Individual Preference for Longshot

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October 2014

Evidence from racetrack betting and lottery ticket purchase suggests that individuals may exhibit risk seeking behavior when chances of winning are small and prizes sizable. We investigate individual longshot preference in an incentivized choice experiment. Using fixed-odds-fixed-outcome state lotteries in China, we construct a set of lotteries with winning odds between 10^{-1} and 10^{-5} and payoffs from *RMB10* to *RMB10,000,000*, grouped under three levels of expected payoffs: *1*, *10*, and *100*. Comparing lotteries with the same expected payoffs of *1* and *10*, we find significant incidence of risk affinity exhibiting single-peak behaviour, i.e., favoring lotteries involving specific winning odds. In contrast, subjects were predominantly risk averse for lotteries with expected payoff of *100*. Comparing risk attitude across expected payoffs, subjects tend to switch from risk averse to risk seeking as expected payoff decreases while maintaining the same winning probability or outcome. They exhibit a similar switch in risk attitude across pairs of lotteries with the same winning outcomes and ratio of winning probabilities, i.e., risk averse for the pair with higher expected payoff and risk seeking for the pair with lower expected payoff, which corresponds to Allais behavior over the probability triangle formed by the two winning outcomes and *0*. We further arrive at conditions for several models of non-expected utility preferences, namely, rank-dependent utility, disappointment aversion utility, weighted utility and salience utility, to account for the observed attitudes towards longshot risk. Interestingly, our evidence rejects the adoption of a power utility function for all the models considered.

Keywords: longshot, prospect theory, rank dependent utility, betweenness, salience utility

JEL Code: C91, D81

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1. Introduction

Gambling activities in various forms, from casino games, parimutuel and sports betting, to perhaps even stock markets as observed by Keynes (1936, Chapter 12, VI), suggest that ordinary risk averse individuals may exhibit a preference for longshot in being risk seeking when there is a small chance of winning a sizable prize.[1] Moreover, evidence in the racetrack betting literature suggests a tendency among betters to overbet on longshot horses and to underbet on favorite ones. This phenomenon dubbed the favorite-longshot bias has been reported in the literature in the United States (Griffith, 1949), Australia (Tuckwell, 1983), United Kingdom (Bruce and Johnson, 2000), and Germany (Winter and Kukuk, 2006).

Besides evidence of favorite-longshot bias from racetracks observed at odds as low as 1 in 1000, demand data for state lotteries in the United States appear to exhibit a similar pattern albeit at much smaller odds of winning. In enhancing profitability, lottery commissions in different territories have added more numbers to the popular form of state lottery called Lotto resulting in much lower odds of winning but disproportionate increase in demand by the public,[2] e.g., in the highly popular Lotto game called Powerball, the rules have been changed gradually towards drastically smaller odds until 2009 when the odds became 1:195,249,053 for the jackpot. However, in 2012, the odds were slightly increased to 1:175,223,509, with a decrease in the number of red balls from 39 to 35. This development hints at a limit to the reach of the favorite-longshot bias, settling for a more moderate longshot probability for winning the jackpot.

A natural question is whether favorite-longshot bias can arise at the individual level without market interactions when probabilities and outcomes are explicitly stated. Put differently, how do individuals value longshot risks? Do they have an intrinsic preference for longer odds? This thinking can be traced to Kahneman and Tversky (1979) who wrote: "*Because people are limited in their ability to comprehend and evaluate extreme probabilities, highly unlikely events are either ignored or overweighed, and the difference between high probability and certainty is either neglected or exaggerated. Consequently, pi [probability weight] is not well-behaved near the end-points*." Towards addressing these questions, this

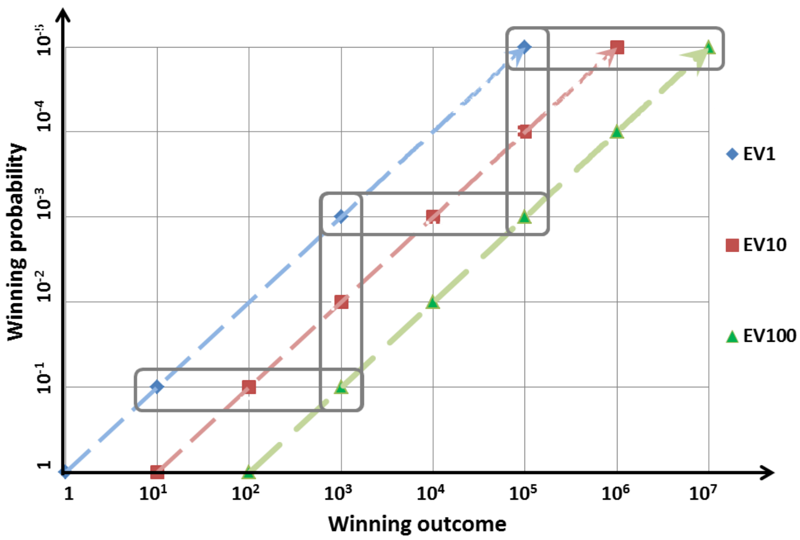
[1] In financial markets, it has been suggested that a positively skewed security can be "overpriced" and earn a negative average excess return (see, e.g., Kraus and Litzenberger's, 1976), and that the preference for skewed security might offer an explanation for a number of financial phenomena such as low long-term average return on IPO stock and the low average return on distressed stocks (Barberis and Huang, 2008).

[2] For example, over the years, Hong Kong's *Mark Six* has progressively decreased the odds of winning from drawing 6 out of 14 with a chance of 1/3,003, to picking 6 out of 49 numbers with a chance of 1/13,983,816 in 2002.

paper investigates experimentally individual preference for longshot involving small to extremely small probabilities in a laboratory setting.

We performed an incentivized experimental study with 836 subjects taking advantage of the availability of three fixed-odds-fixed-outcome state lottery products in China – 1D, 3D, and 5D – paying RMB10 (USD1 ≈ RMB6.5) with probability 10^{-1}, RMB1,000 with probability 10^{-3}, and RMB100,000 with probability 10^{-5}, respectively. Using different combinations of these three kinds of lottery tickets, we construct a set of lotteries with explicit winning odds ranging from 10^{-5} to 10^{-1} and explicit winning payoffs ranging from RMB10 to RMB10,000,000 grouped by three levels of expected payoff – RMB1, RMB10, and RMB100 (see Figure 1 below). Subjects make binary choices among lotteries with the same expected payoff.

Figure 1. Structure of lotteries used in our experiment.



Note. Illustration of lotteries grouped under $EV = 1$, $EV = 10$, and $EV = 100$ involving the probabilities of 10^{-1}, 10^{-2}, 10^{-3}, 10^{-4}, and 10^{-5} and winning outcomes (in RMB) of 10, 10^2, 10^3, 10^4, 10^5, 10^6, and 10^7, using different combinations of 1D, 3D, and 5D tickets. Three sets of lotteries with the same winning probability and two sets of lotteries with the same winning outcome are separately highlighted.

We first examine choice behavior over four options with the same expected payoffs: three lotteries with winning probabilities of 10^{-1}, 10^{-3}, and 10^{-5} in addition to receiving the expected payoff for sure. This design enables us to assess subjects' risk attitude for small winning probabilities up to 10^{-1} while holding expected payoff constant. Specifically, at expected payoff m, a subject who is purely *risk averse* would rather receive the expected payoff for sure than any of the other three lotteries. Departing from pure risk aversion, subjects may display limited risk affinity in being risk seeking for lotteries with winning probabilities up to some level θ, and be risk averse otherwise. We say that such subjects exhibit a *preference for* *longshot* at expected payoff m over a range of winning probabilities $(0, \theta)$. For $\theta > 10^{-1}$, longshot choice patterns in which receiving the expected payoff for sure is less preferred than receiving any of the 10^{-1}, 10^{-3}, and 10^{-5} lotteries are highly significant against the chance rate for EV1 (*61.8%*) and EV10 (*37.7%*) lotteries but not for EV100 (*7.4%*) lotteries. For θ between 10^{-3} and 10^{-1}, there are two longshot preference patterns – 10^{-3} and 10^{-5} each preferred to receiving the expected payoff for sure, which is in turn preferred to 10^{-1} – which are significant only for EV1 lotteries (*5.4%*) but not for EV10 (*2.3%*) and EV100 (*1.2%*) lotteries. For θ between 10^{-5} and 10^{-3}, the longshot preference patterns – 10^{-5} being preferred to receiving expected payoff for sure which is in turn preferred to 10^{-3} as well as 10^{-1} – are not significant at each of the three levels of expected payoffs.

For subjects with longshot preference encompassing $(0, 10^{-1}]$, we are further interested in whether they exhibit a *single-peak property*, i.e., favoring lotteries involving specific winning odds over other lotteries within a given range of small probabilities $(0, \theta)$ (discussed in more detail in the next section). For EV1 and EV10, we observe significant incidence of single-peak behavior at all three winning probabilities. For EV100 lotteries however, single-peak longshot preference is only significant at 10^{-5}, but not at 10^{-1} or 10^{-3}. Notably, for EV1 and EV10, the behavior of subjects with longshot preference encompassing $(0, 10^{-1}]$ is largely captured by single-peak behavior at 10^{-1}, 10^{-3}, and 10^{-5}. Interestingly, among subjects with single-peak longshot preference, we find that the favored winning odds tend to increase as expected payoff increases.

Comparing risk attitude across expected payoffs, our data reveal a robust tendency to switch from risk aversion to risk affinity as expected payoff decreases. This switching behavior is observed for the majority of our subjects (from *57.9%* to *65.5%*) when either winning probability or winning outcome is fixed. We also observe this tendency to switch in risk attitude across two pairs of lotteries sharing the same winning outcomes and the same ratio of winning probabilities (from *13.6%* to *27.4%*). This latter behavior, reflecting a fanning-out pattern of the indifference curves in a probability simplex defined by the two winning outcomes together with 0, corresponds to an instance of common-ratio Allais behavior.[3]

We examine the implications of the observed choice behavior, within the same expected payoff and across different expected payoffs, on four non-expected utility models under risks,

[3] Kahneman and Tversky (1979) offer an early example of equal-mean common ratio Allais behavior involving two binary comparisons – 90% chance of winning 3,000 versus 45% chance of winning \$6,000 and 0.2% chance of winning 3,000 versus 0.1% chance of winning \$6,000.

namely rank-dependent utility (Quiggin, 1982), weighted utility (Chew, 1983), disappointment averse utility (Gul, 1991), and salience utility (Bordalo, Gennaioli, and Shleifer, 2012), in addition to expected utility. With a non-concave utility function, expected utility can exhibit single-peak longshot preference but the favored winning probability and expected payoff are in the same ratio. This implication is inconsistent with the observed prevalence of single-peak longshot preference at 10^{-3} and 10^{-5} for expected payoffs of 1 but not at 10^{-1} and 10^{-3} for the expected payoff of 100. Our observation of switching behavior in risk attitude with winning probability fixed is compatible with rank-dependent utility and disappointment averse utility, but not when they employ a power utility function. This switching behavior is also not compatible with the use of a power utility function for weighted utility with an increasing weight function. At the same time, the observed switching behavior in risk attitude with winning outcome fixed further rules out the use of probability weighting function whose initial slope is finite in the rank-dependent model along with the disappointment averse utility model. The salience utility model can exhibit the switching behavior by allowing higher salience (overweight) for winning outcome when expected payoff is lower, and lower salience (underweight) for winning outcome when expected payoff is higher. Further structural estimation discriminates among the utility models investigated using a negative exponential utility function points to salience utility as offering the best overall fit.

Our findings contribute to understanding decision making under risk in a number of ways. Firstly, our results shed light on our understanding of gambling behavior and the working of gambling markets. To account for the phenomenon of favorite-longshot bias in different market settings, researchers have offered various theoretical accounts including asymmetric information, heterogeneity in betters' behavior, misperception of winning probability, and betters being generally risk loving (see Ottaviani and Sørensen, 2008 for a review). Since winning odds are estimated using aggregate data for favorite-longshot bias, current approaches cannot differentiate between whether the estimated winning odds arise from misperception of probability or from nonlinear probability weighting (Barseghyan, et al 2013). In our experimental setting, with probabilities being explicitly specified, we can rule out misperception of probability and focus on nonlinear probability weighting in accounting for the observed choice behavior. Specifically, we find a significant incidence of longshot preference in a controlled lab setting with fixed odds and fixed outcomes. This suggests that favorite-longshot bias may arise from people's preference for longshot prospect apart from market interactions or information asymmetry.[4] Interestingly, while some individuals do exhibit an increasing preference for longshot as winning probability decreases to 10^{-5}, the bulk of our subjects with longshot preference display single-peak behavior favoring 10^{-1} and 10^{-3}. This runs counter to the favorite-longshot bias, and suggests a limit to this phenomenon which may have been reflected in the design of racetrack betting in terms of the number of horses in a typical race and the range of winning odds available. The presence of 1D, 3D and 5D lottery tickets in China also suggests that there is heterogeneity in consumer demand in terms of favoring the specific winning probabilities of 10^{-1}, 10^{-3} and 10^{-5}. Relatedly, the strong incidence of longshot preference for EV1 and EV10 lotteries but not for EV100 lotteries corroborates a general observation about lottery ticket pricing. The nominal prices of lottery tickets tend to be priced low; scaling up the price together with their prizes may not pay.

Secondly, our results contribute to the understanding of attitude towards longshot risks. The high proportions of transitive patterns observed in our data (from *82.9%* to *86.7%*) suggest that subjects' choices are well-behaved when choosing among lotteries with small to extremely small winning probabilities. This is corroborated by our observation of pervasive common-ratio Allais behavior involving equal-mean comparisons over small probabilities, which complements a sizable literature on Allais behavior generally involving moderate probabilities (MacCrimmon and Larson, 1979; Kahneman and Tversky, 1979; Chew and Waller, 1986; Cubitt, Starmer and Sugden, 1998; Conlisk, 1989). Notably, we do not find a certainty effect underpinning our observed Allais behavior.

Lastly, using structural estimation, a good number of papers have jointly estimated an inverse S-shape probability weighting function and a concave utility function over different ranges of moderate probabilities based on experimental data (see Wakker, 2010, Chapter 7, for an overview). Using a large racetrack betting data set, Jullien and Salanié (2000) compare the fitness of various models and find that rank-dependent utility models do not fit the data noticeably better than expected utility models, while cumulative prospect theory has higher

[4] Ali (1977) shows how favorite-longshot bias can arise from betters having heterogeneous beliefs if their median belief equals the empirical probability. For pari-mutuel betting markets, Shin (1991) explains the favorite-longshot bias as the response of an uninformed bookmaker to the private information possessed by insiders. Subsequently, Hurley and McDonough (1995) demonstrate how favorite-longshot bias can arise when price-taking (and risk-neutral) bettors possess superior information, since the amount of arbitrage is limited by the presence of the track take and the inability to place negative bets. More recently, Ottaviani and Sørensen (2006) show that this bias arises in pari-mutuel markets if privately informed bettors place last-minute bets without knowing the final distribution of other bettors' bets. An alternative approach to account for favorite-longshot bias is to rely on individuals themselves preferring risk or skewness (Weitzman 1965; Quandt, 1996; Golec and Tamarkin, 1998) or misestimating the winning probability (Griffith, 1949).

explanatory power. In a more recent study using racetrack betting data with compound bets, Snowberg and Wolfers (2010) find that relying on a probability weighting function with a linear utility function as in Yaari's (1987) dual theory fits the data better than relying solely on a utility function from a EU model. While these studies involving racetrack betting data also generally support the hypothesis of overweighting of small probabilities, the estimation of winning odds relies on aggregate data, and cannot differentiate between whether the estimated odds arise from misperception of probability or from nonlinear weighting of probability (Barseghyan, et al 2013). In using probabilities that are explicitly specified, our estimation of the probability weighting function is not subject to this objection. Moreover, in our estimation, we focus on using a negative exponential utility function after ruling out the use of a power function including the linear case based on the theoretical implications of our the observed choice behavior.

The paper proceeds as follows. Section 2 describes the structure of lotteries and how we implement them, and presents our experimental design. Section 3 presents the observed choice patterns. Section 4 focuses on the implications of our results on different models and the structural estimations the probability weighting functions. We conclude in Section 5.

2. Experimental Design

As discussed in the Introduction, we develop an experimental design using three kinds of fixed-odds-fixed-payoff state lotteries in China known as 1D, 3D and 5D. A 1D ticket pays RMB10 if the buyer chooses a one-digit number between *0* and *9* which matches a single winning number. Similarly, for each 3D ticket, each consumer chooses one 3-digit number from *000* to *999* and wins RMB1,000 if it matches a single winning number. This is similarly the case for each 5D ticket which pays RMB100,000 if the consumer's 5-digit number matches the winning number. The digit lottery tickets are on sale daily, including weekends, through authorized outlets by two state-owned companies at RMB2 each. The China Welfare Lottery sells the 1D lottery and the China Sports Lottery sells both 3D and 5D lotteries. The winning numbers for each lottery are generated using Bingo blowers by independent government agents and are telecast live daily at 8pm. Consumers can pick their own numbers or have a computer generate random numbers at the sales outlet. Winners can cash winning tickets at the lottery outlets.

Figure 1 in the Introduction presents the parametric structure of the binary lotteries used in this paper. Aside from 10^{-1}, 10^{-3}, and 10^{-5}, we can generate EV10 and EV100 lotteries with winning probabilities of 10^{-2} and 10^{-4} using different combinations of tickets. Each lottery used in the experiment is binary, paying outcome x with probability p and paying outcome 0 otherwise. We denote such a lottery as (x, p) and the certainty case of $(z, 1)$ as $[z]$. For example, $(10^3, 10^{-2})$ can come from ten 3D tickets with different numbers and $(10^5, 10^{-4})$ corresponds to ten 5D tickets with different numbers. We can similarly generate two EV100 lotteries, $(10^4, 10^{-2})$ and $(10^6, 10^{-4})$, with these winning probabilities. Notice that this approach does not work for EV1 lotteries and we are limited to using 10^{-1}, 10^{-3}, and 10^{-5} as the winning probabilities for our EV1 lotteries (see Appendix Table AI for more details on these lottery products and how we generate the lotteries used in the experiment).[5] Overall, we include *4* lotteries for EV1, *10* lotteries for EV10, and *10* lotteries for EV100 (see Table AI). Each subject always chooses between two lotteries the bulk of which have the same expected payoffs except for *4* comparisons in which one choice stochastically dominates the other (see Table AIII for details) to test for subjects' "rationality" or attentiveness. We randomize the order of appearance of the binary comparisons as well as the order of appearance within each comparison.

Definition and elicitation of risk attitude. Our design enables the elicitation of subjects' risk attitude among lotteries with the same expected payoff,[6] giving rise to *6* binary choices for EV1 and *45* binary choices for EV10 and EV100 lotteries. Subjects choose between pairs of equal-mean lotteries $(m/q, q)$ and $(m/r, r)$ with $q > r$. As is customary, we refer to a preference for $(m/q, q)$ over $(m/r, r)$ as being *risk averse* and the opposite preference for $(m/r, r)$ over $(m/q, q)$ as being *risk preferring*. We say that the decision maker exhibits *longshot preference* at expected payoff m for winning probabilities over $(0, \theta)$ if receiving the lottery $(m/p, p)$ is preferred to receiving its expected payoff m for sure for p in $(0, \theta)$, and for p in $(\theta, 1)$, $(m/p, p)$ is not preferred to receiving its expected payoff m for sure. For a decision maker with longshot preference at m over $(0, \theta)$, we further say that she exhibits a *single-peak property* at p^* in $(0, \theta)$ if $(m/p, p)$ is monotonically increasing in preference for p in $(0, p^*)$ and monotonically decreasing in preference for p in (p^*, θ). As the most preferred winning

[5] One product, 2D, paying RMB98 rather than RMB100 at 1% chance, is used in constructing four binary comparisons to detect violations of stochastic dominance (see Table AIII in Appendix A). It is part of the main design in Figure 1.

[6] We do not use other elicitation mechanisms, e.g., Holt and Laury's (2002) the price-list design since subject's willingness to pay may presumably be limited by the market price of RMB2 for the lotteries.

odds goes to infinity, the limiting preference is consistent with Chew and Tan's (2005) definition of a *monotonic longshot preference* corresponding to the case decision maker is increasingly risk seeking once she becomes risk seeking at a sufficiently small probability of winning.

Implementation. The experiment was conducted in an internet-based setting. Running experiments online has become increasingly common in experimental economics research. For example, Von Gaudecker et al (2008) compare laboratory and internet-based experiments and show that the observed differences arise more from sample selection rather than the mode of implementation. Moreover, they find virtually no difference between the behavior of students in the lab and that of young highly educated subjects in the internet-based experiments. The internet-based experiment is convenient for collecting large samples, which could be helpful to conduct individual level analysis.

The potential subjects (*N = 1,282*) are Beijing-based universities students who have received compensations from participating previously in our experiment in both classroom and online settings. We sent email invitations followed by two reminder emails over a two-month period. Appendix B displays the instructions and a sample screen for the experiment. Each subject received RMB20 for participation. In addition, in order to incentivize their choices, *10%* of the subjects are randomly selected to be compensated by receiving his/her chosen lottery from a randomly selected choice out of 100 choices made. Based on our survey data, the average monthly expenses of the students is about RMB1,200. In the end, we have a sample of *836* subjects (*50.0%* females; average age = *21.8*) with a high response rate of *65%*. On average, subjects spent *19.3* minutes in the experiment.

3. Results

In this section, we report the risk preference among lotteries with the same expected payoffs of *1*, *10* and *100* as well as comparisons of risk attitudes elicited at different expected payoffs. An overall sense of observed behavior can be seen from Table I presenting the aggregate proportions of risk averse choice at the three levels of expected payoffs (see Table AI in the appendix for details of additional lotteries considered).

At expected payoff of *1*, subjects generally exhibit risk affinity except for being risk averse between 10^{-3} and 10^{-5}. In particular, the winning probability of 10^{-3} seems favored since $(1000, 10^{-3})$ seems preferred to *[1]*, and preferred to $(100000, 10^{-5})$. This suggests that subjects may favor winning odds of 10^{-3} in aggregate among EV1 lotteries. At expected payoff of *10*, subjects are generally risk seeking relative to receiving expected payoff for sure but are risk averse between pairs of lotteries. For EV100, subjects are risk averse for all comparisons. Overall, we can discern a trend in switching from risk aversion to risk affinity as expected payoff decreases.

3.1. **Preference within the same EV**

To investigate longshot preference, we examine subjects' choice behavior among equal-mean lotteries. There are four lotteries with winning probabilities of 1, 10^{-1}, 10^{-3}, and 10^{-5}, which are common to three levels of expected payoffs. This yields six binary choices which in turn give rise to *64* possible choice patterns.[7] To compare across all three levels of expected payoff, we focus on the *64* possible patterns from the six comparisons involving probabilities of 1, 10^{-1}, 10^{-3}, and 10^{-5}. Of these, *24* patterns are consistent with transitivity and can be listed in an ascending order (e.g., 1053 refers to $10^{-3} \succ 10^{-5} \succ 1 \succ 10^{-1}$) as displayed in Table AII in the appendix. At all three levels of expected payoff, subjects exhibit high rates of transitive choice – *84.4%* (EV1), *82.9%* (EV10), and *86.7%* (EV100) – significantly exceeding the chance rate of *24/64* in each case ($p < 0.001$) with *61.5%* exhibiting transitivity across all three levels of expected payoff. This suggests that subjects' choices among equal-mean lotteries with probabilities of 1, 10^{-1}, 10^{-3}, and 10^{-5} are well-behaved.

We categorize the observed transitive choice patterns into two main classes. The first refers to six purely risk averse patterns − 1350, 1530, 3150, 3510, 5130, and 5310 − which reflect the behavior of subjects who would rather not take on any of the three lotteries. The second refers to the six choice patterns with receiving the expected payoff for sure as being the least preferred − 0135, 0153, 0315, 0351, 0513, and 0531 − which are compatible with having a preference for longshot over an interval encompassing $(0, 10^{-1}]$. Of these, four exhibit a single-peak property: 0531 (*at* 10^{-1}); 0153 and 0513 (*at* 10^{-3}); and 0135 (*at* 10^{-5}).

Table II displays the frequencies of choice patterns corresponding to the two main classes of behavior over equal-mean lotteries for each EV. For EV1 lotteries, a majority of our subjects (*61.8%*) exhibit longshot preference encompassing $(0, 10^{-1}]$ with the bulk of them (*56.6%*) being single-peak while only *12.3%* are risk averse. Among those with single-peak

[7] For EV10 and EV100, we have six lotteries with winning probabilities of 1, 10^{-1}, 10^{-2}, 10^{-3}, 10^{-4}, and 10^{-5}, giving rise to 2^{15} possible binary choice patterns which is *512* times more than is the case for EV1.

preference, the observed frequency at each peak is significantly higher than the corresponding chance rate.

For EV10 lotteries, a good proportion (*37.7%*) exhibit longshot preference comprising predominantly of those with single-peak behavior (*31.9%*) while *29.7%* are risk averse. As with the EV1 lotteries, among those with single-peak preference, the observed frequencies at each peak are significantly higher than the corresponding chance rate. For EV100 lotteries, a strong majority (*69.4%*) of the subjects are risk averse while a small proportion (*7.4%*) have longshot preference the bulk of whom (*6.0%*) are single-peak. The only significant single-peak pattern is 10^{-5} which may pick up choices by subjects with single-peak preference beyond 10^{-5} and is observationally indistinguishable from monotonic longshot preference.

As expected payoff increases, there is an overall migration in choice frequencies from longshot preference towards risk aversion with single-peak patterns showing signs of persistence, especially at 10^{-5}. Tests of difference in patterns reveal significantly different proportions of longshot preference, single-peak preference, and risk averse patterns across three EV levels in each case (Wilcoxon test, $p < 0.001$).

At the individual level, among subjects with single-peak preference, there is a consistent tendency for the favored winning probability to increase as expected payoff increases. This is apparent from the two-way tables in Table III focusing on subjects who are either risk averse or have single-peak longshot preference encompassing $(0, 10^{-1}]$ across EV1 and EV10 (*Panel A*), across EV10 and EV100 (*Panel B*) and across EV1 and EV100 (*Panel C*). Results of Pearson's Chi-squared tests show that the occurrences of the different types across expected payoffs are not statistically independent ($p < 0.001$). Of *120* subjects who favor 10^{-3} at EV1, *52* switch to 10^{-1}, *9* switch to 10^{-5}, 16 switch to being risk averse, with *43* remaining at 10^{-3}, when comparing among EV10 lotteries. Of *50* subjects favoring 10^{-1} at EV1, *43* become risk averse at EV10. By contrast, all *95* subjects who are risk averse at EV1 remain risk averse at EV10. Between EV10 and EV100, of 163 subjects with single-peak preference at 10^{-1}, 10^{-3} or 10^{-5} at EV10, 119 become risk averse at EV100. Between EV1 and EV100, of 340 subjects with single-peak preference at 10^{-1}, 10^{-3} or 10^{-5} at EV1, 296 become risk averse at EV100.

Besides longshot preference and single-peak behavior over an interval encompassing $(0, 10^{-1}]$, we identify additional choice patterns corresponding to longshot preference over narrower ranges of small probabilities, encompassing $(0, 10^{-3}]$ and $(0, 10^{-5}]$. For longshot preference encompassing $(0, 10^{-3}]$, the corresponding choice patterns are 1035 and 1053. The choice patterns for longshot preference encompassing *(0, 10^{-5}]* are 1305 and 3105. The observed frequencies are respectively *0.2%* (EV1), *0%* (EV10), and *0.6%* (EV100) for *(0, 10^{-3}]* and *5.4%* (EV1), *2.3%* (EV10) and *1.2%* (EV100) for *(0, 10^{-5}]* (see Table AII in the appendix). Here, the only significant pattern occurs at EV1 (*5.4%*) with longshot preference encompassing *(0, 10^{-5}]*. While the risk averse and longshot/single-peak classifications capture the bulk of the observed transitive patterns, there remain four individually significant choice patterns – 5301 (*5.4%*), 3501 (*2.3%*), and 5031 (*3.8%*) at EV10 and 5301 (*5.3%*) at EV100, each with 10^{-1} as the favored winning probability.

Summarizing, we have the following overall observation of risk attitude involving equal-mean comparisons.

Observation 1. *Subjects exhibit significant incidence of single-peak longshot preference encompassing (0, 10^{-1}) across both EV1 and EV10 while they are predominantly risk averse for EV100 lotteries and the favored winning probability tends to increase as expected payoff increases.*

3.2. **Preference across EVs**

Our design enables us to investigate small-probability risk attitude as expected payoff increases in the following ways: keeping winning outcome fixed or winning probability fixed; keeping the same ratio of winning probabilities in pairs of lotteries with common winning outcomes.

Common winning probability and common winning outcome. We observe risk attitude relative to expected payoff across the three levels of expected payoff while fixing the same winning probability at 10^{-1}, 10^{-3}, and 10^{-5} successively. We also do this while fixing the winning outcome at *1,000* and *100,000* as winning probability varies between 10^{-5} and 10^{-1}. In each case, there are three comparisons between a lottery and receiving its expected payoff for sure, giving rise to eight possible choice patterns. Of these, four are compatible with the tendency of a switch from risk aversion to risk affinity as expected payoff decreases: being risk averse across all three levels of expected payoff (AAA), being risk seeking at EV1 and EV10 and risk averse at EV100 (SSA), being risk seeking for EV1 and risk averse for EV10 and EV100 (SAA), and being risk seeking at all the three EVs (SSS). Table IV displays the percentage for these patterns with the four remaining patterns – ASS, AAS, SAS, and ASA – denoted collectively as “Others”.

From Table IV, we see that the bulk of our subjects exhibit switching behavior with high degree of consistency. Specifically, the proportions of single-switch behavior – *61.5%* ($x = 10^3$), *64.4%* ($x = 10^5$), *57.9%* ($p = 10^{-1}$), *63.4%* ($p = 10^{-3}$), and *65.5%* ($p = 10^{-5}$) – are each significantly higher than those of no-switch ($p < 0.001$). Note that the proportions of "Others", given by *7.4%, 2.3%, 1.8%, 3.8%,* and *2.6%,* are each minuscule relative to the corresponding chance rate of *1/2 (*4 out of 8 possible patterns, $p < 0.001$ in each case).

Summarizing, we have:

Observation 2A. *Subjects tend to switch from being risk averse to risk seeking as expected payoff decreases when <u>either</u> winning outcome <u>or</u> winning probability is fixed.*

Common ratio of winning probabilities in pairs of lotteries. We compare the observed risk attitudes towards different pairs of equal-mean lotteries when they share the same winning outcomes – z and z/α – and the same ratio α of winning probabilities, e.g., (z, q) and $(z/\alpha, \alpha q)$ versus (z, r) and $(z/\alpha, \alpha r)$. This comparison gives rise to four possible choice patterns – SS (expected utility), SA (Allais behavior), AA (reverse Allais behavior) and AS (expected utility) – with the first letter referring to the observed risk attitude – risk averse (A) or risk seeking (S) – for the low-EV comparison and second letter referring to the observed risk attitude for the high-EV comparison. Notice that the SA pattern reflects a fanning-out pattern of the indifference curves in the probability triangle defined by the outcomes of *z*, and z/α and zero which corresponds to an instance of common-ratio Allais behavior.

The overall pattern of switching behavior in risk attitude displayed in Table I reveals 14 instances of Allais behavior. For example, *82.4%* are risk averse in preferring $(10^3, 10^{-1})$ to $(10^5, 10^{-3})$ at EV100 while *59.7%* are risk averse in choosing $(10^3, 10^{-3})$ over $(10^5, 10^{-5})$ at EV1. At the individual level, we observe that 27.4% of the subjects exhibit the SA pattern for *CR4* as shown in Table V with winning outcomes of 10^3 and 10^5 and common ratio of *0.01*. There are 13 additional pairs of common-ratio comparisons including three across EV1 and EV10 (CR1, CR2 and CR3) and ten comparisons across EV10 and EV100 (CR5 – CR14), all involving *0.1* as the common ratio parameter.

The observed incidence of individual-level Allais choice pattern ranging from *13.6%* to *27.4%* is in line with what is reported in the literature based generally on moderate probabilities. For instance, Conlisk (1989) observes that the proportion of individual-level Allais pattern is *43.6%* for his basic treatment and *10.8%* for his three-step treatment. In a recent study, List and Haigh (2005) find the proportion of such patterns to be *43%* among student subjects and only *13%* for professional traders. More recently, with a sample of *1424*, Huck and Muller (2012) report the proportion of Allais behavior to be *49.4%* in a high hypothetical-payoff treatment, *19.6%* in a low hypothetical-payoff treatment, and *25.6%* in a low real-payoff treatment.

One may ask whether the observed patterns of EU violation are systematic. We investigate this question using Conlisk's (1989) test which takes as null hypothesis the violations of expected utility and compares the frequencies of Allais and reverse Allais behavior. Taking the 14 comparisons in Table V together, we find Allais violations to be significantly more pronounced than reverse Allais behavior ($Z = 27.17$, $p < 0.001$). For these 14 comparisons, the proportion of Allais pattern is each significant at $p < 0.003$, suggesting that violations of expected utility at small probabilities are pervasive.

We further test for the possible presence of a certainty effect in the observed Allais behavior (Kahneman and Tversky, 1979). Examining common-ratio comparisons involving a sure outcome (CR1, CR2, CR5 – CR8) with those without a sure outcome (CR3, CR4, CR9 – CR14), we find that the average proportion common-ratio Allais behavior of *18.8%* for the former and is not significantly different from *16.7%* for the latter ($D = 1.118$, $p > 0.1$). This finding does not support a certainty effect underpinning the observed common-ratio Allais behavior in our experiment.

Summarizing, we have the following overall observation.

Observation 2B. *Subjects exhibit systematic equal-mean common-ratio Allais behavior for small probabilities. Interestingly, we do not observe the presence of a certainty effect.*

3.3. **Robustness Analysis**

We include four binary choices (summarized in Table AIII), in which one lottery stochastically dominates another lottery within the pair, and find that *50%* of subjects show no violation with *31%* having *1* violation, *15%* having *2* violations, *4%* having *3* violations, and the remaining *1%* having *4* violations. We make use of the observed degree of violation, which may reflect their level of attention and effort in participating in our experiment, to test whether this factor has influence over the observed choice behavior. Subjects are divided into two groups – one without violations and another with at least one violation. Overall, we find that the qualitative features of the observed longshot preference behavior, switching behavior in risk attitude across expected payoffs, and equal-mean common-ratio Allais behavior remain robust for subjects who are more prone to violations of stochastic dominance (see detailed results summarized in tables AIV, AV and AVI in Appendix A).

4. Theoretical Implications and Structural Estimation

In this section, we study the implications of our results for four non-expected utility models of decision making under risk: rank-dependent utility (RDU – Quiggin, 1982), weighted utility (WU – Chew, 1983), disappointment aversion utility (DAU – Gul, 1991), and salience utility (SU – Bordalo, Gennaioli, and Shleifer, 2012) – in addition to expected utility (EU).[8] This is followed by a structural estimation of the utility models considered under specific parameterizations of the utility function and decision weight function. Our estimation results help discriminate among utility models beyond their abilities to account for the observed choice behavior at a theoretical level.

4.1 **Theoretical implications**

In our setting of lotteries of the form (x, p) with outcome $x > 0$, for RDU, DAU, and WU, the utility of (x, p) is obtained by taking the product of a utility function on outcome, $u(x)$, and a decision weight assigned to the outcome x, which may be different from p, except for EU when it always coincides with p. In this setting, RDU shares the same specification of a probability weighting function $\pi(p)$ with prospect theory and cumulative prospect theory (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992), while DAU can be viewed as a one-parameter specialization of the RDU model with $\pi(p)$ given by $p/[1 + (1 - p)\beta]$ where $\beta > -1$. In contrast, both WU and SU incorporate a dependence of the degree of probability weighting on the magnitude of the winning outcome. The WU probability weighting function is given by $ps(x)/[ps(x) + 1 - p]$ with a positive-valued weight function s which equals 1 at 0. Between (x, p) and $[px]$, SU first compares the salience for the state of winning (x, px) and the state of losing $(0, px)$. If the winning state is assigned a higher salience value, the winning probability p would then be over weighted using $p/[p + (1 - p)\delta]$ $(\delta < 1)$, which coincides with DAU with $\delta = 1 + \beta$.[9] Otherwise, p is under weighted using $p\delta/[p\delta + (1 - p)]$.

[8] WU and DAU axiomatize different subclasses of preferences satisfying the *betweenness* axiom (Chew, 1983; Dekel, 1986) – when two lotteries are indifferent, each is indifferent to any probability mixture of the two lotteries.

[9] When overweighting, the SU probability weighting function also coincides with Rachlin, Raineri, and Cross's (1991) form $(1 + \delta(1 - p)/p)^{-1}$ with δ interpreted in terms of hyperbolic discounting of the odds $(1 - p)/p$ against yourself winning.

Using EU, to model the possible incidence of risk affinity, it is necessary to introduce a nonconcave utility function. For the other non-expected utility models, risk affinity can occur in conjunction with a concave utility function over gains if the decision weight assigned to the winning outcome exceeds its probability of occurrence p sufficiently. Under RDU, this decision weight is given by $\pi(p)$ which is typically assumed to be inverse S-shape, i.e., $\pi(p) > p$ over $(0, \tau)$ and $\pi(p) < p$ over $(\tau, 1)$ for some crossing point τ in $(0, 1)$.

For RDU, we shall be examining three well-known forms of π in the literature:

$p^c/[p^c+(1-p)^c]^{1/c}$	TK92 – Tversky and Kahneman (1992)
$\tau p^d/[\tau p^d+(1-p)^d]$	LBW92 – Lattimore, Baker, and Witte (1992)
$exp\{-\beta[-\ln p]^{\alpha}\}$	P98 – Prelec (1998)

Under the betweenness approach, the probability weighting function of its DAU subclass (Gul 1991 – G91) discussed earlier coincides with LBW92 with $\tau = (1+\beta)^{-1}$ and $d = 1$. For its WU subclass, the winning outcome x is always over weighted by its decision weight $ps(x)/(ps(x) + 1 - p)$ with an increasing s function, and the degree of overweighting increases in the size of the outcome. Between (y, p) and $[py]$, SU assigns different salience values to the winning state (y, py) and the losing state $(0, py)$, using a salience function σ. One specific salience function $\sigma(x, y)$ taking the form of $\frac{|x-y|}{x+y+\theta}$ assigns a higher salience for (y, py) than $(0, py)$ when $\theta/y > p^2/(1 - 2p)$, and consequently overweighs the winning outcome with $p/(p + (1 - p)\delta)$ $(\delta < 1)$. Otherwise, the winning state is under weighted by $p\delta/(p\delta + 1 - p)$. We refer to this probability weighting function as BGS12, which coincides with G91 when overweighing smaller probabilities.

4.1.1 <u>Preference for longshot</u>

Expected utility. To exhibit longshot preference at expected payoff m over a range of probabilities $(0, \theta)$, it is necessary for the utility function u to satisfy $u(y)/u(m) > y/m$, for $y \geq m/\theta$. While this requirement is not compatible with u being concave, it is compatible with u being convex beyond the winning payoff m/θ (consider, e.g., the utility functions in Friedman and Savage, 1948, and Golec and Tamarkin, 1998). This would deliver monotonic longshot preference which, in terms of our choice data, would correspond to 10^{-5} being the favored winning probability. With an S-shaped utility function which is initially convex and eventually concave, EU can exhibit single-peak longshot preference at intermediate probabilities with the peak winning probability p^* solving the following FOC:

$$(m/p)u'(m/p)/u(m/p) = 1. \qquad (1)$$

In this case, as m varies, the ratio of p^* and m remains the same, which is not consistent with the choice behavior summarized under Observation 1. Specifically, from Table II, we see that *24.5%* of our subjects are single-peak at 10^{-3} and *23.3%* are single-peak at 10^{-5} when expected payoff equals *1*. Yet, only *1.7%* and *3.2%* are single-peak at 10^{-1} and at 10^{-3} when expected payoff equals *100*. Thus, the observed departure from constancy in the ratio of m and p^* may be viewed as a new behavioral anomaly for expected utility.

Rank-dependent utility. RDU can exhibit longshot preference at m over $(0, \theta)$ under the maintained assumption of u being concave as long as $\pi(m/y) > u(m)/u(y)$ for $m/y < \theta$ and $\pi(m/y) \leq u(m)/u(y)$ for $m/y > \theta$.[10] This condition can be satisfied as long as π overweighs sufficiently over $(0, \theta)$ and does not overweigh much over $[\theta, 0)$. In particular, Yaari's (1987) model, corresponding to RDU with $u(x) = x$, exhibits longshot preference over $(0, \theta)$ as long as $\pi(p) > p$ and $\pi(p) \leq p$ over $(\theta, 1)$. RDU can further exhibit single-peak longshot preference at p^* in $(0, \theta)$ if it solves the following FOC:

$$(m/p)u'(m/p)/u(m/p) = p\pi'(p)/\pi(p), \qquad (2)$$

i.e., when utility elasticity on the LHS equals that of the probability weighting function on the RHS. Thus, for RDU to exhibit single-peak longshot preference over $(0, \theta)$, it suffices for u to be sufficiently concave to compensate for its argument m/p which is convex in p so that the composite function $u(m/p)$ remains concave in p, i.e., $-u''(m/p)/u'(m/p) > 2p/m$ for p over $(0, \theta)$. For a negative exponential u function, as p decreases towards 0, LHS of (2) decreases asymptotically towards 0. This also delivers the following implication – p^* increases as m increases – which is supported by our experimental evidence in Observation 1. It is straightforward to verify that the RHS of (2) is decreasing in p for each of the three parametric classes of TK92, LBW92 and P98. For RDU with a power u function, the LHS of (2) becomes constant implying that the single-peak probability p^* would be independent on m. This implication is inconsistent with our observation of 10^{-1} and 10^{-3} being peaks at EV1 and EV10, but not at EV100. Notably, Yaari's model with a concave π function over small probabilities cannot exhibit single-peak behavior since its utility of $(m/p, p)$ strictly increases as p, *i.e.*, it always exhibits monotonic longshot preference.

[10] Should u be a convex function, the π function would also need to be convex to accommodate any risk averse behavior. This precludes single-peak longshot preference behavior since the utility of $(m/p, p)$, given by $\pi(p)u(m/p)$, would be a convex function of p. Moreover, having a convex u function will imply the opposite switching behavior – from risk aversion to risk affinity – as expected payoff increases with p fixed.

Betweenness. The DAU subclass of betweenness conforming preferences can account for Observation 1 given that it behaves similarly as RDU with G91 as its probability weighting function.[11] For its WU subclass, the condition for longshot preference at m over $(0, \theta)$ is given by:

$$ps(m/p)\,/[ps(m/p) + 1 – p] > u(m/p)/u(m),$$

for p in $(0, \theta)$ and $ps(m/p)\,/[ps(m/p) + 1 – p] \le u(m/p)/u(m)$ for p in $(\theta, 1)$. The corresponding FOC for single-peak behavior is given by

$$u'(m/p)/u(m/p) = s'(m/p)/\{s(m/p)[1 + s(m/p)(p^{-1}– 1)^{-1}]\}. \tag{3}$$

It follows that a solution p^* to (3) exists when its LHS increases in p while its RHS decreases in p. As with RDU, WU delivers the experimentally supported implication that p^* increases as m increases. We can verify that condition (3) is satisfied by a negative exponential u and a power s function given by $1 + bx^{\gamma}$ ($b, \gamma \in (0, 1)$). If instead, we adopt an increasing exponential s function given by $e^{\rho x}$ ($\rho > 0$), then (3) has no solution and the decision maker exhibits monotonic longshot preference behavior as shown in Chew and Tan (2005) which is observationally equivalent to single-peak preference at 10^{-5} for our data. In general, we can show that WU exhibits monotonic longshot preference behavior as long as

$$s'(y)/s(y) \ge 1/(y – m). \tag{4}$$

Notice that condition (4) becomes more stringent as m increases. This is compatible with the observed declining proportion of single-peak preference at 10^{-5}, as proxy for monotonic longshot preference, as expected payoff increases. We can further check that condition (4) is satisfied by WU with a power s function whose exponent γ exceeds unity.

Salience utility. In comparing $[py]$ with (y, p), the winning state (y, py) is overweighted when $\sigma(y, py) > \sigma(0, py)$ for small p, which coincides with DAU. Hence, SU can similarly account for Observation 1.

4.1.2 Switching behavior across expected payoffs

Given that Observation 2B on the pervasiveness of common-ratio Allais behavior is compatible with all three non-expected utility models considered but not for EU, we focus our exposition here on the implications of Observation 2A.

Expected utility. As discussed in the preceding sub-subsection, to exhibit longshot preference over an interval of small probabilities, the utility function under EU would need to be convex

[11] It suffices to observe that the RHS of (2) given by $(1 – p + p/\beta)^{-1}$ which decreases from 1 to β as p increases from 0 to 1.

for sufficiently high outcomes. However, this implies the opposite behavior to what is exposited in Observation 2A, i.e., switching from risk aversion to risk seeking as expected payoff increases keeping winning probability or winning outcome fixed.

Rank-dependent utility. Consider the difference, $u(px) - \pi(p)u(x)$, between the utility of receiving the expected payoff px for sure and the utility of receiving the lottery (x, p) with decision weight $\pi(p)$. This can be expressed in terms of the difference between the utility ratio $u(px)/u(x)$ and decision weight $\pi(p)$:

$$u(px)/u(x) - \pi(p). \quad (5)$$

To exhibit the fixed-probability switching behavior in Observation 2A, it suffices for the utility ratio $u(px)/u(x)$ to be increasing in x, as would be the case with a negative exponential u function. Notice that this analysis rules out the case of the utility ratio $u(px)/u(x)$ being constant in x, as with the case of a power u function which includes the linear case of Yaari (1987).

To exhibit the fixed-outcome switching behavior in Observation 2A, it is necessary for the decision weight $\pi(p)$ to increase in p faster than $u(px)/u(x)$ for p small. As a function of p, the initial slope of the utility ratio term is given by $xu'(0)/u(x)$ which is unbounded in x if u is bounded from above, as would be the case of a negative exponential function. For such a u function, a sufficient condition for the fixed-outcome switching behavior is for the π function to have infinite initial slope at 0. We note that this is the case for TK92, P98, LBW92 (when $d < 1$), but not for a polynomial (e.g., Blavatskyy, 2013) or LBW92 with $d = 1$ which coincides with the specification in Rachlin, Raineri, and Cross (1991) and in Gul (1991). We further observe that this infinite-initial-slope condition is necessary if we require this switching property to hold for any fixed outcome x.

Betweenness. As observed in the preceding discussion, in terms of switching behavior, DAU behaves much like RDU with a π function which has finite initial slope. For WU, consider the difference between the utility ratio $u(px)/u(x)$ and the decision weight assigned to the winning outcome x:

$$u(px)/u(x) - ps(x)/[ps(x) + 1 - p]. \quad (6)$$

To exhibit the fixed-probability switching behavior in Observation 2A, observe that condition (6) can be satisfied with $u(px)/u(x)$ increases in x initially slower than $ps(x)u(x)/[ps(x)+1- p]$. This rules out using a power u function (including convex ones) for which the utility ratio $u(px)/u(x)$ would not depend on x. The resulting behavior would then be opposite to the fixed-probability switching behavior in Observation 2A. With a negative exponential u function, we can verify that WU can exhibit the fixed-outcome switching behavior with s being a power function but not an exponential function.

To exhibit the fixed-outcome switching behavior in Observation 2A, it suffices for $u(px)/u(x)$ to be initially increasing in p slower than $ps(x)u(x)/[ps(x)+1-p]$. This rules out using a u function whose initial slope is infinite, e.g., the power function with exponent less than 1, while the initial slope of the right-hand term is given by $s(x)$. In contrast, for a negative exponential $u = 1 - e^{-\lambda x}$, condition (6) is satisfied as long as $s(x) \geq \lambda x$.

Salience utility. That SU can exhibit the switching behavior in Observation 2A follows from observing that its probability weighting function BGS12 switches from the winning state (y, py) being more salient to the losing state $(0, py)$ being more salient as winning probability p or winning outcome y increases.[12]

4.2 **Structural Estimation**

In view of the discussion in the previous subsection about the power utility function not being compatible with the observed choice behavior in conjunction with either of the rank-dependent, the weighted utility or the salience utility model,[13] we focus on using the negative exponential utility function in our structural estimation of goodness-of-fit of the models. We first compare the fitness of different parametrizations within each model. Subsequently, we compare the best parametrizations from the respective models and arrive at salience utility delivering the best overall fit.

With our binary choice data, the probability of choosing (x, p) over (y, q) is given by.

$$\Phi((U(x, p) - U(y, \theta))/\mu)$$

where $\Phi(\cdot)$ is the cumulative normal distribution and μ is a 'noise' term. In coming up with group estimates, we pool the 96 observed choices of the 836 subjects. This yields the following likelihood function:

$$\ln L(R; x, X) = \Sigma_j \Sigma_i \{ \ln \Phi(U(x\ p) - U(y, \theta)) I(y_i=1)) + \ln(1 - \Phi(U(x, p) - U(y, \theta))[1 - I(y_i=1))\},$$

[12] For the specific σ function suggested Bordalo, Gennaioli, and Shleifer (2012), this difference $\frac{(1-p)y}{(1+p)y+\theta} - \frac{py}{py+\theta}$ with $\theta = 0.1$ could switch when p is fixed at 10^{-3} while winning outcome increases and when winning outcome is fixed at 10^3 while winning probability increases.

[13] Besides theoretical considerations, our data being exclusively based on one positive outcome would not enable identification of a power utility function, as pointed out in Wakker (2010) and Fehr-Duda and Epper (2012).

where R represents the parameters to be estimated and X represents the lottery-related parameters. The indicator function $I(y_i = 1)$ equals one when the j-th subject chooses (x, p) over (y, q) during the i-th comparison, and equals zero otherwise. The maximum likelihood estimation is done in *Stata 10*, and variances are clustered by individuals and our estimation results are reported in Table VI.

To discriminate among non-nested models, Clarke (2003, 2006) offers a non-parametric sign test which is especially suitable when the underlying distribution of the log of the likelihood ratios is not normally distributed. We conduct a Shapiro-Wilk test for normality for the likelihood ratios for all the models, and find that they are all significantly different from normality ($p < 0.001$).

EU model. The λ parameter in the exponential function is marginally but significantly greater than zero. This suggests that subjects are on average slightly risk averse.

RDU models. In our estimation of TK92, LBW92, and P98, and λ in the exponential utility function are significantly greater than zero, pointing to a concave utility function. In all three specifications, the estimated parameters in the probability weighting function reflect overweighting of winning probabilities. We further compare the fitness of the three models using the Clarke test and find that LBW98 performs significantly better than TK92 ($p < 0.001$) as well as P98 ($p < 0.001$).

Betweenness models. The estimated parameters correspond to overweighting of winning probabilities. The result of Clarke test favors WU with a power *s* function over an exponential *s* function and favors WU with an exponential *s* function over DAU ($p < 0.001$).

Salience utility. We make use of the specific σ function discussed in the preceding subsection and find that the estimated parameters correspond to overweighting of the winning outcome in two ways of comparing between two lotteries: being independent of each other and having the lower probability winning state subsumed in the higher winning probability state. We further find that the latter specification fits the data significantly better ($p < 0.001$). [14]

[14] There are some issues specific to estimating SU. Firstly, there is some flexibility in defining the states of the world under SU. When comparing between two lotteries, (x, p) and (y, q) with $p > q$, we may define three states $\{(x, y), (x, 0), (0, 0)\}$ or four states $\{(x, y), (x, 0), (0, y), (0, 0)\}$. We report the estimates under both specifications in Table VI. Secondly, the parameter θ determining relative salience is not uniquely determined, i.e., there is a range of θ values giving rise to the same level of relative salience, the same levels of likelihood and the same levels of utility for the lotteries considered. We estimate the likelihoods for a range of θ from 0 to 100 at increment of 0.01, and choose an interval which delivers the maximum likelihood ratio. For the three-state specification, maximum likelihood ratio is attained when θ is within the interval of [0.26, 0.40]. For the four-state specification, maximum likelihood ratio is attained when θ is 2.01.

Overall fit. We apply the Clarke test to compare the best of the four classes of models. Adopting the perspective of viewing the lower probability winning state in one lottery as being subsumed in the higher winning probability state of another lottery, salience utility performs better than RDU with LBW98 and WU with a power *s* function which in turn performs better than EU with exponential utility ($p < 0.001$).

5. Conclusion

Our study makes use of a novel lottery ticket design in an incentivized experimental setting to investigate individual preference over longshot risks involving fixed outcomes which can be extremely sizable, and fixed probabilities which can be extremely small. We find strong evidence of longshot preference for EV1 and EV10 lotteries but not EV100 where subjects are predominantly risk averse. Moreover, our longshot preferring subjects tend to exhibit single-peak behavior, favoring specific winning odds, and that the favourite odds tend to increase as expected payoff increases. When comparing the elicited risk attitudes across lotteries with different expected payoffs, we find a robust pattern of switching from risk aversion to risk affinity as expected payoff decreases, including a form of common-ratio Allais behavior.

To account for our experimental evidence, we examine four non-expected utility models: RDU, WU, DAU, and SU. Interestingly, we find that the use of a power *u* function in conjunction with each of these models is incompatible with the overall evidence. With an exponential *u* function, the qualitative features of the observed choice behavior are generally compatible with the models considered under specific conditions: RDU whose π function has infinite initial slope, WU with an increasing *s* function and SU whose salience function assigns higher salience to the winning state when expected payoff is small and low salience when expected payoff is large. In particular, RDU can model the limiting case of monotonic longshot preference only with a linear *u* function which is part of the class of power *u* functions and WU can model single-peak and monotonic longshot preference and the observed switching behavior across expected payoffs with a power s function, but it can only exhibit monotonic longshot preference and exhibit the opposite switching behavior holding winning probability fixed. In a structural estimation using a negative exponential *u* function, we find that LBW92 fits the data better than TK92 and P98 under RDU and that power *s* function performs better than exponential *s* function under WU. Overall, SU performs better in than both RDU with LBW92 and WU with a power *s* function.

Besides helping to discriminate among utility models which can describe a rich range of attitude towards longshot risk, our results demonstrate that longshot preference, especially single-peak behavior, can arise in a controlled laboratory setting with fixed odds and fixed outcomes without relying on market interactions or a role for information asymmetry. The observed behavior, including the high degree of transitive choice in Table II, stable patterns of migration in single-peak preference in Table III, and consistency in switching behaviour in observations 2A and 2B, suggests that people have well-behaved preferences for risks involving extremely small probabilities. The significant incidence of single-peak longshot preference at smaller expected payoffs but not for high expected payoff suggests a rationale for pricing lottery tickets low and for moderating the winning odds in the design of lottery products.

One direction of future research, both theoretical and experimental, is to study the influence of longshot preference in different market and institutional settings. For instance, sales campaigns being tied to sweepstakes as a marketing tool (Kalra and Shi, 2010) variations of the lottery used by charities to induce contributions (Morgan, 2000), and the winner-take-all feature in a patent race and the star system in sports and the performing arts (Rosen, 1981) may lead aspirants to invest disproportionately. The observed prevalence of single-peak preference, however, points to the need to moderate the winning probabilities in implementing marketing and promotional strategies and tournament incentive schemes. Another direction of follow up research involves studying attitude towards longshot hazards, building on earlier findings in the setting of insurance purchase that people tend to be more pessimistic when facing sizable losses than smaller ones (see, e.g., Barseghyan et al., 2013; Etchart-Vincent's, 2004). Kunreuther (1978) reveals that the demand for disaster insurance may decline when the probability of a significant loss becomes non-negligible leading to sizable expected loss. This finding, in line with the reflection effect posited in Kahneman and Tversky (1979), leads us to ask if we may observe single-peak behavior also in the loss domain and, if so, might there be a corresponding tendency for the most undesired losing odds to become greater with an increase in expected loss? Further research towards addressing these questions may help shed light on the design of insurance policies as well as complement the formulation of corporate strategy for risk management.

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Table I. Proportion of Risk Seeking Choice at Each EV.

Winning probability		*% Risk seeking choices*		
Higher	*Lower*	*EV1*	*EV10*	*EV100*
1	*10^{-1}*	75.8%	60.2%	19.6%
1	*10^{-2}*	-	55.0%	18.5%
1	*10^{-3}*	80.3%	55.3%	16.0%
1	*10^{-4}*	-	52.8%	14.5%
1	*10^{-5}*	79.8%	51.9%	14.5%
10^{-1}	*10^{-2}*	-	33.3%	24.7%
10^{-1}	*10^{-3}*	61.5%	35.2%	17.6%
10^{-1}	*10^{-4}*	-	31.3%	19.3%
10^{-1}	*10^{-5}*	63.3%	32.3%	17.8%
10^{-2}	*10^{-3}*	-	29.7%	28.6%
10^{-2}	*10^{-4}*	-	27.5%	24.5%
10^{-2}	*10^{-5}*	-	28.5%	24.5%
10^{-3}	*10^{-4}*	-	37.8%	38.0%
10^{-3}	*10^{-5}*	40.3%	39.1%	32.8%
10^{-4}	*10^{-5}*	-	43.8%	41.1%

Note. The first (second) column presents the winning probability for the lottery with higher (lower) probability. The third, fourth and fifth columns display the proportions of risk seeking choice for EV1, EV10 and EV100 respectively.

Table II. Frequencies of Choice Patterns corresponding to Different Risk Attitudes.

Risk Attitude	*Chance Rate*	*EV1*	*EV10*	*EV100*
Risk Aversion	6/64	12.3%**	29.7%***	69.4%***
Longshot Preference	6/64	61.8%***	37.7%***	7.4%
Single-Peak	4/64	56.6%***	31.9%***	6.0%
@ 10^{-1}	1/64	8.7%***	9.7%***	1.7%
@ 10^{-3}	2/64	24.5%***	10.6%***	1.1%
@ 10^{-5}	1/64	23.3%***	11.6%***	3.2%***
Total Transitive	24/64	84.4%***	82.9%***	86.7%***

Note. The table presents the choice patterns for the chance rate (Second column) and the frequency of EV1, EV10 and EV100 respectively (column 3 to 5). The first choice pattern – risk aversion – is summarized in the second row. The second choice pattern – longshot preference – is summarized in the third row. Single-peak, one significant type of longshot preference, is summarized in the fourth row. We separately count the frequency of each of the single peak pattern at 10^{-1}, 10^{-3}, 10^{-5} (row 5 to row 7). The last row summarizes the frequencies for the total transitive patterns. We test the difference between the chance rate and the observed frequency and the three levels of significance 10%, 5%, and 1% based on proportion tests are indicated by *, **, and *** respectively.

Table III. Single-peak Longshot Preference across EVs.

	Panel A: EV1 and EV10					
		EV10				
		1	*10^{-1}*	*10^{-3}*	*10^{-5}*	*Total*
EV1	*1*	95	0	0	0	*95*
	10^{-1}	43	4	2	1	*50*
	10^{-3}	16	52	43	9	*120*
	10^{-5}	2	10	30	72	*114*
	Total	156	66	75	82	379

	Panel B: EV10 and EV100					
		EV100				
		1	*10^{-1}*	*10^{-3}*	*10^{-5}*	*Total*
EV10	*1*	231	0	0	0	*231*
	10^{-1}	62	1	0	0	*63*
	10^{-3}	35	12	4	1	*52*
	10^{-5}	22	1	2	23	*48*
	Total	350	14	6	24	*394*

	Panel C: EV1 and EV100					
		EV100				
		1	10^{-1}	10^{-3}	10^{-5}	Total
EV1	*1*	96	0	0	0	*96*
	10^{-1}	67	0	0	0	*67*
	10^{-3}	145	10	2	1	*158*
	10^{-5}	84	3	4	24	*115*
	Total	392	13	6	25	*436*

Note. Panel A shows the counts for subjects who are either risk averse, denoted by "*1*", or have single-peak longshot preference at *10^{-1}, 10^{-3}* or *10^{-5}* across EV1 and EV10 respectively. Panel B (resp: Panel C) shows the corresponding counts for subjects across EV10 and EV100 (resp: across EV1 and EV100). Pearson's chi-squared tests are highly significant (*$p < 0.001$*).

Table IV. Percentage of Across-EV Choice Patterns.

Panel A: Fixed winning probability								
Probability	*EV1*	*EV10*	*EV100*	*SSS*	*SSA*	*SAA*	*AAA*	*Others*
10^{-1}	10	10^2	10^3	16.9%	37.3%	20.6%	17.8%	7.4%
10^{-3}	10^3	10^4	10^5	14.8%	37.9%	25.7%	18.1%	2.3%
10^{-5}	10^5	10^6	10^7	13.6%	37.2%	28.3%	19.0%	1.8%

Panel B: Fixed winning outcome								
Outcome	EV1	EV10	EV100	SSS	SSA	SAA	AAA	Others
10^3	10^{-3}	10^{-2}	10^{-1}	16.9%	37.1%	24.4%	18.9%	3.8%
10^5	10^{-5}	10^{-4}	10^{-3}	14.1%	37.6%	26.8%	18.9%	2.6%

Note. Panel A presents the percentage of choice patterns across three levels of EVs fixing the winning probability constant. Panel B presents the percentage of choice patterns across three levels of EVs fixing the winning outcome constant. SSS (risk seeking at all three EVs), SSA (risk seeking at EV1 and EV10 and risk averse at EV100), SAA (risk seeking at EV1 and risk averse at EV10 and EV100), and AAA (risk averse at all three EVs).

Table V. Allais Behavior across Three Levels of EV.

CR	*Lower EV*	*Higher EV*	*Allais*	*Reverse*
1	$(10,10^{-1})$ vs $(10^3,10^{-3})$	$[10]$ vs $(10^3,10^{-2})$	15.6%	9.1%
2	$(10,10^{-1})$ vs $(10^5,10^{-5})$	$[10]$ vs $(10^5,10^{-4})$	17.1%	6.6%
3	$(10^3,10^{-3})$ vs $(10^5,10^{-5})$	$(10^3,10^{-2})$ vs $(10^5,10^{-4})$	18.5%	5.7%
4	$(10^3,10^{-3})$ vs $(10^5,10^{-5})$	$(10^3,10^{-1})$ vs $(10^5,10^{-3})$	27.4%	4.7%
5	$(10^2,10^{-1})$ vs $(10^3,10^{-2})$	$[10^2]$ vs $(10^3,10^{-1})$	20.7%	7.1%
6	$(10^2,10^{-1})$ vs $(10^4,10^{-3})$	$[10^2]$ vs $(10^4,10^{-2})$	20.9%	4.3%
7	$(10^2,10^{-1})$ vs $(10^5,10^{-4})$	$[10^2]$ vs $(10^5,10^{-3})$	18.3%	3.0%
8	$(10^2,10^{-1})$ vs $(10^6,10^{-5})$	$[10^2]$ vs $(10^6,10^{-4})$	20.3%	2.5%
9	$(10^3,10^{-2})$ vs $(10^4,10^{-3})$	$(10^3,10^{-1})$ vs $(10^4,10^{-2})$	15.0%	10.0%
10	$(10^3,10^{-2})$ vs $(10^5,10^{-4})$	$(10^3,10^{-1})$ vs $(10^5,10^{-3})$	15.7%	5.7%
11	$(10^3,10^{-2})$ vs $(10^6,10^{-5})$	$(10^3,10^{-1})$ vs $(10^6,10^{-4})$	15.1%	6.0%
12	$(10^4,10^{-3})$ vs $(10^5,10^{-4})$	$(10^4,10^{-1})$ vs $(10^5,10^{-3})$	18.5%	9.3%
13	$(10^4,10^{-3})$ vs $(10^6,10^{-5})$	$(10^4,10^{-2})$ vs $(10^6,10^{-4})$	20.7%	6.1%
14	$(10^5,10^{-4})$ vs $(10^6,10^{-5})$	$(10^5,10^{-3})$ vs $(10^6,10^{-4})$	13.6%	7.9%

Note. The first column numbers the CR (common-ratio Allais) cases. The second (third) column presents the lower (higher) EV comparison. The last two columns display rates of Allais behavior and the corresponding rates of reverse Allais behavior. CR1 – CR3 compare EV1 and EV10; CR4 compares EV1 and EV100; CR5 – CR14 compare EV10 vs EV100.

Table VI. Structural Estimation of Utility Models.

Variable	*Estimate*	*Standard Error*	*z-value*	*p-value*	*Lower 95% CI*	*Upper 95% CI*
EU: Exponential function				Log-likelihood		-50856.3
λ	0.0000841	9.65E-06	8.72	0	6.52E-05	0.000103
RDU: TK92				Log-likelihood		-49981.8
λ	0.0025828	0.0001131	22.84	0	0.0023612	0.0028045
τ	0.4256265	0.0061708	68.97	0	0.413532	0.4377209
RDU: LBW92				Log-likelihood		-49522.614
λ	0.0117622	0.0008753	13.44	0	0.0100466	0.0134778
τ	0.436473	0.0070104	62.26	0	0.4227328	0.4502132
d	1.944978	0.0617912	31.48	0	1.823869	2.066086
RDU: P98				Log-likelihood		-49444.952
λ	0.0632548	0.0026253	24.09	0	0.0581092	0.0684004
α	0.9357821	0.0531202	17.62	0	0.8316683	1.039896
β	0.1010325	0.0118087	8.56	0	0.077888	0.1241771
DAU				Log-likelihood		-50126.569
λ	0.026721	0.0020717	12.9	0	0.0226605	0.0307815
β	0.9962899	0.0004715	-2113.02	0	-0.9972141	-0.9953658
WU: Power s function				Log-likelihood		-49962.471
λ	0.0178705	0.0009655	18.51	0	0.0159783	0.0197628
B	0.5836361	0.0369564	15.79	0	0.5112029	0.6560693
γ	0.6141595	0.1853776	3.31	0.001	0.2508262	0.9774929
WU: Exponential s function				Log-likelihood		-50856.25
λ	0.0000841	9.65E-06	8.72	0	0.0000652	0.000103
ρ	3.49E-10	6.50E-11	5.37	0	2.22E-10	4.76E-10
SU: Correlated states				Log-likelihood		-49713.69
λ	0.017875	0.001291	13.85	0	0.015345	0.020405
δ	0.043355	0.005623	7.71	0	0.032333	0.054376
SU: Independent states				Log-likelihood		-50782.361
λ	0.000131	1.29E-05	10.12	0	0.000131	1.29E-05
δ	0.829006	0.014805	56	0	0.829006	0.014805

Note. The first column presents parameters for the specific models considered. The second, third, fourth, and fifth column presents the estimates, standard error, z-value and p-value, respectively. The last two columns display the lower and upper limits of the 95% confidence interval.

Appendix A: Supplementary tables

Table AI. Lotteries used in Experiment.

x	*EV1*			*EV10*			*EV100*		
	P	*1 Lottery*	*Choice*	*p*	*10 lotteries*	*Choice*	*P*	100 lotteries	Choice
1	1	1 cash	-	-	-	-	-	-	-
10	10^{-1}	1D	75.8%	1	10 cash	-	-	-	-
10^2	-	-	-	10^{-1}	same 1D	60.2%	1	100 cash	-
10^3	10^{-3}	3D	80.3%	10^{-2}	different 3D	55.0%	10^{-1}	different 3D	19.6%
2×10^3	-	-	-	5×10^{-3}	5 same 3D	56.8%	-	-	-
5×10^3	-	-	-	2×10^{-3}	2 same 3D	54.4%	-	-	-
10^4	-	-	-	10^{-3}	same 3D	55.3%	10^{-2}	10 x 10 3D	18.5%
2×10^4	-	-	-	-	-	-	5×10^{-3}	50 same 3D	17.6%
5×10^4	-	-	-	-	-	-	2×10^{-3}	20 same 3D	16.5%
10^5	10^{-5}	5D	79.8%	10^{-4}	different 5D	52.8%	10^{-3}	same 3D	16.0%
2×10^5	-	-	-	5×10^{-5}	5 same 5D	51.9%	-	-	-
5×10^5	-	-	-	2×10^{-5}	2 same 5D	51.6%	-	-	-
10^6	-	-	-	10^{-5}	same 5D	51.9%	10^{-4}	10 x 10 5D	14.5%
2×10^6	-	-	-	-	-	-	5×10^{-5}	50 same 5D	15.0%
5×10^6	-	-	-	-	-	-	2×10^{-5}	20 same 5D	14.0%
10^7	-	-	-	-	-	-	10^{-5}	same 5D	14.5%

Note. Besides the lotteries listed in Table I, the present table lists additionally eight lotteries in boldfaced. The choice frequencies of the additional lotteries relative to [EV] appear similar to those corresponding to the adjacent lotteries. Column 1 displays the winning outcome. Columns 2, 5 and 8 displays the winning probability for EV1, EV10 and EV100, respectively. Columns 3, 6 and 9 displays the way we implement the individual lotteries using different combinations of 1D, 3D, and 5D tickets for EV1, EV10 and EV100, respectively. Columns 4, 7 and 10 displays the percentage choosing the lottery over the corresponding expected payoff for EV1, EV10 and EV100, respectively.

Table AII. Percentage of Transitive Choice Patterns.

	Transitive Pattern				*Risk Attitude*	*EV1*	*EV10*	*EV100*
A1	5	3	1	0	RA	8.6%***	20.3%***	47.2%***
A2	3	5	1	0	RA	1.30%	5.7%***	14.0%***
A3	5	1	3	0	RA	0.50%	1.00%	2.8%***
A4	1	5	3	0	RA	0.50%	0.00%	0.50%
A5	1	3	5	0	RA	1.20%	2.20%	2.8%***
A6	3	1	5	0	RA	0.20%	0.50%	1.00%
A7	5	3	0	1	-	1.10%	5.4%***	5.3%***
A8	3	5	0	1	-	0.70%	2.3%*	1.70%
A9	5	1	0	3	-	0.10%	0.00%	0.00%
A10	1	5	0	3	-	0.10%	0.20%	0.00%
A11	3	1	0	5	LSP5	0.00%	0.00%	0.10%
A12	1	3	0	5	LSP5	0.20%	0.00%	0.50%
S12	5	0	3	1	-	1.40%	3.8%***	0.60%
S11	5	0	1	3	-	0.40%	0.40%	0.10%
S10	3	0	5	1	-	0.60%	1.00%	0.50%
S9	3	0	1	5	-	0.20%	0.20%	0.00%
S8	1	0	5	3	LSP3	2.6%**	0.80%	0.50%
S7	1	0	3	5	LSP3	2.8%***	1.40%	0.70%
S6	0	3	5	1	LSP1	3.0%***	4.2%***	0.60%
S5	0	3	1	5	LSP1	2.3%*	1.60%	0.80%
S4	0	5	3	1	SP1/LSP1	8.7%***	9.7%***	1.70%
S3	0	5	1	3	SP3/LSP1	3.5%***	2.9%***	0.60%
S2	0	1	5	3	SP3/LSP1	21.1%***	7.8%***	0.50%
S1	0	1	3	5	SP5/LSP1	23.6%***	11.6%***	3.2%***
					Total	84.4%***	82.9%***	86.7***

Note. Each pattern lists the 4 options in ascending order of preference, e.g., 1053 (S8) means that *(10^3, 10^{-3})* $\succ$ *(10^5, 10^{-5})* $\succ$ *[1]* $\succ$ *(10, 10^{-1})* for EV1. Against a chance rate of 1.6% (1 out of 64 possible patterns), the per cell threshold frequencies for the three levels of significance *10%, **5%, ***1% are 2.3%, 2.5% and 2.8% respectively. RA stands for risk aversion, LSP1, LSP3, and LSP5 stand for longshot preference encompassing (0, 10^{-1}], encompassing (0, 10^{-3}], and encompassing (0, 10^{-5}] respectively.

Table AIII. Lotteries with Stochastic Dominance

1A	1/100,000 chance receiving RMB100,000 and 99,999/100,000 chance of receiving 0.
1B	1/100,000 chance receiving RMB10,000 and 99,999/100,000 chance of receiving 0.
2A	1/10,000 chance receiving RMB100,000 and 9,999/10,000 chance of receiving 0.
2B	1/100,000 chance receiving RMB100,000 and 99,999/100,000 chance of receiving 0
3A	50/1,000 chance receiving RMB980,500/1,000 chance of receiving RMB98,and 450/1,000 chance of receiving 0
3B	50/1,000 chance receiving RMB9,800,500/1,000 chance of receiving RMB980,and 450/1,000 chance of receiving 0
4A	10/100,000 chance receiving RMB1,000,000,5000/100,000 chance of receiving RMB1,000,and 94,990/100,000 chance of receiving 0.
4B	5/100,000 chance receiving RMB1,000,000,5000/100,000 chance of receiving RMB1,000,and 94995/100,000 chance of receiving 0 Yuan

Note. The table presents four pairs of lotteries in which one dominates another in terms of first order stochastic dominance.

Table AIV. Effect of Violation of Dominance on Longshot Patterns.

Longshot Risk Attitude	*Chance*	*With Violation*			*Without Violation*		
		EV1	*EV10*	*EV100*	*EV1*	*EV10*	*EV100*
Risk Aversion	6/64	9.3%	24.6%	60.5%	15.3%	34.7%	78.2%
Longshot Preference	6/64	61.7%	40.2%	9.8%	62.0%	35.2%	5.0%
Single-Peak	4/64	56.0%	33.7%	7.9%	57.2%	30.1%	4.1%
@ 10^{-1}	1/64	7.7%	7.7%	2.2%	9.8%	11.7%	1.2%
@ 10^{-3}	2/64	21.1%	11.0%	1.2%	28.0%	10.3%	1.0%
@ 10^{-5}	1/64	27.3%	15.1%	4.5%	19.4%	8.1%	1.9%
Total Transitive	24/64	81.8%	78.5%	81.6%	87.1%	87.3%	91.9%

Note. The table presents the choice patterns for the chance rate (Second column), the frequency of EV1, EV10 and EV100 respectively (column 3 to 5) for those with violation, and the frequency of EV1, EV10 and EV100 respectively (column 6 to 8) for those without violation. The first choice pattern – risk aversion – is summarized in the second row. The second choice pattern – longshot preference – is summarized in the third row. Single-peak, one significant type of longshot preference is summarized in the fourth row. Separately, we report the frequencies of single-peak behavior at 10^{-1}, 10^{-3}, 10^{-5} (row 5 to row 7). The last row summarizes the total frequencies for transitive patterns.

Table AV. Effect of Violation of Stochastic Dominance on Across-EV Choice Patterns.

Panel A: Fixed winning probability					
p	*Choice Pattern*	*With Violation*		*Without Violation*	
		Mean	*Std. Dev.*	*Mean*	*Std. Dev.*
	AAA	0.156	0.018	0.201	0.020
	SAA	0.194	0.019	0.218	0.020
10^{-1}	SSA	0.371	0.024	0.376	0.024
	SSS	0.194	0.019	0.144	0.017
	Others	0.086	0.014	0.062	0.012
	AAA	0.148	0.017	0.213	0.020
	SAA	0.251	0.021	0.263	0.022
10^{-3}	SSA	0.373	0.024	0.409	0.024
	SSS	0.189	0.019	0.108	0.015
	Others	0.038	0.009	0.007	0.004
	AAA	0.151	0.018	0.230	0.021
	SAA	0.258	0.021	0.309	0.023
10^{-5}	SSA	0.376	0.024	0.368	0.024
	SSS	0.187	0.019	0.086	0.014
	Others	0.029	0.008	0.007	0.004
Panel B: Fixed winning outcome					
x	*Choice Pattern*	*With Violation*		*Without Violation*	
		Mean	*Std. Dev.*	*Mean*	*Std. Dev.*
	AAA	0.156	0.018	0.206	0.020
	SAA	0.234	0.021	0.254	0.021
1,000	SSA	0.366	0.024	0.376	0.024
	SSS	0.206	0.020	0.132	0.017
	Others	0.038	0.009	0.033	0.009
	AAA	0.156	0.018	0.222	0.020
	SAA	0.249	0.021	0.287	0.022
100,000	SSA	0.380	0.024	0.371	0.024
	SSS	0.182	0.019	0.100	0.015
	Others	0.033	0.009	0.019	0.007

Note. Panel A presents the percentage of choice patterns across three levels of EVs fixing the winning probability constant for those with and without violation. Panel B presents the percentage of choice patterns across three levels of EVs fixing the winning outcome constant for those with and without violation. SSS (risk seeking at all three EVs), SSA (risk seeking at EV1 and EV10 and risk averse at EV100), SAA (risk seeking at EV1 and risk averse at EV10 and EV100), and AAA (risk averse at all three EVs). Using multinomial logistic regression, we find that no-violation subjects tend to exhibit more AAA and less SSS, suggesting that they are generally more risk averse ($10^{-1}, p < 0.103$; $10^{-3}, p < 0.001$; $10^{-5}, p < 0.001$; $10^{3}, p < 0.039$; $10^{5}, p < 0.002$). The overall single-switch behavior for both groups appear similar.

Table AVI. Effect of Violation of Stochastic Dominance on Allais Behavior.

Allais Behavior	*With Violation*		*Without Violation*		*p-value*
	Mean	*Std. Dev.*	*Mean*	*Std. Dev.*	
EV1 – EV10	0.175	0.241	0.163	0.235	0.584
EV10 – EV100	0.210	0.824	0.149	0.166	0.001
EV1 – EV100	0.299	0.458	0.249	0.433	0.104

Note. The table lists the mean and standard deviation of the incidence of Allais behavior for those with violation (column 2, 3), those with violation (column 4, 5), and the level of significance in the difference between the two group using ordered Probit with robust standard error (column 6). The overall proportions of Allais behavior for these two groups appear similar. While subjects without violation exhibit significantly lower incidence of Allais behavior for EV10 vs EV100 than those with violation, we do not observe significant difference between EV1 and EV10 and between EV1 and EV100.

Appendix B: Experimental Instructions

Thank you for participation in the study on decision making. Please read the following instructions carefully before you make decisions.

Tasks

In this study, you will make a number of binary choices as illustrated in the following two examples.

Example 1. In the following two options, which one will you choose?

A. 1/1000 chance receiving 2000 Yuan, 999/1000 chance receiving 0

B. 1/100,000 chance receiving 200,000 Yuan, 99,000/100,00 receiving 0

Choosing A means that you have 1/1000 chance to get 2000 Yuan, 999/1000 chances to get 0. Choosing B means that you have 1/100,000 chances to get 200,000 Yuan, 99,000/100,000 chances to get 0.

Example 2. In the following two options, which one will you choose?

A. 1/1000 chance receiving 100,000 Yuan, 999/1000 chance receiving 0

B. receiving 100 for sure

Choosing A means that you have 1/1000 chance to get 100,000 Yuan, 999/1000 chances to get 0. Choosing B means that you get 100 Yuan for sure.

In each round, you have two options to choose, and there are 100 rounds in total. The probability and amount of money may be different in each round. We will use lotteries with different combination to realize the corresponding probability and amount of money.

Details of Rules for Lottery

Three types of lotteries are used in this study including “Array 3” and “Array 5” of China Sports Lottery, and “3D” of China Welfare Lottery. You can refer to the detailed rules of these three lotteries. Below is a brief introduction of these three types of lotteries.

Array 3. Buyers can choose a 3-digit number from 000 to 999. If the number chosen by the buyer is the winning number (same digit numbers with same order), the buyer of the lottery wins 1000 Yuan. That is, the probability to win 1000 Yuan is 1/1000 for a randomly chosen number.

For example, if the winning number is 543 and you have 10 lotteries with number of 543, you will get 10,000 Yuan. That is, you have 1/1000 chance to win 10,000 Yuan with 10 lotteries of same number.

Array 5. Buyers can choose a 5-digit number from 00000 to 99999. If the number chosen by the buyer is the winning number (same digit number with same order), the buyer of the lottery wins 100,000 Yuan. That is, the probability to win 100,000 Yuan is 1/100,000 for a randomly chosen number.

For example, if the winning number is 54321 and you have 10 lotteries with number of 54321, then you will get 1000,000 Yuan. That is, you have 1/100,000 chance to win 1000,000 Yuan with 10 lotteries of same number.

3D. 3D is similar to Array 3. Buyers can bet on a 3-digit number from 000 to 999. If the number chosen by the buyer is the winning number (same digit numbers with same order), the buyer of the lottery wins 1000 Yuan. The probability to win 1000 Yuan is 1/1000 for a randomly chosen number. Lottery 3D has another two ways of betting.

"2D" Betting: Buyers can bet on the first two digits, last two digits or the first and last digit of a 3-digit number from 000-999. The chosen two digits should have the same order and in the same position as the winning number. The winning amount is 98 Yuan for each ticket.

"1D" Betting: Buyers can bet on the ones, tens and hundreds of a 3-digit number from 000-999. The chosen digit should have the same order and in the same position as the winning number. The winning amount is 10 Yuan for each ticket.

Detailed rules for "Array 3in China Sports Lottery:

http://www.lottery.gov.cn/news/10006630.shtml

Detailed rules for "Array 5" in China Sports Lottery:

http://www.lottery.gov.cn/news/10006657.shtml

Detailed rules for"3D" in China Welfare Lottery:

http://www.bwlc.net/help/3d.jsp

We will realize corresponding probability and the amount by combining kinds of lotteries. In Option A of Example 1, you have 1/1000 chance to receive 2000 Yuan with two "Array 3" lotteries with same number. In Option A of Example 2, you have 1/1000 chances to win 100,000 Yuan with 100 "Array 3" with same number.

In a similar manner, you will get lottery combinations with different probability to win various amounts. In this experiment, all the numbers of lotteries are generated randomly by computer. We will buy these lotteries from lottery stores.

Payment

Every participant in the experiment will get 20 Yuan for the base payment. You have 10% chances to get the additional payment. It is randomly chosen in the following ways. We will add your birthday (year, month and date, 8 numbers for total) to get a one-digit number (0-9). If this number is the same as the sum of "3D" Welfare lottery on Feb 28, 2013, you will get the additional payment. Which means, you have approximately 10% chances to get the additional payment.

The amount of additional payment is decided in the following way. You will be asked to randomly choose one number of 1-100, which determines one decision out of your 100 decisions. Your payment will depend on that decision you made on that particular round. If what you choose on that round is certain amount of money, you will get that amount of money. If what you choose on that round is a lottery, then your payment is through lottery.

Time for payment

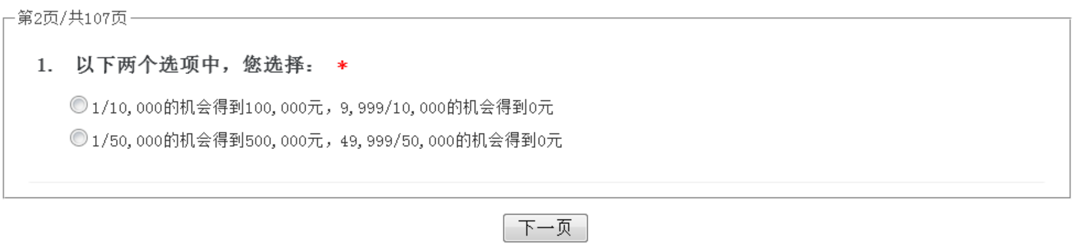
The payment will be implemented around March – April, 2013. The specific date will be announced later.

Summary for Rules:

1. You will be asked to make decisions between two options in each of the 100 rounds.
2. The probabilities and amounts of money in each decision can be realized by combinations of lotteries.
3. Every participant will get 20 Yuan for base payment.
4. 10% of participant will be randomly chosen to get additional payment, and the payment will be based on one randomly chosen decision out of the 100 decisions they made.

If you have any questions for this experiment, please feel free to email us at b2ess@nus.edu.sg. If you are clear about the instructions, you can start and make your decisions now.

Sample Screen



Translation

Page 2/107 Pages

1. In the following two options, which one will you choose?
   - □ 1/10,000 chance receiving 100,000 Yuan, 9,999/10,000 chance receiving 0
   - □ 1/50,000 chance receiving 500,000 Yuan, 49,999/50,00 receiving 0