2013). Finally we demonstrate that Reference Dependent Utility (RDU), as in Tversky and Kahneman (1992), can explain subjects' behavior, but only for implausible values of the loss parameter.

Our primary result is that subjects appear to behave in a manner consistent with treating the outcomes as independent, rather than interdependent. This behavior is likely not based on a preference for only selecting outcomes with the highest expected utility but rather a result of a heuristic used to solve a hard problem. Moreover, this heuristic is used even when subjects are given experience, detailed instructions, and precise expected values - all of which are unlikely to be given in other environments. Our findings are consistent with Pallais (2015) which examines a policy change in which the average number of college applications per student increases. She finds that "when students sent more score reports, they sent scores to a wider range of colleges: that is, those that were both more- and less-selective than any they would have sent scores to otherwise."(Pallais, 2015, p. 503) This behavior is inconsistent with expected utility maximization and consistent with our finding that subjects in this type of environment make choices as if the outcomes independent rather than rival.

2 Experiment

We design an experiment to study decision making with rival risky outcomes. We do so using lotteries in which people earn only the maximum winning prize from all lotteries they select. Here, the outcomes are rival as subjects are required to take the maximum payout. A justifiable assumption as one normally takes the best date to the dance, accepts the best job offer, or enrolls in the best school while also pulling from a "realistic" distribution of potential dates/jobs/schools.[2] Although different in many regards, each of these are cases of rival outcomes.

Real world decisions also involve a strategic component to the decision problem taking into account the decisions of other applicants. Our experiment simplifies the decision problem by making the probabilities for each lottery exogenous thus eliminating strategic considerations. We believe this a reasonable assumption given that in many cases the applicant pool is sufficiently large and relatively homogeneous - which would suggest the outcomes have a large random component.

2.1 Experiment Design

In the experiment, we vary the number of choices subjects have and the payment rule. Payments are either RIVAL and based on the maximum successful outcome, or RANDOM and based on one randomly selected lottery. Regardless of how we pay subjects, subjects participate in sessions where they choose 1, 2, 4, or 6 lotteries from the set of 20 lotteries shown in Table 1. Subjects observe each lottery's prize and the probability of winning. Moreover, to prevent a conflation between lottery selection and the ability to calculate expected values, we present each lottery's expected value.[3]

[2] For example, when selecting what college to apply to, students, of all quality types, may apply to schools which they are not likely to be admitted into and schools which they are very likely to be admitted into. Presumably, the schools in which they are not likely to be admitted into have a higher return to a degree while those that are less selective provide lower returns.

[3] As a robustness check, we later remove expected values and have a different set of subjects participate in a session with 4 choices. Results can be found in Figure O.4 in the Online Appendix. There are no significant differences.

Table 1: Lotteries Used in Experiment

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T
Prob	.05	.10	.15	.20	.25	.30	.35	.40	.45	.50	.55	.60	.65	.70	.75	.80	.85	.90	.95	1.00
Prize	5.00	4.75	4.50	4.25	4.00	3.75	3.50	3.25	3.00	2.75	2.50	2.25	2.00	1.75	1.50	1.25	1.00	0.75	0.50	0.25
EV	0.25	0.48	0.68	0.85	1.00	1.13	1.23	1.30	1.35	1.38	1.38	1.35	1.30	1.23	1.13	1.00	0.85	0.68	0.48	0.25

Notes: Prizes and Expected Values (EV) are in US dollars.

For ease of exposition we refer to treatments using both payment rule (RANDOM or RIVAL) and the given number of choices (1, 2, 4, and 6). As such, we have 7 treatments because 1|RIVAL and 1|RANDOM have identical payment rules. We also index the lotteries from 1 to 20 to simplify the coming analysis. Lotteries lower in number are riskier but have a higher payout. However in the experiment we label lotteries by letters.

We conduct experiments on Amazon Mechanical Turk (AMT). AMT is an online workplace where workers (or subjects, in context of the experiment) can complete tasks for wages.[4] Prior to starting the main task, subjects consent to participate then complete a short survey that includes two expected value questions and English comprehension questions.[5] For participating, we pay subjects a base wage of 25 cents. Subjects can only participate once which can be verified by their unique AMT worker id number. We view AMT as occupying the middle ground between field and lab experiments. This is because AMT has a somewhat controlled environment (but not as much as a lab) with a diverse population in a familiar environment, like a field experiment (Harrison and List, 2004).[6]

In addition to the base wage, subjects earn a bonus contingent on the outcome of their lottery choices and payment rule. In RIVAL sessions, for each lottery a subject chooses, we generate a uniform random number between 0 and 1. A number less than or equal to the probability of winning the lottery results in the lottery having a favorable outcome for the subject. If the randomly generated number exceeds the probability of winning the

[4]For more details about AMT see Paolacci, Chandler, and Ipeirotis (2010) and Cooper and Johnson (2013).

[5]Ideally, we would have preferred to conduct the survey after the main experiment however the requirement that subjects be able to comprehend English required us to begin with the survey. This should not bias results as it occurs in all treatments.

[6]Given the diversity of our subject pool we are especially confident our results generalize to the population as a whole. However, we also find that demographics have little influence on subject behavior.

lottery, the lottery results in an unfavorable outcome for the subject. The subject then receives payment equal to the maximum favorable outcome across her selected lotteries. In RANDOM sessions, we randomly select a chosen lottery, and generate a uniform random number. If the number exceeds the probability of winning the lottery, the lottery result is unfavorable for the subject. The other lotteries the subject selected (regardless of their outcome) do not affect the subject's final earnings.

After selecting their lotteries, but before we reveal outcomes, we ask subjects to indicate what they consider to be the best and worst lotteries from the 20 possible lotteries. We assume that subjects view their favorite lottery as the best and denote this lottery as their "Favorite". While identifying these lotteries, subjects see which lotteries they selected but are unconstrained by their actual selections. Finally, subjects complete a short questionnaire consisting of a demographic survey, un-incentivized risk preference questions, the Barrat impulsivity scale (Patton et al., 1995), and a Ellsberg paradox task, explained in Appendix A.2.

We ask subjects multiple risk preference questions across various domains but we are primarily interested in responses to the most general question. All questions come from the German Socio-Economic Panel (Burkhauser and Wagner, 1993; Schupp and Wagner, 2002), with the following wording:

> *How do you see yourself: Are you generally a person who is fully prepared to take risks or do you try to avoid taking risks?*

Subjects answer the question above using an 11 point scale ranging from 0 to 10 - with 0 being "I avoid risk" and 10 being "Fully prepared to take risks". We use this question because Dohmen et al. (2011) shows that this specific risk question provides "a reliable predictor of actual risky behavior". Moreover, we repeatedly find that this question significantly predicts subjects' decisions and that the estimated coefficients are always consistent with theoretical predictions. Subjects that are more prepared to take risks select riskier lotteries.

3 Theory

Decision maker j's utility is determined by the outcome of a subset of k lotteries (l) chosen from the set L, where k is the number of lotteries j can pick. The lotteries in L (indexed by i), vary by their unconditional probability (p_i) of paying a prize (w_i).[7] The lotteries are Bernoulli random variables, with outcomes w_i with probability p_i and 0 with probability $1 - p_i$. j is not allowed to pick the same lottery twice. The utility from winning prize w_i is denoted as $v(w_i)$ and is continuous as well as increasing in w_i. The indexing of w_i and p_i is also of importance. Note that $w_i > w_{i+1}$ and $p_i < p_{i+1}$ $\forall i$ which implies that the riskier lotteries (i.e., lotteries with lower probabilities of winning) offer greater prizes than safer lotteries.

3.1 Expected Utility Maximization (EU)

Unsurprisingly, an expected utility maximizing strategy results in j choosing a bundle to maximize her expected utility. When outcomes are rival, the probability of winning each outcome is a function of joint probabilities, and thus calculating the expected value of a bundle is a non-trivial task for decision makers. To begin, we denote ψ_i as the realization of the stochastic variable determining the success or failure of lottery i. $I_i(.)$ is an indicator function equal to 1 if $\psi_i \leq p_i$ and zero otherwise. Since j's utility is solely a function of the utility derived from the lottery with the highest ex-post payout, j's utility is written as,

$$U = max\{v(w_i)I_i(\psi_i \leq p_i) \quad \forall \quad i \in k\}. \tag{1}$$

[7] We say "unconditional" because, in the primary treatments, subject j is only paid for the outcome of, at most, one of the lotteries - the one most favorable to her.

As ψ_i is uniform the probability that $I_i(.) = 1$ is p_i. In expectation, j's expected utility can be written as,

$$E[U_j] = p_1 v(w_1) + (1 - p_1) p_2 v(w_2) + (1 - p_1)(1 - p_2) p_3 v(w_3)... + \prod_{i=1}^{k-1} (1 - p_i) p_k v(w_k) \quad (2)$$

which can be rewritten as,

$$E[U_j] = \sum_{i=1}^{k} \left(\prod_{h=1}^{i-1} (1 - p_{h-1}) \times p_i v(w_i) \right), \quad (3)$$

where k is the number of choices and $p_0 = 0$.

With the previous assumptions it is easy to see that if j maximizes expected utility ($E[U]$), the initial lottery selection with $k = 1$ will be the lottery with the max $E[U]$. We denote this lottery l^{1*}.[8] If j is more risk loving, $l^{1\star}$ is riskier. If she is more risk averse, $l^{1\star}$ is safer. Since the distribution of the lotteries' $E[U]$ are single peaked, it implies j's first selection will be the lottery which maximizes her $E[U]$. With $k = 2$ we now show that j will select an additional lottery that is riskier than her lottery selection when $k = 1$ but awards a higher prize if won.

Consider a continuum of lotteries, which exist along a straight line in the p_i, w_i plane. In the context of the experiment, the slope of this line is -5 with lotteries (p, w) ranging from $(0.00, 5.25)$ to $(1.00, 0.25)$. With some loss of generality, consider choosing among a set of three lotteries, l^{1*}, l_1, and l'_1, where l^{1*} is the lottery chosen when $k = 1$. We define these

[8] In the context of the experiment, we assume that this lottery is the subject's favorite or the lottery they regard as the best.

lotteries by:

$$l^{1*} = p_* v(w_*),\ l_1 = p_1 v(w_1),\ \text{and}\ l_1' = p_1' v(w_1')$$

where

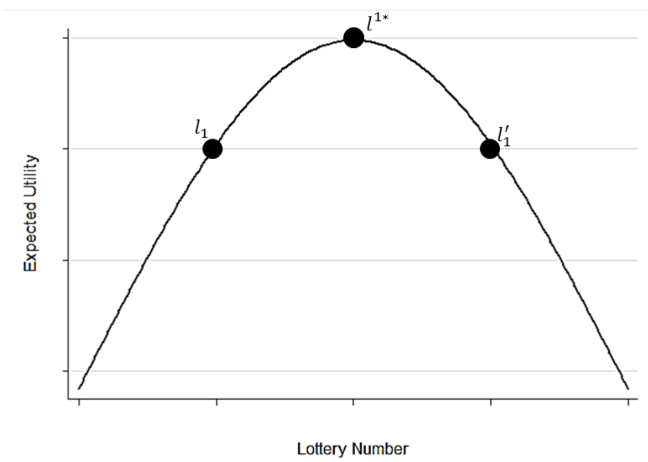
$$\theta < 1 \ \&\ (1+\theta)p_* < 1 \tag{4}$$

$$p_1 = (1-\theta)p_*,\ w_1 = v^{-1}((1+\theta)v(w_*))$$

$$p_1' = (1+\theta)p_*,\ w_1' = v^{-1}((1-\theta)v(w_*))$$

The probability that l_1 awards a favorable outcome for j is $(1-\theta)$ percent less than the probability that l^{1*} rewards the favorable outcome. However, l_1 delivers utility that is θ percent more if the favorable outcome occurs. Alternatively, lottery l_1', results in θ percent less utility upon the occurrence of the favorable outcome. This loss in monetary winnings is fully compensated with a θ percent increase in the probability of the favorable outcome occurring. Thus $E[U(l^{1*})] > E[U(l_1)] = E[U(l_1')]$ which is graphically illustrated in Figure 1.

Figure 1: Expected Utility of l_1, l_0, & l_1'



With three lotteries in the choice set, we consider what the individual would pick when choosing 1, 2, or 3 lotteries if maximizing expected utility. The preferred bundle when choosing 3 lotteries is trivial, as she would choose all available lotteries. The preferred bundle with one choice is also straightforward; lottery l^{1*} has the highest expected utility and would thus be chosen.

The choice with a bundle of two is more complicated. The individual has the option of choosing (l^{1*}, l_1), (l^{1*}, l_1'), or (l_1, l_1'). We now demonstrate that the individual would choose (l^{1*}, l_1). We do this by demonstrating that $(l^{1*}, l_1) \succ (l_1', l_1)$ and that $(l^{1*}, l_1) \succ (l^{1*}, l_1')$.

In comparing (l^{1*}, l_1) and (l_1', l_1), consider what happens when the outcomes of the lotteries are realized. Recall that l_1 is the lottery with the highest payout. If either bundle is selected, and l_1 is successful, then she would enjoy $v(w_1)$ and the outcome of the other lottery is irrelevant as both award a payoff less than w_1. If l_1 is unsuccessful, then the payout received will solely depend on either l^{1*} or l_1'. As $E[U(l^{1*})] > E[U(l_1')]$, she would choose the bundle containing l^{1*}, thus $(l^{1*}, l_1) \succ (l_1', l_1)$.

We now compare the bundles (l^{1*}, l_1) and (l^{1*}, l_1'). In this case, the comparison is a bit less straight forward as the two bundles no longer share the lottery with the highest prize. One bundle (l^{1*}, l_1) contains a relatively risky lottery (i.e., riskier than l^{1*}) that will matter with certainty because it offers the highest prize. The other bundle (l^{1*}, l_1') contains a relatively safe lottery but this lottery will only matter if l^{1*} is unfavorable. In other words, bundle (l^{1*}, l_1') offers a safe backup lottery if the highest paying lottery fails, while bundle (l^{1*}, l_1) offers a higher paying lottery that will matter with certainty.

We now demonstrate that $(l^{1*}, l_1) \succ (l^{1*}, l_1')$ by way of proof by contradiction. First assume that the $E[U(l^{1*}, l_1)] < E[U(l^{1*}, l_1')]$. In terms of expected utilities, this can be written as,

$$E[U(l_1)] + (1 - p_1)E[U(l^{1*})] < E[U(l^{1*})] + (1 - p_*)E[U(l_1')] \tag{5}$$

Which can be further rewritten in terms of θ, p_*, and w_*:

$$\begin{multline}(1 - \theta)p_*(1 + \theta)v(w_*) + (1 - (1 - \theta)p_*)p_*v(w_*) < \\ p_*v(w_*) + (1 - p_*)(1 + \theta)p_*(1 - \theta)v(w_*) \tag{6}\end{multline}$$

However, this implies that $1 < \theta$ while θ is defined as less than one, so we have a proof by contradiction and therefore $(l^{1*}, l_1) \succ (l^{1*}, l_1')$. Thus when faced with the bundle choices of (l^{1*}, l_1) and (l^{1*}, l_1'), she will choose bundle (l^{1*}, l_1). That bundle will include a riskier lottery when compared with the bundle with only one choice.

Proposition 1 *Assuming a continuous distribution of lotteries, increasing the number of choices will lead to j choosing lotteries which are riskier than the lottery chosen with only one choice.*

The exercise above provides some intuition to the general decision making process. To illustrate, consider adding a lottery (l_r) to an existing bundle of k lotteries, B_k, and denote the new lottery bundle as B_r. Lottery l_r is riskier and has a higher payoff, if successful, than any other lottery in B_k. Alternatively, consider adding a lottery l_s to the existing bundle, B_k (where $E[U(l_s)] = E[U(l_r)]$), and denote this new bundle B_s.

Because the lotteries are interdependent, we can think of the payoff function as having a set of stopping rules, which begins by sorting all of the selected lotteries in bundles B_r and B_s by their payoffs, if favorable, in descending order. Consequently, each lottery is only relevant if all the previous lotteries offering higher prizes (if favorable) are unfavorable, which occurs with probability,

$$\omega_i = (1 - p_1)(1 - p_2)....(1 - p_{i-1}) \tag{7}$$

This means that l_r will be relevant with probability ω_r and l_s will be relevant with probability ω_s. Since the expected utilities of l_r and l_s are equal, j is better off selecting l_r since $\omega_r > \omega_s$.

Note that this line of reasoning rules out *any* lottery that is safer than the lottery j would pick when $k = 1$. This is because for any lottery safer than the expected utility maximizing lottery when $k = 1$ there also exists a riskier lottery with an equal expected utility. Because this riskier alternative always will have a higher probability of being relevant, choosing the risky alternative will always dominate the safe choice.

Proposition 2 *Increasing the number of choices increases j's expected utility.*

The likelihood that j wins 0 from her chosen bundle is

$$\prod_{i=1}^{k}(1-p_i), \tag{8}$$

which decreases in k, the number of lotteries that j can pick. Moreover, any additional lottery only increases j's utility as each additional lottery is adding a positive component to Equation 3 - thus increasing expected utility.

3.2 Expected Utility Maximization as if Independent (EU-I)

Alternatively, j may select lotteries in reference to her favorite lottery ($l^{1\star}$) which is the lottery that maximizes her expected utility. As before, if j is more risk loving, $l^{1\star}$ is riskier. If she is more risk averse, $l^{1\star}$ is safer. Subsequently selected lotteries are then based upon the difference in the expected utility between $l^{1\star}$ and the second most preferred lottery.

In other words, j selects her k favorite lotteries from the set L where L is defined as

$$L = \{l^1, l^2, \ldots, l^n\}$$

with payoffs

$$l^i = p_i v(w_i).$$

Her selected lotteries are a subset of L made up of k elements such that $l^\star \in L$, with

$$l^\star = \{l^{1\star}, l^{2\star}, \ldots, l^{k\star}\}.$$

Therefore, the first step in j's decision process identifies the lottery which maximizes her utility and satisfies

$$l^{1\star} = max\{l^1, l^2, ..., l^n\}. \tag{9}$$

Once she selects $l^{1\star}$, j then selects the lottery most similar to her first choice in expected utility, and therefore selecting the lottery offering the second highest expected utility. This minimizes the absolute difference between the expected utility of her first choice and her second choice, such that

$$l^{2\star} = min\{|l^1 - l^{1\star}|, |l^2 - l^{1\star}|..., |l^n - l^{1\star}| : l^{2\star} \neq l^{\star}\}.$$

This decision rule also maximizes expected utility if all the lotteries contributed to her final earnings or were independent. She goes through this process k times (or the given number of choices) until she arrives at a bundle that minimizes the sum of the differences in payoffs between $l^{1\star}$ and her subsequent choices,

$$l^{k\star} = min\{|l^1 - l^{1\star}|, |l^2 - l^{1\star}|..., |l^n - l^{1\star}| : l^{k\star} \neq l^{k\star-1}\}. \tag{10}$$

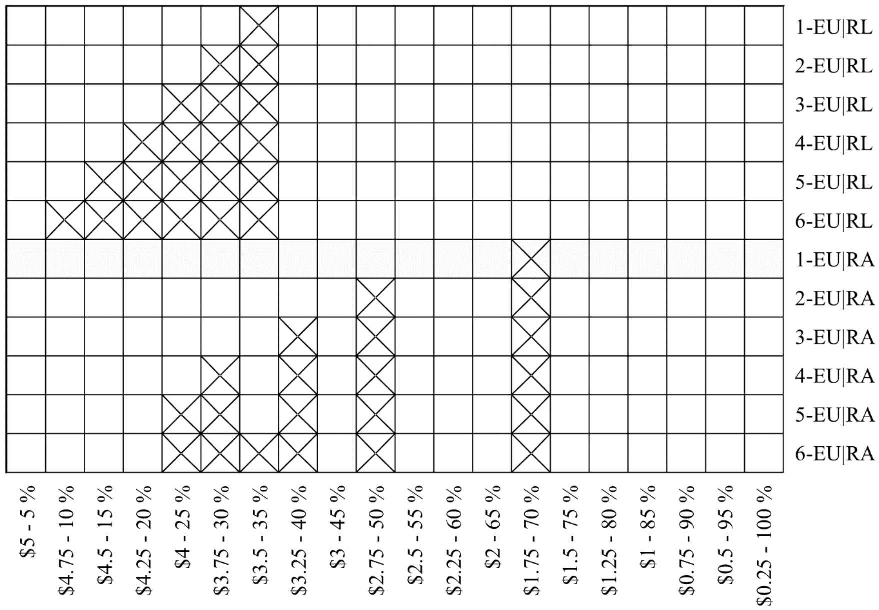
With a continuum of lotteries, these would be the k lotteries closest in $E[U]$ to the $E[U(l^{1\star})]$.

4 Simulation Results

4.1 Expected Utility

While the foregoing discussion considered a continuum of lotteries, our experiment naturally involves a set of discrete lotteries. Solving for the optimal bundle as k increases is burdensome as there are N "choose" k permutations of lottery selections. The set of lotteries, L, in the experiment can be found in Table 1. We solve for the optimal bundle in our experiment numerically, by calculating the subsets of 1, 2, 3, 4, 5 and 6 lotteries that maximize j's expected utility. Note, in all of these numerically solved bundles we are assuming exponential utility (i.e., $v(w_i) = w_i^{\alpha}$). However, general results also hold for Constant Relative Risk Aversion specifications (Dyer and Sarin, 1982). With *very* minor differences related to the spread between the riskiest lottery and the utility maximizing lottery.

Figure 2: Expected Utility Maximizing Choices with Various Risk Preferences



Notes: RL and RA indicate a risk loving ($\alpha = 2$) and risk averse ($\alpha = .5$) decision maker.

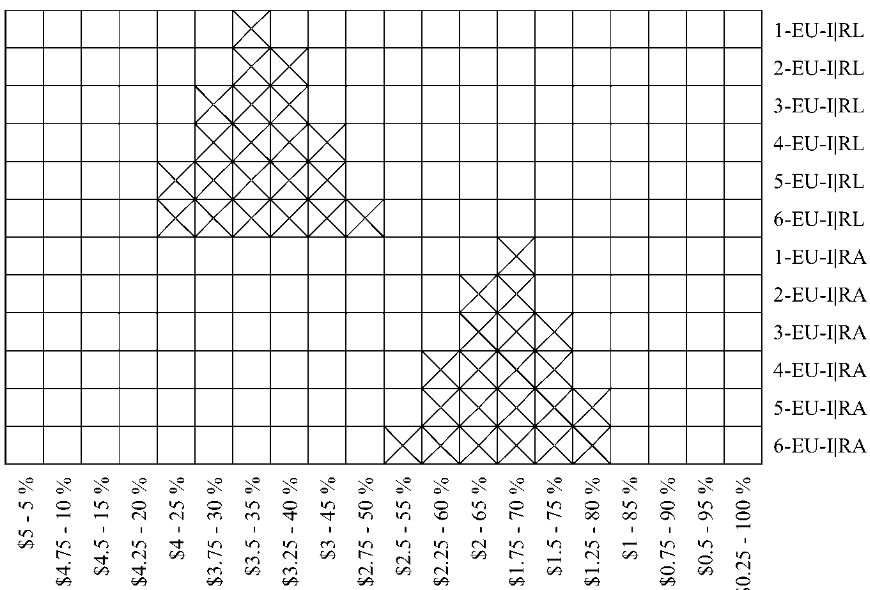
Figure 2 demonstrates how risk preferences affect the optimal bundle under EU. As can be seen in Figure 2, when α increases the selected portfolios j selects shift in the direction of riskier lotteries and the choices are less disperse. Conversely, as α decreases the selected portfolios shift towards safer lotteries and the dispersion increases.

Figure 2 illustrates other predictable results: (1) Increasing the number of choices increases expected utility because adding a lottery results in a nonzero probability of winning a specific amount. If the new lottery's payout is greater than the current highest payout in the existing bundle, the additional, higher paying lottery simply gives the decision maker a chance at a higher prize. In the event of an unfavorable outcome of the new lottery, the conditional expected utility is unchanged in comparison to the previous bundle. (2) Increasing the number of choices weakly increases the maximum riskiness of the lotteries j selects.

4.2 Expected Utility Maximization as if Independent (EU-I)

We next simulate choice bundles that maximize EU-I as a function of the given number of choices, while also varying risk preferences. The results are in Figure 3. As with EU, risk preferences shift the initial lottery j picks. That is, more risk averse agents pick a safer initial lottery and risk loving agents select a riskier initial lottery. However, there are substantive differences in choices between the two decision rules. Most notably, under EU-I, j selects roughly equal numbers of lotteries that are riskier and safer than their initial pick. Under EU, this is not the case since j only selects lotteries that are riskier. In essence, EU-I does not take into account the rival nature of the lotteries, but instead treats lotteries as "next best" outcomes.

Figure 3: EU-I Maximizing Choices under Various Risk Preferences



Notes: RL and RA indicate a risk loving ($\alpha = 2$) and risk averse ($\alpha = .5$) decision maker.

5 Hypotheses

The theoretical discussion leads to testable hypotheses which are stated in terms of the null. Recall that under EU, j will select $k - 1$ lotteries riskier than l^*. If EU types dominate the population, we expect to observe an increase in the number of risky lottery selections as j receives more choices - which would drive down the average index number of lotteries selected. This logic leads us to Hypothesis 1.

Hypothesis 1 *The riskiness of the average lottery selected will not be affected by the number of choices.*

Alternatively, a failure to reject the null of Hypothesis 1, is consistent with subjects following EU-I as subjects pick roughly the same number of riskier and safer lotteries in comparison to their initial lottery selection.

If subjects follow EU, the safest lottery should always be the choice subjects made when given only one choice, l^{*1}. With EU-I, the safest choice will get safer as the number of choices increases.

Hypothesis 2 *The number of choices a subject receives has no effect on their safest lottery selection.*

Rejecting the null suggests subjects behave in manner consistent with EU-I.

Results in Section 4 suggest that the bundles selected will depend on subject's risk aversion. While we do not measure risk aversion using an incentivized mechanism, we do test whether the unincentivized risk aversion question has any relevance for subjects' behavior and check whether stated preferences have any affect on average lottery selections and what they regard as their favorite or least favorite (worst) lottery.

Hypothesis 3 *Stated risk aversion preferences will have no affect on subjects' lottery selections.*

6 Subject Characteristics and Behavioral Consistency

6.1 Subject Characteristics

Table 2 presents unconditional summary statistics of demographic characteristics and choices. We gather information regarding the gender, age, education, country of residence, and income of subjects. As expected, subjects in our experiment are more heterogeneous than subjects in laboratory studies - especially in terms of age and education.[9] Appendix A.1 contains the variable descriptions. The gender ratio of subjects is slightly unbalanced: 63 percent of subjects indicate they are male. The average age of subjects is 35 years. The modal income of subjects is between \$25,000 - \$37,499 per year and the modal education is a bachelor's degree.

Table 2: Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
AMB	294	0.473	0.5	0	1
RISK	293	5.179	2.78	0	10
MALE	294	0.631	0.483	0	1
AGE	294	34.771	19.06	18	323
INCOME	293	4.275	2.813	1	10
EDUC	294	4.756	1.728	1	7
FAVORITE	294	11.372	4.713	1	20
LEAST FAV.	294	7.318	8.514	1	20
RISKIEST	294	8.411	4.599	1	20
SAFEST	294	13.661	4.233	1	20
PICKED FAV.	294	0.723	0.448	0	1

The data are generally high quality as the software ensures fields are not left empty.[10] Unfortunately, there are a few accidental submissions, which we omit. Further evidence of the data quality can be seen in subjects' responses to the unincentivized expected value questions. Overall, 61 percent of subjects correctly calculate the more precise expected value question (question 6 in the instructions contained in the online Appendix).

[9]Roughly 90% of subjects are American and almost all of the remaining are Indian.

[10]There is some user error, as can be seen in Table 2, one subject broke the world record of human lifespan (Weon and Je, 2009).

Table 3: Distribution of Characteristics across Treatments

	AGE	MALE	INCOME	EDUC	RISK	AMB
TWO|RI	-6.727	0.149	-0.258	0.344	0.986*	0.098
	(4.211)	(0.103)	(0.591)	(0.358)	(0.58)	(0.103)
TWO|RA	-7.315*	0.028	-0.708	-0.421	-0.095	0.088
	(4.349)	(0.106)	(0.611)	(0.37)	(0.599)	(0.106)
FOUR|RI	-7.946*	0.234**	-0.339	0.043	0.904	-0.077
	(4.237)	(0.103)	(0.599)	(0.36)	(0.587)	(0.103)
FOUR|RA	-8.762**	0.121	-0.554	-0.492	-0.314	-0.084
	(4.38)	(0.107)	(0.615)	(0.372)	(0.603)	(0.107)
SIX|RI	-6.294	0.048	-0.53	0.787**	0.562	-0.054
	(4.237)	(0.103)	(0.595)	(0.36)	(0.583)	(0.103)
SIX|RA	-8.741**	0.14	-0.129	-0.003	0.513	0.325***
	(4.319)	(0.105)	(0.607)	(0.367)	(0.594)	(0.105)
CONSTANT	41.341***	0.511***	4.554***	4.703***	4.788***	0.426***
	(2.929)	(0.072)	(0.411)	(0.249)	(0.403)	(0.072)
Obs.	294	294	293	294	293	294
R^2	0.0211	0.0045	0.007	0.0535	0.0283	0.0695
F-Test	0.4042	0.2944	0.9171	0.0144	0.2182	0.0020

Notes: Standard errors in parentheses. ***: $p < .01$, **: $p < .05$, and *: $p < .10$. Treatment names abbreviated for space. RI - Rival, RA - Random. CONSTANT corresponds to the ONE treatment.

The average values of demographic variables and individual characteristics are approximately equal across treatments. In Table 3, we regress AGE, MALE, INCOME, EDUCTION, RISK, and AMB against the treatments to check for differences in subject characteristics across treatments. As expected, there are few substantive differences as the values of demographic variables are roughly evenly distributed across treatment groups. However, FOUR|RIVAL has more male subjects; SIX|RIVAL has more educated subjects; SIX|RANDOM has a higher percentage of ambiguity averse subjects; ONE has older subjects; TWO|RIVAL has subjects more prepared to take risks.

With the observable characteristics split relatively evenly across the treatments, we take differences in outcomes to be a result of the different treatments. In regards to outcomes, subjects generally indicate that their favorite lottery is the safer lottery of the two that maximize the expected payoff – lottery 11. Subjects generally regard the riskiest (lottery 1) *or* the safest (lottery 20) lotteries as the worst. This results in an average worst lottery of

7.3.

6.2 Behavioral Consistency Results

Regardless of the number of choices subjects have or the way they are paid (i.e., RANDOM or RIVAL), l^{1*} should remain the same for a given strategy whether or not subjects follow EU or EU-I. At the same time, subjects should regard the worst lottery as the one furthest from l^{1*}. As l^{1*} is independent of the treatments, it also implies that the worst lottery should be as well - as logically it is the one furthest from l^{1*}. If subjects select the lottery that maximizes their expected value (e.g, lottery 10 or 11) as l^{1*}, it follows that the worst lottery is lottery 1 or 20.

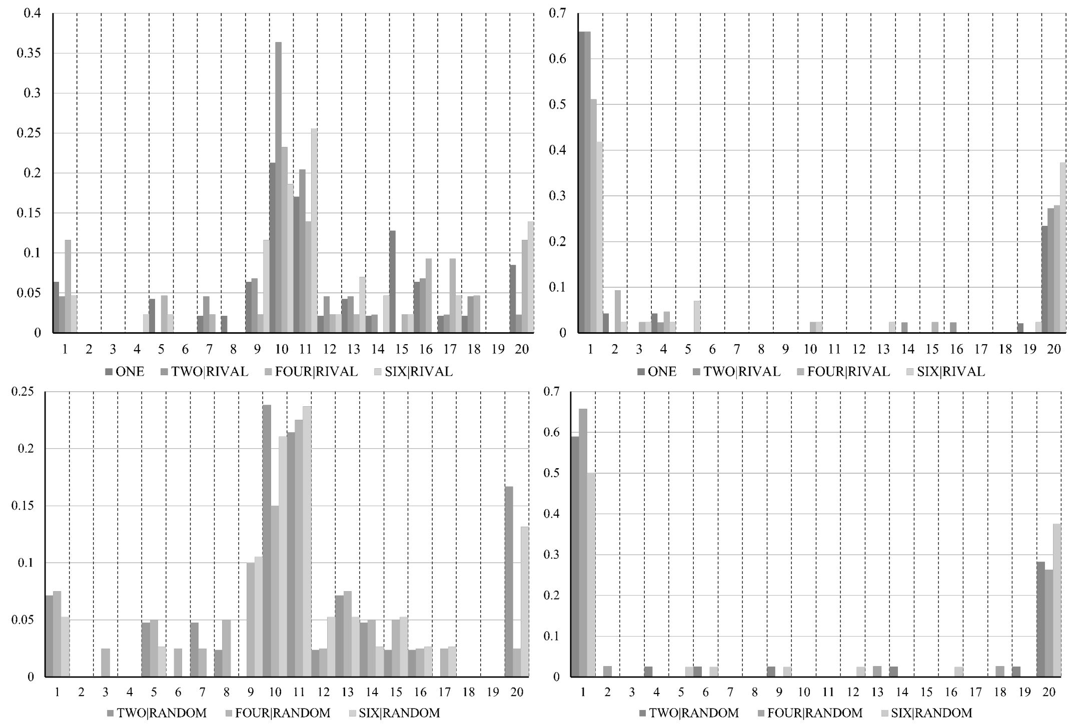
Actual subjects' decisions are consistent with this logic. Figure 4 presents the lotteries that subjects identify as their favorite and least favorite. As predicted, subjects have a strong preference for the lotteries with the highest expected values and have little regard for the lotteries offering rather low expected values. More detailed analysis regarding subjects' favorite and least favorite lotteries is provided in the online appendix (Section A.2).[11]

7 Experimental Results

We now analyze treatment effects. Unless stated otherwise, all reported p-values are derived from t-tests. Recall that lottery 1 is the riskiest and lottery 20 is the safest. Table 4 displays average outcomes across the primary treatments. All statistics are in terms of index numbers on the lottery, except PICKED FAV. (which is equal to 1 if the subject picked her favorite lottery). AVERAGE is the average index number of selected lotteries, which

[11] In the Online Appendix we also examine the likelihood of selecting the stated favorite lottery. In general, subjects' favorite lottery is more likely to be chosen when subjects have four or six choices, with most of the coefficients being statistically significant. Surprisingly, some of the estimated coefficients for two choices are negative, though not statistically significant. The only demographic variable which is statistically significant is male, which is estimated to considerably reduce the likelihood of picking one's favorite lottery. Unconditional on treatment, subjects select their identified favorite lottery 72 percent of the time and are more likely to select their favorite lottery when given additional choices.

Figure 4: Favorite and Least Favorite Lotteries by Treatment



Note: Left Panels are the Favorite Lottery, Right Panels are the Least Favorite Lottery.

for all treatments is between 10.4 and 12.1. SAFEST is the maximum index number in the portfolio, which is smallest for ONE and increases with the number of choices. RISKIEST is the minimum index number, which decreases with the number of choices for both RIVAL and RANDOM treatments. FAVORITE is the index value of the lottery identified as 'the best' by subjects. For all treatments, the average favorite lottery was between 10 and 12 and suggests subjects are rather risk neutral. Similarly, LEAST FAV. is the index value associated with the lottery identified as 'the worst'.

7.1 Lottery Selections

Recall from Section 3 that subjects following Expected Utility (EU) will select lotteries that are riskier than l^{1*}. If the population is predominantly made of subjects using an EU, one should observe subjects picking 5, 3, or 1 riskier lotteries/lottery than l^{1*}. Alternatively, EU-I types will evenly distribute their additional picks between lotteries that are riskier and

Table 4: Primary Treatment Effects

	AVERAGE	SAFEST	RISKIEST	FAVORITE	LEAST FAV.	PICKED FAV.
ONE	10.936	10.936	10.936	11.66	6.000	0.638
	(0.637)	(0.637)	(0.637)	(0.679)	(1.205)	(0.071)
TWO|RIVAL	11.239	12.932	9.545	11.068	6.886	0.636
	(0.449)	(0.549)	(0.543)	(0.548)	(1.303)	(0.073)
TWO|RANDOM	10.615	12.256	8.974	11.308	7.564	0.487
	(0.609)	(0.631)	(0.718)	(0.841)	(1.394)	(0.081)
FOUR|RIVAL	11.401	14.86	7.953	11.744	7.116	0.837
	(0.582)	(0.597)	(0.777)	(0.863)	(1.295)	(0.057)
FOUR|RANDOM	11.875	14.132	9.605	11.816	6.789	0.737
	(0.619)	(0.639)	(0.716)	(0.731)	(1.404)	(0.072)
SIX|RIVAL	12.004	15.953	7.674	11.744	9.395	0.837
	(0.515)	(0.518)	(0.625)	(0.704)	(1.363)	(0.057)
SIX|RANDOM	10.492	14.425	5.900	10.050	9.200	0.900
	(0.519)	(0.597)	(0.631)	(0.663)	(1.427)	(0.048)

Notes: Standard errors in parentheses.

safer than their favorite lottery.

Result 1 *The number of choices has no affect on the average lottery selected within a portfolio.*

Hypothesis 1 suggests choice restriction will have no impact on the average lottery selected. We fail to reject the null. The first column of Table 4, presents the average indicator number of the selected lotteries, by treatment. First, note the average of the lotteries selected is in the range of 10 to 12 for all treatments. Moreover, not one average is statistically significantly different from any other. This is evidence in support of EU-I because as the number of choices increases, subjects who are EU types will have a lower average choice. This occurs because EU types would choose lotteries riskier than l^{1*} as the number of choices increases and this occurs regardless of their risk preferences. Conversely, EU-I subjects will have selections centered around a particular lottery and expand out in both directions - leaving the mean unchanged across the treatments.

OLS results (Table 5) generally confirm the preceding discussion while also demonstrating that the average lottery selected is negatively correlated to subjects' willingness to take risks. However, after controlling for traits and demographics, subjects in SIX|RIVAL tend to have a safer average bundle than subjects in ONE. Though this effect is only significant at the 10 % level and in the opposite direction one would expect if subjects are using EU.

Table 5: Average Lottery Selected

	(1)	(2)	(3)	(4)
TWO|RIVAL	0.302	0.551	0.553	0.621
	(0.769)	(0.759)	(0.767)	(0.783)
TWO|RAND	-0.321	-0.369	-0.355	-0.13
	(0.794)	(0.779)	(0.789)	(0.803)
FOUR|RIVAL	0.465	0.838	0.755	0.808
	(0.774)	(0.767)	(0.778)	(0.783)
FOUR|RAND	0.939	0.873	0.804	0.885
	(0.8)	(0.785)	(0.797)	(0.809)
SIX|RIVAL	1.068	1.237	1.344*	1.426*
	(0.774)	(0.76)	(0.772)	(0.782)
SIX|RAND	-0.445	-0.386	-0.404	-0.506
	(0.789)	(0.787)	(0.796)	(0.802)
AMB	-	0.257	0.176	0.026
	-	(0.436)	(0.444)	(0.451)
RISK	-	-0.277***	-0.287***	-0.314***
	-	(0.077)	(0.078)	(0.08)
MALE	-	-	0.58	0.638
	-	-	(0.449)	(0.457)
INCOME	-	-	0.068	-
	-	-	(0.077)	-
EDUC	-	-	-0.102	-
	-	-	(0.126)	-
AGE	-	-	0.003	0.001
	-	-	(0.011)	(0.011)
CONSTANT	10.936***	12.153***	11.998***	5.53†
	(0.535)	(0.669)	(1.036)	(3.745)
Adj. R^2	0.0007	0.0395	0.0349	0.0382
Obs.	294	293	293	293
Cat. Dum.	NO	NO	NO	YES

Notes: Standard errors in parentheses. ***: $p < .01$, **: $p < .05$, and *: $p < .10$. Cat. Dum. are categorical dummies for income and education.

Subjects in SIX|RIVAL on average pick 2.74 (±.586) lotteries safer than their subjectively judged Best lottery and 2.42 (±.567 lotteries that are riskier than their favorite). Second, their counterparts in FOUR|RIVAL behave similarly and on average pick 1.53 (±.421) lotteries safer than their favorite and 1.84 (±.435) lotteries that are riskier than their favorite. Subjects in TWO|RIVAL on average pick .88 (±.22) lotteries that are safer than their favorite and .55 (±.22) lotteries riskier than their favorite. Thus subjects are roughly distributing their choices evenly across lotteries that are riskier and safer than their favorite - evidence against EU.[12]

Result 2 *Subjects with more choices select riskier "risky" lotteries, and subjects with more choices select safer "safe" lotteries.*

We find evidence to reject Hypotheses 2. In Table 6 we estimate subjects' riskiest and safest lottery selected, conditional on individual characteristics and treatments. Regardless of the specification, increasing the number of choices, induces subjects to select riskier risky lotteries and safer safe lotteries. The first part of Result 2 is consistent with EU maximizing behavior and EU-I behavior; however, *only* the second part is inconsistent with EU maximization. Result 2 suggests (again) that subjects are behaving in a manner that is consistent with an EU-I strategy.[13] This observation coupled with the lack of significant differences in the average lottery selected across treatments is particularly strong evidence against subjects making choices consistent with EU.

7.2 Risk Aversion

In Table 6 it is easy to see that risk aversion is correlated with what subjects pick as their riskiest lottery. Comparatively risk-loving subjects pick considerably riskier risky lotteries. Additionally, risk aversion is also negatively related to subject's average lottery selection

[12] We find further evidence consistent with subjects using an EU-I strategy by analyzing the frequency and distribution of the selected lotteries across treatments. These figures are found in the Online Appendix (Figure O.1).

[13] As a robustness check, we allow subjects to repeat selections, see Section 7.4 for details.

Table 6: Riskiest and Safest Choice by Treatment

	Riskiest Choice				Safest Choice			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TWO|RIVAL	-1.449	-1.103	-1.136	-0.977	2.139**	2.283**	2.317**	2.241**
	(1.002)	(0.977)	(0.972)	(0.977)	(0.908)	(0.905)	(0.912)	(0.915)
TWO|RANDOM	-2.146**	-2.205**	-2.116**	-1.836*	1.426	1.373	1.324	1.474
	(1.038)	(1.006)	(1.004)	(1.004)	(0.937)	(0.929)	(0.938)	(0.938)
FOUR|RIVAL	-3.368***	-2.793***	-2.995***	-3.017***	4.339***	4.658***	4.659***	4.736***
	(1.016)	(0.993)	(0.993)	(0.984)	(0.92)	(0.921)	(0.931)	(0.922)
FOUR|RANDOM	-1.359	-1.459	-1.57	-1.452	3.634***	3.615***	3.56***	3.597***
	(1.042)	(1.011)	(1.011)	(1.01)	(0.952)	(0.944)	(0.955)	(0.955)
SIX|RIVAL	-3.342***	-3.115***	-2.952***	-2.914***	5.707***	5.84***	5.935***	5.952***
	(1.009)	(0.98)	(0.981)	(0.977)	(0.928)	(0.921)	(0.935)	(0.93)
SIX|RANDOM	-5.546***	-5.444***	-5.496***	-5.552***	3.917***	3.886***	3.877***	3.725***
	(1.04)	(1.024)	(1.022)	(1.013)	(0.938)	(0.945)	(0.953)	(0.944)
AMB	-	0.345	0.14	-0.046	-	0.404	0.427	0.311
	-	(0.563)	(0.566)	(0.564)	-	(0.524)	(0.532)	(0.531)
RISK	-	-0.384***	-0.412***	-0.451***	-	-0.191**	-0.189**	-0.218**
	-	-	(0.1)	(0.101)		(0.093)	(0.094)	(0.095)
MALE	-	-	1.419**	1.497***	-	-	0.019	0.116
	-	-	(0.573)	(0.575)	-	-	(0.539)	(0.54)
INCOME	-	-	0.145	-	-	-	-0.004	-
	-	-	(0.099)	-	-	-	(0.093)	-
EDUC	-	-	-0.119	-	-	-	-0.112	-
	-	-	(0.161)	-	-	-	(0.152)	-
AGE	-	-	0.007	0.006	-	-	0.001	-0.002
	-	-	(0.014)	(0.013)	-	-	(0.013)	(0.013)
CONSTANT	10.864***	12.556***	11.653***	6.074	10.875***	11.617***	12.107***	4.416
	(0.697)	(0.864)	(1.32)	(4.653)	(0.632)	(0.802)	(1.239)	(4.365)
Obs.	294	294	293	293	294	293	293	293
R^2	0.0203	0.0291	0.0338	0.0402	0.0302	0.0337	0.0341	0.0408
LL	34	34	33	33	3	3	3	3
UL	1	1	1	1	36	36	36	36
Cat. Dum.	NO	NO	NO	YES	NO	NO	NO	YES

Notes: Tobit estimates. Standard errors in parentheses. ***:$p < .01$, **:$p < .05$, and *:$p < .10$. Upper Limit (UL) and Lower Limit (LL) are lotteries 1 and 20. Cat. Dum. are categorical dummies for income and education variables.

(Table 5). After controlling for the treatment, a 1 Likert unit increase in subjects willingness to take risks is associated with a .28 decrease in the average lottery selected ($p < 0.001$).

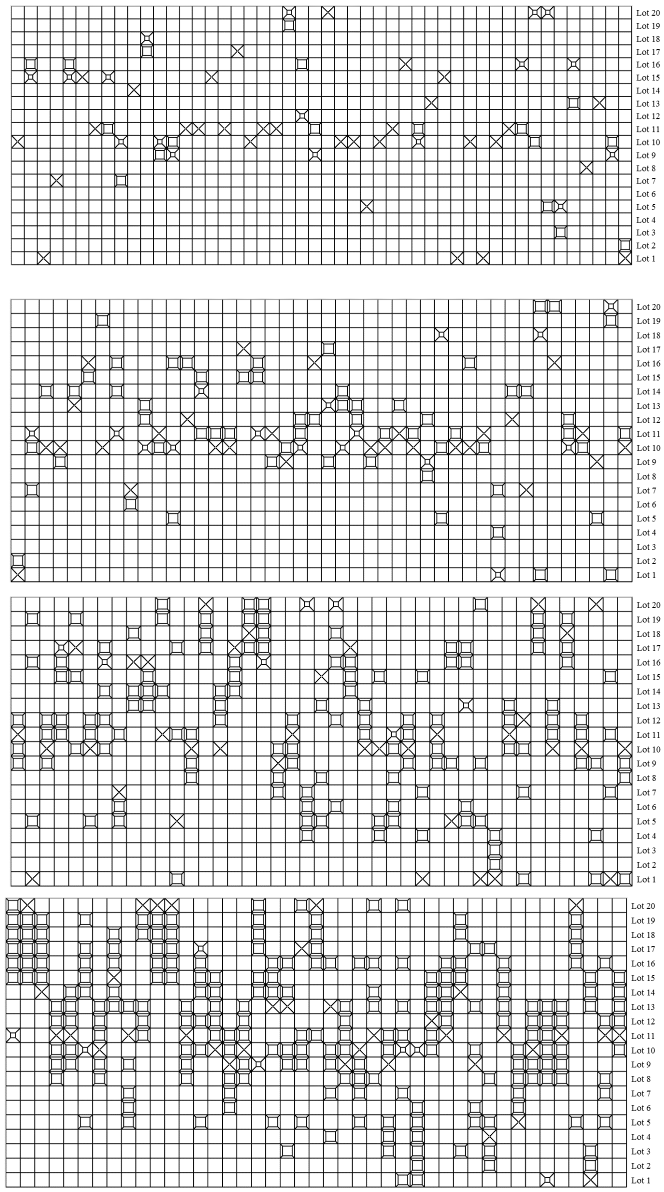
Result 3 *Subjects who indicate that they are more prepared to take risks have relatively riskier "safe" picks and riskier "risky" picks.*

Hypothesis 3 suggests that stated (and unincentivized) individual risk preferences will have no affect on lottery selection. We find strong evidence against this null. Recall that after subjects select their lotteries, we ask about their risk preferences. As one would expect, individual risk preferences have a close relationship with subjects' lottery selection. Visually, this can be seen in the graphs shown in Figure 5, which presents subjects' choices in each treatment, sorted as stated from most risk averse to most risk loving. Each column represents a subject and each row represents a lottery. A large square within a lottery square is a subject's choice and smaller square indicates the subject's favorite lottery. "X" indicates the subject selected what they indicated as the best lottery. As can be seen in these figures, subjects often pick a series of lotteries, with their favorite lottery being somewhat in the middle of their k selections. These figures when combined with Table O.4 in the Appendix (which shows the percentage of subjects who selected only adjacent lotteries - e.g., 5,6,7, and 8) and results pertaining to riskiest and safest lottery selections are strong evidence in support of EU-I.

7.3 Reference Dependent Utility

Rather than following EU-I, subjects may be selecting lotteries using Reference Dependent Utility (Tversky and Kahneman, 1991, 1992). In this case, subjects select lotteries using the utility function specified in Equation 11. While somewhat cumbersome, this utility function implies that the decision maker would first select a payoff that serves as her reference lottery ($\bar{w}$) and her utility is derived based upon the difference of the reference payoff and her ex-post payoff. If the lottery she selects earns her a payoff greater than $\bar{w}$, her utility is $v(w_i - \bar{w})$. If

Figure 5: Subjects' Decisions Sorted by Risk Preferences



Notes: A large square within a lottery square is a subject's choice and smaller square indicates the subject's favorite lottery. "X" indicates the subject selected what they indicated as the best lottery. Rows correspond to treatments as follows: ONE, TWO|RIVAL, FOUR|RIVAL, and SIX|RIVAL, respectably.

her payoff is less than $\bar{w}$, her utility is $-\lambda f(-(w_i - \bar{w}))$ - where $w_i = 0$ if no lottery is won.

$$U = \max\{v(w_i - \bar{w})^{\alpha} I_i(\psi_i \leq p_i \forall i \in k)\} \text{ if } \max\{I_1 ... I_k\} \neq 0 \ \& \ w_i \geq \bar{w}$$
$$U = \max\{-\lambda v(-(w_i - \bar{w}))^{\alpha} I_i(\psi_i \leq p_i \forall i \in k)\} \text{ if } \max\{I_1 ... I_k\} \neq 0 \ \& \ w_i < \bar{w} \tag{11}$$
$$U = -\lambda(-\bar{w})^{\alpha} \text{ if } \max\{I_1 ... I_k\} = 0$$

To test this possibility, we simulate subjects' decisions while varying λ. As in Tversky and Kahneman (1992), we assume $v(.)$ and $f(.)$ are exponential in terms of α and β, respectably. We further assume, that $\alpha = .88$. In Figure 6, we present the results of the simulations. With these parameters, regardless of the value of λ, the reference lottery/payoff is lottery 11 which rewards \$2.50 with a probability of 55 percent. As can be seen in Figure 6, Reference Dependent Utility preferences do a fair job predicting actual subject behavior but only at extreme values of λ. That is, only when λ is in the neighborhood of 30 do we begin to observe the pattern of behavior consistent with what we see in the experiment. The intuition for the pattern of choices observed in the simulations of RDU is actually quite simple: back-loading lotteries (i.e., adding safer but lower value lotteries) is costly. While these lotteries lower the probability that the subject walks away with nothing, she would still suffer a cost due to the prize of the lottery being less than her reference lottery.

While simulations using RDU *can* predict subject behavior, doing so requires questionable parameter values.[14] In contrast, we can get similar predictions with EU-I needing only sensible values for risk aversion.

7.4 Diversification Bias and Choice

Arguably the strongest evidence against EU-I comes from the results of an additional treatment (SIX|RIVAL-REPEAT) that serves primarily as robustness check of EU-I. In SIX|RIVAL-REPEAT, subjects are given 6 choices but are allowed to select the same lottery as many times as they wish while also being paid based upon the outcome that is ex-post

[14] Tversky and Kahneman (1992) considers values of λ such that the median was 2.25.

most favorable to them. Theoretically if subjects are following EU-I, we would observe a plurality of subjects picking the same lottery 6 times and this lottery would be the one they report as their favorite. As can be seen in Figure O.2 (Appendix), we do not observe this.

Ex-post, we hypothesized that this behavior was due to a diversification bias. As a test of our diversification hypothesis, we run an additional experiment (SIX|RANDOM-REPEAT). This treatment has the same setup as (SIX|RIVAL-REPEAT) except subjects are paid based upon the outcome of a lottery selected at random. Thus there is clear incentive to repeatedly select the lottery with highest expected value. If subjects' decisions in SIX|RANDOM-REPEAT are similar to those observed in SIX|RIVAL-REPEAT it suggests that the lack of picking the same lottery in SIX|RIVAL-REPEAT is due to diversification bias.

Subjects' decisions in SIX|RIVAL-REPEAT and SIX|RANDOM-REPEAT (i.e., the lotteries they selected) sorted by risk preferences are found in Figures O.2 and O.3 in the Online Appendix. As can be seen in Figures O.2 and O.3, visually the lottery selections in SIX|RANDOM-REPEAT and SIX|RIVAL-REPEAT are quite similar. While there is a slight increase in the number of subjects picking the same lottery in SIX|RANDOM-REPEAT compared to SIX|RIVAL-REPEAT, this difference is not significant (14% vs. 22%; $p = 0.369$).

Other summary statistics of subject decisions are found in Table 7. The bottom row in Table 7 reports p-values resulting from a set of T-tests testing for differences across SIX|RANDOM-REPEAT and SIX|RIVAL-REPEAT treatments. As can be seen the only significant difference to report is a marginally significant difference in the riskiest lottery selected. These findings suggest that lack of picking the same lottery 6 times in SIX|RIVAL-REPEAT is partially due to a diversification bias.

7.5 Improving Bundle Selection with Experience

We now explore how bundle selection changes with experience to test whether the observed behavior is due to lack of experience. These treatments are replications of the FOUR|RIVAL treatment but with the addition of practice. We denote these treatments as "FOUR|P"

Table 7: Subject Decisions in Repeat Treatments

	Average	Safest	Riskiest	Favorite	Worst	Pick Fav.	n
SIX|RIVAL-REPEAT	10.54 (0.556)	14.048 (0.736)	6.405 (0.712)	11.524 (10.833)	5.786 (1.127)	0.714 (0.071)	42
SIX|RANDOM-REPEAT	11.023 (0.589)	13.611 (0.576)	8.222 (0.827)	10.833 (0.931)	8.361 (1.497)	0.75 (0.073)	36
$p - value$	0.553	0.65	0.098	0.569	0.167	0.727	

Notes: Standard Errors in parentheses.

hereafter. In each of these treatments, we give subjects 4 choices. Subjects make 3 practice bundle selections prior to making their final bundle selection. After each practice selection, we show subjects the expected value of the bundle and the lotteries within the bundle they selected. This information is displayed during each subsequent period.[15] After making their final lottery selections, subjects in FOUR|P indicate their favorite and least favorite lottery and end the session with the same set of survey questions as subjects in the previous treatments.

Across the practice treatments, we vary the amount and type of information that subjects receive. In the simplest setting, subjects are only presented with the expected value of their bundle, we denote this FOUR|P. A second treatment displays the simple lottery which their bundle reduces to. That is, subjects are told the likelihood of receiving each of the four prizes. We denote this treatment as FOUR|P+ SIMPLE. In addition to receiving this information, before making any selections, subjects in FOUR|P+SIMPLE are given a layperson's explanation of proposition 1. For this reason, we might expect differences in initial selections in this treatment and those in FOUR|P. Finally, in a third treatment, we explicitly tell subjects which bundle maximizes the expected value after they complete their practice rounds, but before they make their final selection. We call this treatment FOUR|P+SIMPLE+BEST.

To evaluate the effect of these treatments, we will see whether the new pre-selection in-

[15]This design was chosen as we want subjects to be able to observe how the expected value of their bundles change with changes in their lottery selections. Moreover, by allowing subjects to see all of their practice decisions, we avoid problems associated with differential memories across subjects.

formation influences initial choices. We do this by comparing the initial choices made in the practice treatments to choices in the FOUR|RIVAL treatment. These comparisons can be found in Table 8. Table 8 presents OLS results to identify significant differences between the practice treatments and FOUR|RIVAL, as well as differences across the three practice treatments. The only statistically significant difference is that subjects in FOUR|P+SIMPLE initially choose riskier safe lotteries than subjects in FOUR|RIVAL. While this might be expected, given the additional information received in this treatment, it is surprising that those in FOUR|P+SIMPLE+BEST did not also select a riskier safe choice as they received the same information. In comparing across practice treatments, the only statistically significant difference is that individuals in FOUR|P+SIMPLE+BEST and FOUR|P+SIMPLE choose riskier risky lotteries than those in FOUR|P. As subjects in FOUR|P+SIMPLE+BEST and FOUR|P+SIMPLE receive the same information prior to participating in the practice stage, it is not surprising that their risky selections are similar. However, we do not want to oversell differences in the initial bundle selections in the FOUR|P sessions because there is only a single significant difference from FOUR|RIVAL. In sum, the differences in initial selections are probably modest at best and thus suggest that providing a more detailed description of the task and payoffs has little impact on subjects' bundle selections. Note this finding is consistent with what we observe in the treatment where subjects are not told the expected value of each lottery and select 4 lotteries (FOUR|RIVAL - NO EV). Bundle selection in FOUR|RIVAL - NO EV is not statistically different than the behavior observed in FOUR|RIVAL.[16]

We now examine how the new information and experience with these types of decisions influences choices by subject. This is done using (subject) fixed effects regressions. The results of these regressions are presented in Table 9. The regressions compare selections in practice rounds 2, 3, and final selections to the initial selection made by the subject. Within the practice only regressions (FOUR|P in Table 9), we find subjects choose both riskier risky

[16]Discussed in detail in the appendix.

Table 8: Initial Selections in Practice Treatments VS. FOUR|RIVAL

	Start EV	Average	Risky	Safe	n
FOUR|P[a]	0.049	-0.02	0.897	-0.86	40
	(0.115)	(0.799)	(1.012)	(0.857)	
FOUR|P+SIMPLE[b]	0.169	-1.244	-1.084	-1.687**	46
	(0.111)	(0.771)	(0.977)	(0.827)	
FOUR|P+SIMPLE+BEST[c]	0.157	-0.895	-0.807	-0.86	41
	(0.114)	(0.793)	(1.006)	(0.851)	
CONSTANT	2.274***	11.401***	7.953***	14.86***	43
	(0.08)	(0.554)	(0.703)	(0.595)	
Obs	170	170	170	170	
R^2	0.0191	0.0228	0.0276	0.0244	
a=b	0.289	0.121	0.048	0.329	
a=c	0.356	0.280	0.098	1.000	
b=c	0.911	0.656	0.780	0.325	

Notes: Standard errors in parentheses. ***: $p < .01$, **: $p < .05$, and *: $p < .10$. p-values for F-test of equality of treatment dummies reported.

picks and safe picks in period 2 and in the final round but not in period 3. Moreover, the coefficients for period 2 and the final selections are quite similar, suggesting that subjects choose quite similarly in period 2 and the final round. The coefficients for period 3 are about half the size of period 2, suggesting that subjects picked slightly less risky riskiest and safest choices in this period. Therefore, subjects seem to benefit from experience due to learning which is also reflected in the expected values of their final bundle selections.[17]

Examining the choices in FOUR|P+SIMPLE and FOUR|P+SIMPLE+BEST reveals that little changes across most of the practice rounds - which is quite different from FOUR|P. However, this is expected. In both of these treatments subjects are informed of how the rival nature of payoffs affects the contribution of risky and safe lotteries to the expected value of their portfolio of lotteries. Within FOUR|P+SIMPLE subjects choose riskier safe picks compared to their initial selections but only in Period 2. Moreover, their final selections were not statistically different from their initial selections.[18] This is quite different from final

[17] Results available upon request.

[18] In results not shown expected values do not change.

practice treatment. Recall that in FOUR|P+SIMPLE+BEST subjects are informed of the expected value maximizing bundle of lotteries prior to making their final selection. Therefore we are not surprised that only in this treatment are the final selections are statistically different than the initial selections, with subjects choosing both risker risky and safe selections. This finding is interesting, as it suggests that subjects were likely trying to maximize their expected winnings, but were not able to do so even with the knowledge of the expected value and the simple lottery a chosen bundle collapses to. This suggests, somewhat unsurprisingly, that optimizing with rival outcomes is non-trivial.

Table 9: The Effect of Practice on Subjects' Decisions

	FOUR|P		FOUR|P+SIMPLE		FOUR|P+SIMPLE +BEST	
	Riskiest	Safest	Riskiest	Safest	Riskiest	Safest
Period 2	-1.775***	-2.2***	-0.804	-1.522**	0.659	-0.512
	0.587	0.491	0.51	0.629	0.441	0.485
Period 3	-0.875	-1.075**	-0.435	0.043	-0.244	-0.78
	0.587	0.491	0.51	0.629	0.441	0.485
Final	-1.8***	-2.325***	-0.565	-0.5	-1.244***	-2.244***
	0.587	0.491	0.51	0.629	0.441	0.485
Constant	8.85***	14***	6.87***	13.174***	7.146***	14***
	0.415	0.347	0.361	0.445	0.312	0.343
ρ	0.582	0.691	0.702	0.431	0.753	0.669
R^2	0.099	0.201	0.019	0.056	0.138	0.164

Notes: Fixed Effects Panel Regression results. Standard errors in parentheses. ***: $p <.01$, **: $p <.05$, and * :$p <.10$. 41-46 groups and 4 observations per group.

We now analyze whether the practice treatments influenced final selections relative to the choices made in FOUR|RIVAL. Table 10 compares several outcomes across the three practice treatments to one another and to FOUR|RIVAL using OLS. All of the practice treatments resulted in increased expected values relative to FOUR|RIVAL. Moreover, the expected value for FOUR|P+SIMPLE+BEST was highest of all, being \$0.417 higher on average, compared to a mean of \$2.274 in FOUR|RIVAL, an increase of 18.33%. The difference between FOUR|P+SIMPLE+BEST and the other practice treatments are also marginally statistically significant. Thus demonstrating that informing subjects of the expected value maximizing bundle increased the expected value of their bundle. No other differences between practice treatments are statistically significant.

Picking the optimal bundle not only requires the decision maker to get the spread between their risky and safe selections correct, but also requires them to pick the correct lotteries within that range. If their bundle is too balanced, the decision maker will end up leaving money on the table. It seems therefore that the explanatory power of EU-I is due to its use as a heuristic rather than a preference for a more balanced portfolio. We explore this possibility in the next section.

Table 10: Final Selections in Practice VS. FOUR|RIVAL

	EV	Average	Risky	Safe	
FOUR|P[a]	0.224**	-1.914**	-0.903	-3.185***	40
	(0.101)	(0.743)	(0.894)	(0.807)	
FOUR|P+SIMPLE[b]	0.258***	-1.792**	-1.649*	-2.187***	46
	(0.098)	(0.717)	(0.863)	(0.779)	
FOUR|P+SIMPLE+BEST[c]	0.417***	-2.621***	-2.051**	-3.104***	41
	(0.101)	(0.738)	(0.888)	(0.801)	
CONSTANT	2.274***	11.401***	7.953***	14.86***	43
	(0.07)	(0.515)	(0.621)	(0.56)	
Obs	170	170	170	170	
R^2	0.0955	0.077	0.0365	0.1107	
a=b	0.741	0.869	0.398	0.210	
a=c	0.063	0.348	0.206	0.921	
b=c	0.110	0.256	0.646	0.246	

Notes: Standard errors in parentheses. ***:$p<.01$, **:$p<.05$, and *:$p<.10$. p-values for F-test of equality of treatment dummies reported.

8 Preference or Heuristic?

We have seen that individuals often make decisions that are more closely aligned with maximizing expected utility as if payoffs are independent, while occasionally exhibiting a preference for diversification. We now consider whether the observed deviations from expected utility maximization are a result of a preference or a heuristic. When we say subjects may have a preference for an EU−I type bundle, we mean that even with full information, subjects wish to select a bundle made up of lotteries that would maximize expected utility as if the payoffs were independent. In other words, they want a bundle made up of their k favorite lotteries. Alternatively, the observed behavior that is consistent with EU−I may be due to a heuristic that is used to simplify a complicated expected value calculation. If subjects are using a heuristic, we should observe a disproportionate fraction of subjects selecting the expected value maximizing bundle when they are informed of which bundle maximizes expected value, when the actual calculation is difficult.[19] On the other hand, if subjects' choices are representative of a preference, the fraction of subjects selecting the expected value maximizing bundle should not change when they are given the expected value maximizing bundle, when the calculation is difficult.

We presume that the calculations become more difficult as the number of choices increase and/or when the payoffs are rival. Therefore, with only one choice the problem is trivial, as subjects are given the expected value of each lottery. With two choices we expect that bundle selection with rival payoffs is more complicated than with random as random only requires maximizing a sum of stated values. Similarly, we expect RIVAL decisions to be more difficult than RANDOM decisions for four and six. The only other treatment where identifying the expected value maximizing bundle is trivial is FOUR|P+SIMPLE+BEST. This is because subjects in this treatment are explicitly given the expected value maximizing bundle. If we assume that the fraction of risk neutral individuals is constant across treatments, than we should expect to see similar fractions of individuals choosing the maximal expected value bundle in FOUR|P+SIMPLE+BEST and ONE, if preferences are all that matter.

Table 11 calculates the fraction of individuals in each treatment that choose the expected value maximizing bundle, and tests whether that fraction is different from the ONE treatment. The fractions are highest in ONE, FOUR|P+SIMPLE+BEST, and the RANDOM

[19]However, the shift should be imperfect because the choices made will be a function of individuals' risk preferences. So, if subjects are given the expected value maximizing bundle, we should only expect subjects who are risk neutral to select this bundle.

Table 11: Share Selecting Maximal Bundle by Treatment

	ONE	2|RI	2|RA	4|RI	4|RA	6|RI	6|RA	4|P	4|P+S	4|P+S+B
share best	46.8%	0.0%	20.5%	2.3%	21.1%	0.0%	18.4%	0.0%	0.0%	34.1%
Diff v. ONE	-	0.00	0.01	0.00	0.02	0.00	0.01	0.00	0.00	0.23

Notes: Treatment names abbreviated for space. 2-TWO, 4-FOUR, and 6-SIX. RI-RIVAL and RA-RANDOM. P-PRACTICE, S-SIMPLE, and B-BEST

choices for FOUR and SIX while near zero elsewhere. This is consistent with our assumption that RIVAL calculations are more difficult. Indeed, the only treatment which does not have statistically significant different fraction of subjects selecting the expected value maximizing bundle from ONE is FOUR|P+SIMPLE+BEST. This is exactly what one would expect if subjects are using a heuristic to make their decisions despite a desire to maximize expected utility.

One might expect all subjects to pick the expected value maximizing bundle, this bundle *only maximizes expected utility for risk neutral individuals.* While there is significant variation in stated risk preferences, stated risk preferences are fairly consistent across treatments. In analysis not shown, the only treatment with a statistically significantly different level of stated risk preferences was TWO|RIVAL.[20] Given that the average stated risk preference was slightly above 5 (corresponding to right between "risk averse" and "fully prepared to take risks") and that the average lottery selected in ONE was 10.96 (the expected value maximizing lottery), we are fairly confident that a plurality of subjects are risk neutral and these subjects picked the expected value maximizing bundle when identifying that bundle was trivial. Deviations from this bundle were therefore likely due to the fact that the expected value maximizing bundle does not maximize expected utility if the subject is not risk neutral. This suggests that the deviation from EU in rival treatments is due to the complicated nature of calculations rather than a preference for a bundle that is made up of lotteries with the highest expected values.

[20]Subjects in TWO|RIVAL indicated a slightly lower level of risk aversion than subjects in other treatments.

9 Conclusion

Having discussed how subjects behave in a manner inconsistent with multiple theories, and how choice restriction results in fewer risks being taken, we now discuss the relevance of these findings for the college application decision. Attending and completing college generally leads to increased lifetime earnings while also providing an opportunity for upward social mobility. However, low income individuals are less likely to apply for college and if they do, they generally apply to less selective schools. Additionally, low income students apply to fewer schools than their high income counterparts. This results in low income students attending less selective schools and reduces the aggregate returns to higher education for low income students.

Our experiment is consistent with findings in Pallais (2015). When our subjects receive more choices, they are more likely to choose both riskier and safer lotteries. This behavior is inconsistent with expected utility theory. In a setting we refer to as "risky rival outcomes" subjects appear to make decisions based on expected utility with independent outcomes rather than expected utility theory. This is an important distinction as previous theoretical and empirical work assumes application portfolio selection is done by maximizing expected utility. For instance, Fu (2014) models the portfolio decision in a large structural model assuming students select their application portfolio by solving an expected utility maximization problem.[21] Our experiments show that the assumption of expected utility maximization may result in too few predicted applications to safer schools.

One policy implication would be to provide low income individuals subsides for college applications. Encouragingly, in the 2014-2015 academic year the College Board enacted such a policy. In it certain low income students are able to both write the SAT for free, and receive vouchers for up to four free college applications, at participating colleges.[22] The

[21] The application decision is part of a larger model determining tuition, applications, admission, and enrollment. The application decision is essentially one of whether to apply to certain categories of schools: public vs. private, elite vs. non-elite, in-state vs. out-of-state, and the interactions of those.

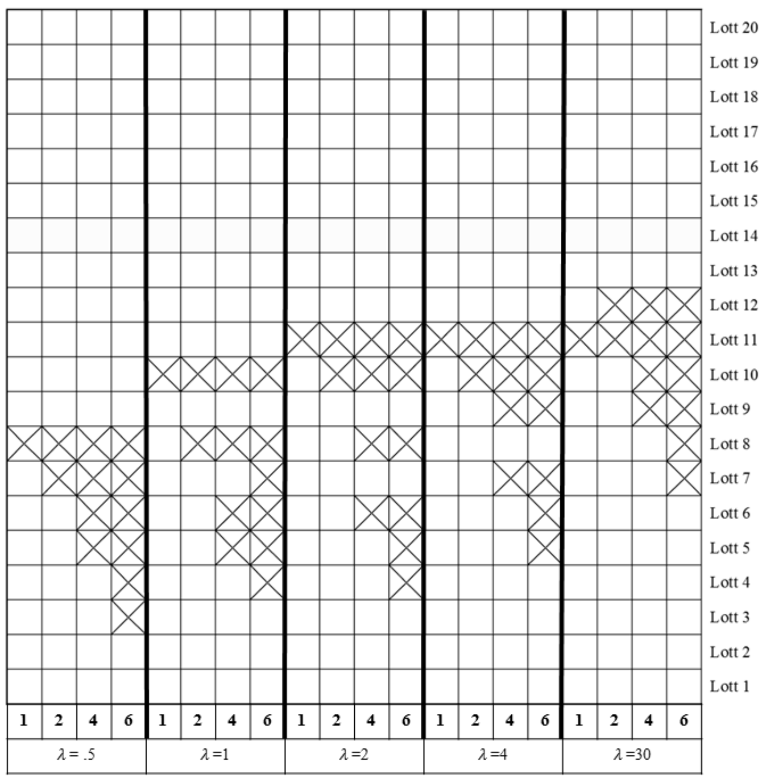
[22] See https://bigfuture.collegeboard.org/get-in/applying-101/college-application-fee-waivers and https://sat.collegeboard.org/register/sat-fee-waivers for details.

analysis from our experiment suggests that this policy may greatly improve the welfare of low income students - particularly those with high ability.

Finally, our findings may help to explain why interventionist policies that use expert advice, like the one discussed by Carrell and Sacerdote (2013) are so effective. We show that individuals do not take into account the rival nature of the lotteries and instead pick lotteries *as if* they are independent. Additionally, when informed of the maximal bundle subjects were more likely to choose it. It stands to reason that in other scenarios with rival uncertain outcomes, like the college application process, people do not maximize their expected utility and instead use a heuristic that simplifies the calculations but decreases the expected value. We find the use of a heuristic in the real life decision making especially likely because during (for example) the college application process, students are not given exact probabilities of admission nor precise expected lifetime earnings gained from attending a given university. Thus, it seems unlikely students will take into account the extremal gains from applying to more selective universities. Unlike most real life decisions, in our experiment, subjects are given the expected values, provided a detailed description of the benefits of selecting riskier choices and, yet, some agents only select the maximal bundle *after* subjects are explicitly told what bundle maximizes expected value.

In the case of the college application process, this is unfortunate because it translates into students applying to additional less selective schools. Essentially, we believe that policies using expert advice correct this heuristic. While the expert advice often also advises students to choose safety schools, which are not predicted under EU, Hoxby and Avery (2013) shows that expert advice also leads to students applying to more selective universities which increases their likelihood of attending more selective schools.

Figure 6: RDU Maximizing Choices under Various Risk Preferences



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A Appendix

A.1 Variable Descriptions

- AMB is a dummy variable equal to 1 if the subject was classified as ambiguity averse.
- RISK self reported risk preference. 0 if risk averse; 10 if full prepared to take risks.
- MALE is a dummy variable that equals 1 if the subject indicates they are male; equal 0 otherwise.
- AGE is the subject's reported age.
- INCOME is the subject's reported income. This variable is categorical, increasing in intervals of $12,500 and can take a value from 1 to 10, with 1 indicating an income less than $12,500 and 10 being greater than $ 100,000. All figures in US dollars.
- EDUC is the subject's level of education. This variable is categorical, increasing in educational achievement.
- BEST is the lottery that the subject specifies as the best.
- WORST is the lottery that the subject specifies as the worst.
- RISKIEST is the subject's riskiest choice.
- SAFEST is the subject's safest choice.
- PICKED FAV. is a dummy variable equal to one if the subject picked what they thought of as the best lottery.

A.2 Ellesberg Details

We use the Ellesberg paradox to classify subjects as ambiguity averse, or not. Below, are the questions we use for ambiguity aversion classification. We classify a subject as ambiguity averse if they indicate that they prefer choice(a) in question 1 and choice (d)in question 2.

1) *Suppose there is a bag containing 90 balls. You know that 30 are red and the other 60 are a mix of black and yellow in unknown proportion. One ball is to be drawn from the bag at random. You are offered a choice to (a) win $ 100 if the ball is red and nothing if otherwise, or (b) win $100 if it's black and nothing if otherwise. Which do you prefer?*

2) *The bag is refilled as before, and a second ball is to drawn from the bag at random. You are offered a choice to (c) win $ 100 if the ball is red or yellow, or (d) win $ 100 if the ball is black or yellow. Which do you prefer?*

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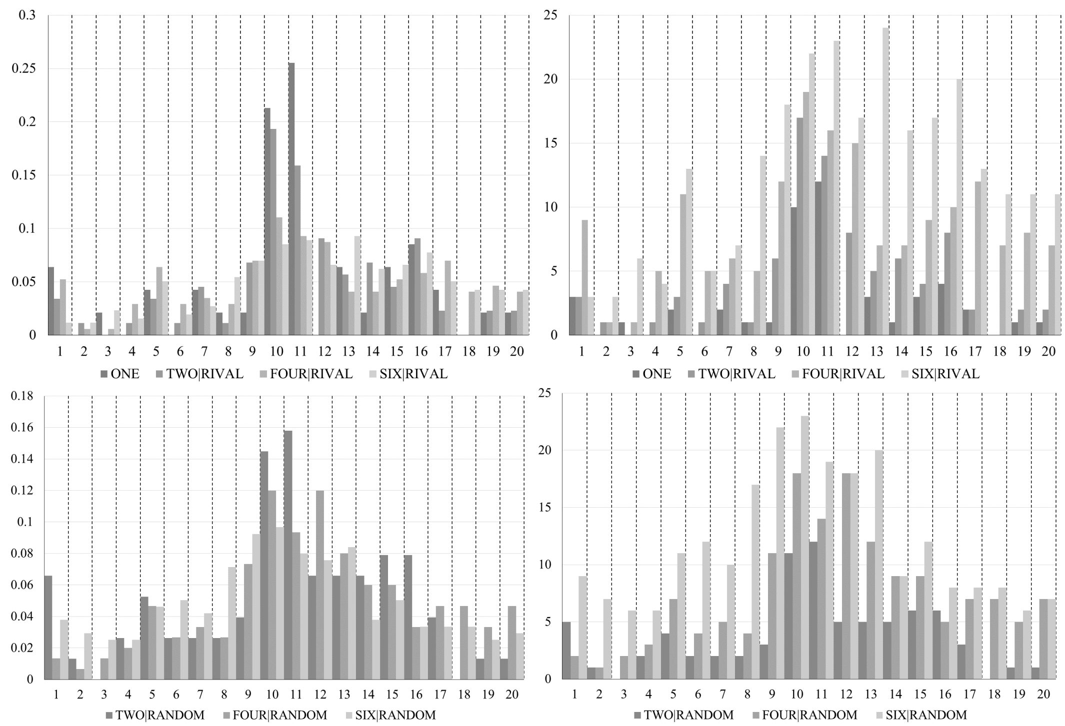
Distribution of Choices

The left side of the Figures in O.1 are the probability distribution function of choices by the *choice* treatments. The right side of these figures are histograms of subjects' actual choices. As expected, the mass is mostly centered on the favorite choices.

Figure O.1: Distribution of Choices and Choice Counts by Treatment



Expected Value

Result 4 *Holding the number of choices fixed, there are few differences in the chosen bundles across random and rival sessions.*

If subjects do not maximize their expected utility it would suggest there to be no significant differences between random and rival sessions assuming an equal number of choices in terms of the choice bundle's expected utility. A failure to reject this proposition would suggest subjects are not maximizing expected utility in rival sessions but are rather using EU-I. This is precisely what we observe. Clearly, while expected utility increases with the given number of choices, there are few significant differences across rival and random sessions. This is most clearly seen in Table O.1 which estimates the expected value of subject i's bundle, conditional on the treatment and demographic characteristics.[23]

Below each regression in Table O.1 we present p-values from a set of f-tests testing if coefficient estimates of X|RIVAL = X|RANDOM for $X = 2, 4, 6$. We find little in the way of differences across RANDOM and RIVAL sessions. The only significant differences are found when testing if SIX|RIVAL is equal to SIX|RANDOM. The test results suggest that the bundles subjects' selected in SIX|RANDOM have a higher expected value than the selected bundles in SIX|RIVAL. This is somewhat surprising and particularly strong evidence that subjects are not maximizing their expected utility. If subject maximized expected utility, then the expected value in rival sessions would be greater than the expected value in random sessions.

[23] Although we only present regression results with the dependent variable calculated using rival expected value, the results are stronger with the dependent variable calculated using random lottery selection expected value - which is consistent with our general result.

Table O.1: Expected Value of Selected Portfolios

	(1)	(2)	(3)	(4)
TWO|RIVAL	0.654***	0.619***	0.618***	0.645***
	(0.104)	(0.103)	(0.104)	(0.106)
TWO|RANDOM	0.603***	0.604***	0.627***	0.627***
	(0.107)	(0.106)	(0.107)	(0.109)
FOUR|RIVAL	1.132***	1.094***	1.092***	1.103***
	(0.104)	(0.104)	(0.105)	(0.106)
FOUR|RANDOM	1.11***	1.122***	1.137***	1.164***
	(0.108)	(0.107)	(0.108)	(0.11)
SIX|RIVAL	1.443***	1.426***	1.424***	1.452***
	(0.104)	(0.103)	(0.105)	(0.106)
SIX|RANDOM	1.638***	1.612***	1.623***	1.649***
	(0.107)	(0.107)	(0.108)	(0.109)
AMB	-	0.027	0.01	0.03
	-	(0.059)	(0.06)	(0.061)
RISK	-	0.033***	0.031***	0.032***
	-	(0.01)	(0.011)	(0.011)
MALE	-	-	0.084	0.061
	-	-	(0.061)	(0.062)
INCOME	-	-	0.008	-
	-	-	(0.01)	-
EDUC	-	-	0.016	-
	-	-	(0.017)	-
AGE	-	-	0.002	0.002
	-	-	(0.001)	(0.001)
CONSTANT	1.143***	0.974***	0.768***	1.408***
	(0.072)	(0.091)	(0.14)	(0.509)
Obs.	293	293	293	293
R^2	0.5396	0.5553	0.5623	0.5788
2ri = 2ra	0.6412	0.8898	0.9308	0.9308
4ri = 4ra	0.8418	0.7980	0.6836	0.6836
6ri = 6ra	0.0738	0.0897	0.0732	0.0732
Cat. Dum.	NO	NO	NO	YES

Notes: Standard errors in parentheses. ***: $p < .01$, **: $p < .05$, and *: $p < .10$. Cat. Dum. are categorical dummies for income and education.

Table O.2: Best and Worst Lottery by Treatment

	Best Lottery		Worst Lottery	
TWO|RIVAL	-0.707	-0.521	3.234	3.061
	(1.145)	(1.143)	(13.602)	(13.425)
TWO|RANDOM	-0.285	-0.37	9.635	11.038
	(1.188)	(1.18)	(13.86)	(13.692)
FOUR|RIVAL	0.053	0.348	13.858	9.125
	(1.159)	(1.162)	(13.427)	(13.316)
FOUR|RANDOM	0.296	0.287	2.72	2.27
	(1.196)	(1.189)	(14.135)	(13.972)
SIX|RIVAL	0.255	0.427	26.691*	24.983*
	(1.157)	(1.151)	(13.694)	(13.457)
SIX|RANDOM	-1.797	-1.864	22.051	25.83*
	(1.176)	(1.187)	(13.896)	(14.052)
AMB	-	0.624	-	-13.596*
	-	(0.658)	-	(7.779)
RISK	-	-0.241**	-	1.793
	-	(0.117)	-	(1.363)
CONSTANT	11.73***	12.612***	-20.072*	-22.864*
	(0.799)	(1.012)	(10.299)	(12.719)
Obs.	294	293	294	293
R^2	0.0027	0.0058	0.0088	0.0153
LL	20	20	168	168
UL	27	27	87	87

Notes: Tobit estimates. Standard errors in parentheses. ***:p <.01, **:p <.05, and *:p <.10. Upper Limit (UL) and Lower Limit (LL) are lotteries 1 and 20.

Favorite and Least Favorite by Demographic Characteristics and Treatment

In Table O.2, we estimate subjects' ex-post classification of the best and worst lotteries as a function of the treatments and individual preferences using a Tobit specification. Individual risk preferences significantly influence subjects perceptions of the best lottery, but not of the worst lottery. Subjects who are relatively prepared to take risk, tend to favor a lottery that is riskier than subjects who are less prepared to take risk. Similar results are found with alternative models (i.e., ordered probit and multinomial logit).

Probability of Selecting Favorite by Demographic Characteristics and Treatment

Table O.3: Probability of Picking Best Lottery

	(1)	(2)	(3)
TWO|RIVAL	-0.006	0.001	0.023
	(0.269)	(0.272)	(0.277)
TWO|RAND	-0.387	-0.378	-0.419
	(0.275)	(0.276)	(0.282)
FOUR|RIVAL	0.63**	0.602**	0.651**
	(0.296)	(0.299)	(0.307)
FOUR|RAND	0.28	0.266	0.252
	(0.288)	(0.289)	(0.294)
SIX|RIVAL	0.63**	0.618**	0.657**
	(0.296)	(0.297)	(0.306)
SIX|RAND	0.928***	0.97***	0.977***
	(0.329)	(0.336)	(0.341)
ABM	-	-0.126	-0.099
	-	(0.168)	(0.172)
RISK	-	0.004	0.015
	-	(0.03)	(0.031)
MALE	-	-	-0.367**
	-	-	(0.179)
INCOME	-	-	0.012
	-	-	(0.031)
EDUC	-	-	-0.035
	-	-	(0.05)
AGE	-	-	-0.005
	-	-	(0.005)
CONSTANT	0.354*	0.393	0.822**
	(0.187)	(0.249)	(0.397)
Obs.	294	293	293
R^2	0.0027	0.0781	0.095

Notes: Standard errors in parentheses. ***:p <.01, **:p <.05, and *:p <.10.

Sequential Lotteries

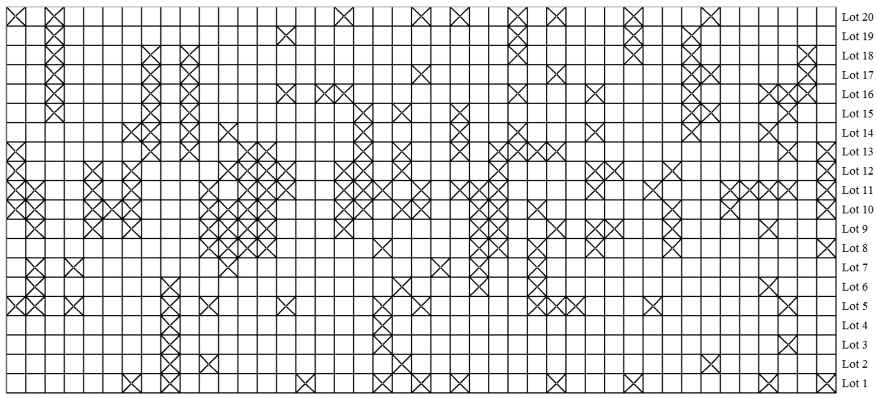
Table O.4: Percentage Choosing Sequential Lotteries

	TWO	FOUR	SIX	ALL
RIVAL	0.5	0.488	0.535	0.508
	(0.076)	(0.077)	(0.077)	(0.044)
RANDOM	0.513	0.737	0.5	0.585
	(0.081)	(0.072)	(0.08)	(0.046)
ALL	0.506	0.605	0.518	0.544
	(0.055)	(0.055)	(0.055)	(0.032)

Notes: Standard Errors in parentheses.

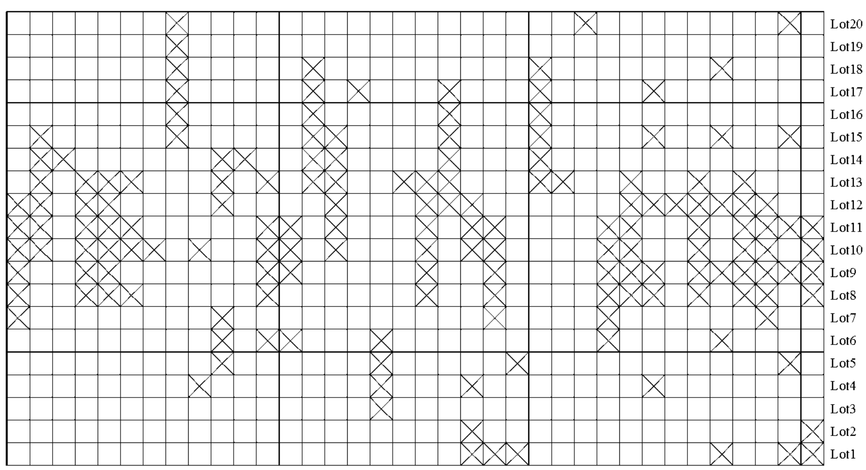
SIX|RIVAL (Repeat) and SIX|RANDOM (Repeat) Decisions

Figure O.2: Subjects' Decisions Sorted by Risk Preferences
Treatment: SIX|RIVAL (Repeat)



Notes: See notes from Figure 5.

Figure O.3: Subjects' Decisions Sorted by Risk Preferences
Treatment: SIX|RANDOM (Repeat)



Notes: See notes from Figure 5.

Removing Expected Value

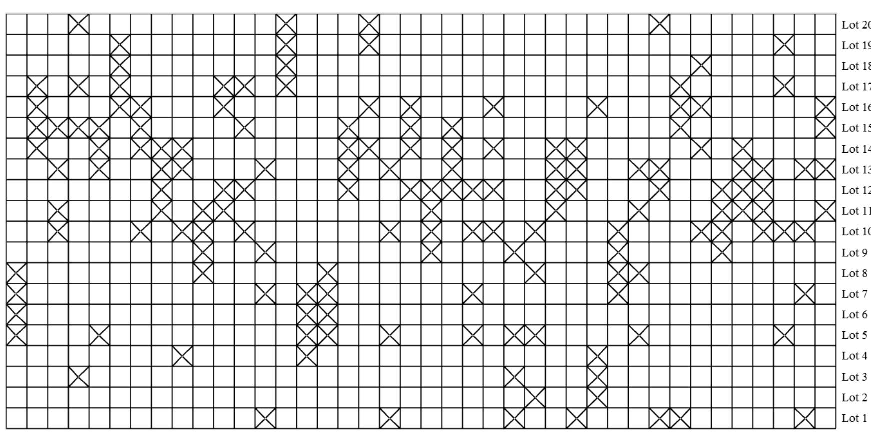
To check if including the expected value of each lottery had an effect on subject behavior, as a robustness check we run an additional treatment where we give subjects four choices but do not reveal what the expected value of each lottery is. The results of the analysis can be found in Table O.5. There are no significant differences between FOUR|RIVAL with or without the expected value of each lottery begin given.

Table O.5: The Effect of Expected Value

	Average	Safest	Riskiest	Favorite	Worst	Pick Favorite	n
FOUR|RIVAL	11.401	14.860	7.953	11.744	7.116	0.837	43
	(0.582)	(0.597)	(0.777)	(0.863)	(1.295)	(0.057)	
FOUR|RIVAL−NO EV	11.269	14.45	7.425	11.8	6.243	0.725	40
	(0.544)	(0.546)	(0.738)	(0.758)	(1.39)	(0.072)	
$p-value$	0.869	0.615	.624	0.962	0.647	0.220	

Notes: Standard Errors in parentheses.

Figure O.4: Subjects' Decisions Sorted by Risk Preferences
Treatment: FOUR|RIVAL − NO EV



Notes: See notes from Figure 5.

Experiment Instructions

Below are the general instructions of the HIT. There are minor changes depending on the treatment, the exclusion of expected values, the ability to select the same lottery more than once, and experience. The specific instructions relating to the robustness checks and exploratory treatments are available upon request.

Introduction

Welcome to the HIT! The instructions for this HIT are straightforward. If you follow them carefully, you can earn a considerable amount of money in addition to your participation fee of 25 cents. The additional amount you earn will be paid through the Amazon Mechanical Turk Bonus. Your confidentiality is assured.

In this HIT, there are 20 lotteries that vary both by their jackpots (payouts) and their odds (probability of winning). As such the expected value of the lotteries(probability of wining times the payout) also vary. You will be asked to select your **X** favorite lotteries, from the 20 available lotteries.

For each chosen lottery, a computer will randomly draw a number between zero and one to determine whether you have won that lottery. If the number drawn is less than or equal to the probability of the lottery winning, then you won that lottery.

For example, let us assume that lottery C has a probability of winning of 15 percent, then any number drawn by the computer between 0.00 and 0.15 would win the lottery and any number between 0.16 and 1.00 would not win the lottery. Your payment for this HIT will be the maximum payment from any successful lottery. If you were to win only one lottery, than the payout from that lottery would be your payment. If you were to win two lotteries, your payment would be the highest value of the two payouts. If you do not win any lotteries, you will only receive your participation fee.

Before you begin, we would like you to complete a brief survey to make sure that you comprehend written English.

Do not click the Submit button until specifically instructed to do so.

Survey

Before we begin please take a few minutes to complete this short survey. When you are finished, please click the "next" button. Note there are two English comprehension questions. If you fail to answer any of them correctly, you will be asked to return the HIT and will not be able to continue. After you finish selecting your favorite lotteries, you will be instructed to complete another short survey.

1. What is your gender?

2. What is your age?

3. What country do you currently live in?

4. Paul bought a baseball for **X** dollars. Jim bought a candybar for one dollar. How much did Paul's baseball cost?

5. You and your friend are playing a game with a coin. If the coin is flipped and ends up heads you win a dollar. If it ends up tails you win nothing. What is the expected value of this game (in CENTS)?

6. What is the expected value of a game that pays 200 dollars with probability 25 percent? Please just enter as an integer number.

Do not click the Submit button until specifically instructed to do so.

Practice

For example, you are asked to select your favourite 3 lotteries from lotteries A, B, C, D and E. The lotteries' payoffs are as follows:

	Lottery A	Lottery B	Lottery C	Lottery D	Lottery E
Prob	10 %	20%	50%	60%	80%
Prize	\$4.50	\$4.00	\$3.00	\$2.00	\$1.00
EV	\$0.45	\$0.80	\$1.50	\$1.20	\$0.80

From the table above you can see that Lottery A pays 4.50 with a probability of 10%, Lottery B pays 4.00 with a probability of 20%, Lottery C pays 3.00 with a probability of 50%, Lottery D pays 2.00 with a probability of 60% and Lottery E pays 1.00 with a probability of 80%.

You select lotteries A, C, and E. The outcomes of each of these lotteries are as follows:

1. Lottery A draws the number .2, which is greater than .1 and therefore unfavorable to you.
2. Lottery C draws the number .1, which is less than .5 and therefore favorable to you.
3. Lottery E draws the number .8, which is equal to .8 and therefore favorable to you.

Your earnings for the lottery part of the HIT would therefore be 3.00 dollars. This is because the outcome of lottery A was unfavorable to you. While both lotteries C and E were favorable to you, the favorable outcome of Lottery C (\$3.00) is greater than the favorable outcome of Lottery E (\$1.00).

	Lottery A	Lottery B	Lottery C	Lottery D	Lottery E
Prob	10 %	20%	50%	60%	80%
Prize	\$4.50	\$4.00	\$3.00	\$2.00	\$1.00
EV	\$0.45	\$0.80	\$1.50	\$1.20	\$0.80

When you are asked to make your actual decisions, you will see a chart like the one shown on the practice stage but there will be more lotteries and there will be a box underneath each lottery. In each of these boxes, there will be two radio buttons. One radio button will correspond to “No” while the other will correspond to “Yes”. The “No” button will be indicated with a “N” while the “Yes” button will be indicated with a “Y”. You will use these radio buttons to indicate your preferred lotteries.

If a given lottery is among your **X** preferred lotteries, click the corresponding “Yes” radio button. If not, click the “No” radio button.

After you have indicated your **X** preferred lotteries, you will be asked to click the “next” button to complete the final parts of the HIT.

Do not click the Submit button until specifically instructed to do so.

Game

Please indicate your **X** favorite lotteries. After you have indicated your **X** preferred lotteries, click the “next” button to finish up the final parts of the HIT.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T
Prob	5%	10%	15%	20%	25%	30%	35%	40%	45%	50%	55%	60%	65%	70%	75%	80%	85%	90%	95%	100%
Prize	$5.00	$4.75	$4.50	$4.25	$4.00	$3.75	$3.50	$3.25	$3.00	$2.75	$2.50	$2.25	$2.00	$1.75	$1.50	$1.25	$1.00	$0.75	$0.50	$0.25
EV	$0.25	$0.48	$0.68	$0.85	$1.00	$1.13	$1.23	$1.30	$1.35	$1.38	$1.38	$1.35	$1.30	$1.23	$1.13	$1.00	$0.85	$0.68	$0.48	$0.25
Pick																				

Do not click the Submit button until specifically instructed to do so.

Game Continued

You have now indicated your most preferred lotteries. We would now like to find out what you think are the best and worst lotteries. Below we have presented a table just like you saw on the previous screen and have indicated the lotteries you selected with the word “Picked”. That is, if you selected Lottery A than you would see the word “Picked” located in the cell above it.

Using the radio buttons in the row marked “Best” below, please indicate the lottery you think is the best of all the lotteries by clicking on the radio button underneath your favorite lottery. After you have selected the lottery that you think is the best, use the radio buttons in the “Worst” row to indicate the lottery that you think is the worst of all the lotteries.

Once you have finished selecting what you think are the best and worst lotteries, click the "next" button to go to the final part of the HIT. You will make an additional 10 cents for completing this final portion of the HIT.

Reminder! Do not click the Submit button until specifically instructed to do so.

END

Thank you for your participation! Please answer the questions below. If you do so, you will earn an additional 10 cent bonus! If you do not wish to complete the survey. Feel free to submit the HIT!

1. What is your Nationality?
2. Which of the following best describes your highest achieved EDUC level?
3. What is the total income of your household?
4. Why do you complete tasks in Mechanical Turk? Please check any of the following that applies:
5. How do you see yourself: Are you generally a person who is fully prepared to take risks or do you try to avoid taking risks?

Instructions - Practice

For example, you are asked to select your favorite 3 lotteries from lotteries A, B, C, D and E. The lotteries' payoffs are as follows:

	Lottery A	Lottery B	Lottery C	Lottery D	Lottery E
Prob	10 %	20%	50%	60%	80%
Prize	\$4.50	\$4.00	\$3.00	\$2.00	\$1.00
EV	\$0.45	\$0.80	\$1.50	\$1.20	\$0.80

From the table above you can see that Lottery A pays 4.50 with a probability of 10%, Lottery B pays 4.00 with a probability of 20%, Lottery C pays 3.00 with a probability of 50%, Lottery D pays 2.00 with a probability of 60% and Lottery E pays 1.00 with a probability of 80%. What this means is that you if you select Lotteries A, C, and E you will win Lottery A with a probability of 10%, Lottery C with probability 45%, and Lottery E with probability 36%.

Note that your probability of winning a given lottery that you select is different than the probability of the lottery being favorable to you. This is because while you will actually win Lottery A with 10% probability, Lottery C will only be relevant if Lottery A is unfavorable to you (which will occur with probability of 90%). As such, the probability you will win Lottery C is .90*.5 which is equal to 45%. Likewise, Lottery E will only be relevant if Lotteries A and C are unfavorable to you. Therefore you will win Lottery D with probability .9*.5*.8 which is equal to 36%. What this means is that as you select lotteries that are more likely to be favorable to you, lotteries that are even more likely to be favorable to you will be less likely to be relevant.

Example: Suppose you select lotteries A, C, and E. The outcomes of each of these lotteries are as follows:

1. Lottery A draws the number .2, which is greater than .1 and therefore unfavorable to you,

2. Lottery C draws the number .1, which is less than .5 and therefore favorable to you.

3. Lottery E draws the number .8, which is greater than .8 and therefore favorable to you.

Your earnings for the lottery part of the HIT would therefore be 3.00 dollars. This is because the outcome of Lottery A was unfavorable to you. While both Lotteries C and E where favorable to you, the favorable outcome of Lottery C ($3.00) is greater than the favorable outcome of Lottery E ($0.80).

	Lottery A	Lottery B	Lottery C	Lottery D	Lottery E
Prob	10 %	20%	50%	60%	80%
Prize	\$4.50	\$4.00	\$3.00	\$2.00	\$1.00
EV	\$0.45	\$0.80	\$1.50	\$1.20	\$0.80

When you are asked to make your actual decisions, you will see a chart like the one shown on the practice stage but there will be more Lotteries and there will be a box underneath each lottery. In each of these boxes, there will be two radio buttons. One radio button will correspond to "No" while the other will correspond to "Yes". The "No" button will be indicated with a "N" while the "Yes" button will be indicated with a "Y". You will use these radio buttons to indicate your preferred lotteries. If a given lottery is among your 4 preferred lotteries, click the corresponding "Yes" radio button. If not, click the "No" radio button.

Before you make your final lottery selections, you will participate in 3 practice rounds. In each of these rounds, after you make practice lottery selections, you will be shown the expected value of your decisions as well as your previous decisions, the probability of winning each lottery in your selection (i.e., the probability of each outcome occurring), and the resulting expected values of your selections. After you finish the practice stage, you will make your final lottery selections and then complete a survey. In this final round, you will also be shown a summary of your practice decisions and their resulting expected values and probabilities of each outcome occurring.

As soon as you are ready, click the NEXT button to begin the practice periods.

Game - Practice

Practice Round 1: Before we begin we would like you to practice a few times before you make your final lottery selections. After each practice selection you will be told which lotteries you selected and the resulting expected value of your selections as well as the probability of winning each lottery in your selection. So to begin and for practice, please indicate your

4 favorite lotteries. After you have indicated your 4 preferred lotteries, please click the "Next" button to see the expected value of your selection and the probabilities of each of each outcome occurring (in your selection). There will be 3 practice rounds. After you have finished making your 3 practice selections, you will be prompted to make your final selections. Your bonus will be based on your final lottery selections.

Reminder! Do not click the Submit button until specifically instructed to do so.

[**After 3 practice period**]

Final round: Please indicate your 4 favorite lotteries. These choices will be used to determine your bonus. After you have indicated your 4 preferred lotteries, you will be asked to click the "next" button to finish up the final parts of the HIT. However, before you make your decision, consider the following: if you select Lotteries J, H, F, and E you will have 25% chance of 4.00, a 22.5% chance of 3.75, a 21% chance of 3.25, and a 15.75% chance of 2.75. If you select this lotteries in expectation you would win 2.96. It is not possible to select a different set of lotteries that have a greater expected value. Reminder! Do not click the Submit button until specifically instructed to do so.