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Abstract

Both risk perception and risk preference jointly determine behavior under risk and uncertainty. It is, however, important to disentangle the effects of the two. In this paper, we focus on the role of risk preference. Using a survey study in the context of housing price, we show that respondents are less risk averse (or more risk loving) when a possible adverse outcome is in presence. A controlled laboratory experiment was then conducted to further investigate the role of possible adverse outcome on risk preference and the experimental results confirm the phenomenon. In addition, a structural analysis demonstrates that the commonly used utility functions (CRRA and Expo – Power) do not explain the observed change in risk preference caused by possible negative outcome. We also discuss some behavioral explanations that could potentially explain the phenomenon.

1 Introduction

People make decisions – whether to purchase a house without knowing its exact future price or whether to invest in a company's stock without knowing its exact future performance – to cope with different risks. Inadequate perception of risks may lead to irrational decisions. The heated housing markets in the near past in cities such as Las Vegas, Miami and Phoenix have been described as good examples of risk misperception. "Investors are prepared to buy houses they will rent out at a loss, just because they think prices will keep rising – the very definition of a financial bubble."[1] Many of us attribute such purchasing behavior to irrationality or a decision driven by risk misperception. For instance, an August 2005 Lehman Brothers report suggests that they realized that a significant decline in house prices would cause subprime securitization deals to suffer enormous losses. Specifically, in the report's "meltdown" scenario for house prices, the cumulative collateral losses would be 17.1 percent as all but the highest-rated securities in the subprime pools default. However, Lehman's analysts assigned the "meltdown" scenario a probability of only 5 percent (Rosengren et al., 2010). Nonetheless, if business decision makers do believe that the probability of the "meltdown" scenario is 5 percent, should their decisions still be explained by risk misperception?

In the current study, we concern a more fundamental question rather than using risk misperception or irrationality as the only explanation. That is, do home buyers or investors, in general, have consistent risk preference that can explain their behavior regardless of market prospects? Despite investors' perception bias, their risk preference undoubtedly plays an important role in their buying or investing decisions. Hence, it is important to distinguish behavior induced by risk misperception and behavior induced by (possible) inconsistent risk preference. Motivated by the above facts in the housing market, in this paper, we first look into individuals' response to hypothetical risks associated with housing purchase in a randomized survey study, and then test the same idea in an incentivized laboratory environment.

Many researchers have studied risk aversion and most of the studies were done within the expected utility theory (EUT) framework (Savage, 1954; Von Neumann and Morgenstern, 1947). Pratt (1964) defined local risk aversion which was henceforth known as the Arrow–Pratt measure of risk aversion.

[1] See the Economist: http://www.economist.com/node/4079027.

More importantly, he argued that risk aversion can be represented by a concave Bernoulli utility function within the EUT framework. Many empirical works also adopt this notion of risk aversion. For example, Koudstaal et al. (2015) studies the risk attitudes of managers and executives with a "lab in the field" study design. Brenner (2015) elicited risk attitudes of U.S. executives by calibrating a subjective option valuation model and concluded moderate relative risk aversion among executives. In recent years, much work has been done to seek alternative explanations to risk averse behavior because many anomalies revealed the inability of EUT to fully explain risk aversion. For example, prospect theory, being the most successful alternative theory to EUT, argues that people treat gains and losses differently at their reference points and distort objective probabilities associated with possible outcomes (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992). There are also empirical evidence as well as psychological evidence supporting explanations provided by prospect theory (Benartzi and Thaler, 1999; Mohr et al., 2010; Takahashi et al., 2010). Using elements from prospect theory(i.e. loss aversion), researchers show that risk preference is affected by losses (Fafchamps et al., 2015; Page et al., 2014).

We are interested in people's risk attitudes when making buying or investment decisions. Therefore, separating the role of risk preference from risk misperception is critical. Unlike Fafchamps et al. (2015) and Page et al. (2014) that studied the effect after a loss, we focus on the change in preference when a possible loss is *simultaneously* presented to decision makers. To achieve this goal, we first conducted a randomized survey in the streets in Beijing with 268 valid responses in total. The respondents had to provide their maximum willingness to pay in 14 different risky scenarios, which are combinations of different housing values in the baseline period and probabilities of housing price appreciation. Respondents were randomly assigned into either control or treatment group. In the control group, there is no probability associated with housing price depreciation. In the treatment group, respondents were asked exactly the same questions except that housing price could potentially fall. By comparing the responses with the same baseline housing value and the same probability of housing price appreciation in both groups, we find that the respondents in the treatment group, where an odd of price depreciation was present, significantly failed to make sufficient downward adjustment to their willingness to pay. Such finding provides preliminary evidence that individuals may underweight the downside risk associated with housing values. Given that the probabilities of possible future outcomes are always revealed to respondents, any bias in their decision making should not be due to incorrect perceptions of the risk itself. Rather, it is due to their inconsistent risk preference in gain and loss domains. Moreover, in analyzing the data, we follow Kechelmeier and Shehata (1992) to use a nonparametric measure of risk aversion which is the certainty equivalent/expected value ratio to show the change in risk preference. We believe that this is a less theory dependent measure of risk aversion when compared with the Arrow–Pratt measure. Similar approach was also adopted by other researchers such as Holm et al. (2013).

Because all the responses we received from the survey study are answers to hypothetical questions, we then designed a controlled laboratory experiment to simulate the same idea in an economic laboratory where subjects were paid real money determined by the decisions they made in the laboratory. The findings in the laboratory experiment also confirm the survey results. Specifically, both the within– and between–subject designs suggest that individuals are significantly less risk averse in the presence of a 10% probability of adverse outcome. A structural analysis shows that both the often used Constant Relative Risk Aversion(CRRA) and the more flexible Expo–power utility function fail to provide a set of uniform parameters that explain the experimental data. If we believe that EUT is the underlying model, this result further suggests that people have different risk preferences when a possible negative outcome is in its presence.

The main contribution of the current study is twofold. On the one hand, we study the effect of possible negative outcome on risk preference through both a survey and incentivized laboratory experiment. This complements the literature that mainly focuses on positive outcomes when examining risk preference. The answer to this question also has immediate policy implications. If the presence of possible negative outcome alters risk preference, it would be sensible for the policy maker to consider such alteration before making any policy. On the other hand, we conduct survey and laboratory studies to disentangle the effect of risk preference change and risk misperception. This cannot be easily achieved with only real world data because decision makers' subjective beliefs are rarely known to researchers (Barseghyan et al., 2013).

The rest of the paper is organized as follows. In section 2, we explain our study design, including the survey and laboratory experiment, in details. Section 3 reports reduced form analysis of the results followed by a structural estimation. In section 4, we briefly discuss the results and provide some possible explanations. Lastly, section 5 concludes the paper.

2 Research Design

To study individual's risk preference under different risky prospects, we start with a randomized survey in the context of housing purchase. We provide various scenarios of price change in the near future and ask the respondents about their willingness to pay, so that we can elicit their risk preferences. We then carry out an incentivized lab experiment using lotteries to elicit individuals' risk preference using both within–subject and between–subject designs.

2.1 Survey Study

The survey study was conducted in year 2014 in Beijing, which is a major metropolitan area in China. Researcher approached people in the streets including both adults and university students. In total, we collected 268 valid responses for both the control and treatment groups. For control group, 106 responses were from adults while 26 responses were from students. For the treatment group, 108 responses were from adults while 28 from students. By checking all the demographic variables collected, we confirm that a balanced sample between control and treatment groups were obtained[2].

To examine their risk attitudes, the respondents were asked the maximum amount they would pay to buy an apartment in different scenarios (different probability of price increase). Panel B in Table 1 shows all the treatments that we have in the survey study. Within each treatment, the probability of housing price appreciation was varied[3].

Respondents were randomly assigned into either control or treatment groups. The baseline housing value is either 2 million or 5 million *yuan*. In the next 3 years, the housing value could either get doubled, remain the same, or cut by half. In the control group, there is no probability associated with housing price depreciation. In the treatment group, respondents were asked exactly the same question except that housing price could potentially fall. For respondents in both groups, they have to provide their maximum willingness to pay for 14 scenarios, which are combinations of dif-

[2]Demographic variables include gender, age, occupation, employment status, education, household size, monthly consumption, and housing purchase experience and plan.

[3]The probabilities we used were 10%, 20%, 30%, 50%, 70%, 80%, and 90%. For the treatment group, there was also a probability associated with the possible housing price depreciation. The probability was always 10%.

ferent housing values in the baseline period and probabilities of housing price appreciation.

For example, the following is one of the scenarios in the questionnaire for control group.

Scenario 1 (control group): You are considering buying an apartment. If housing price will be rising steadily in the next 3 years, the property will worth 4 million yuan in 3 years, otherwise 2 million yuan (no other possibilities). Now, a reliable private information source releases the following information to you: "The property will be worth 4 million yuan in 3 years with a probability of 10%, otherwise it will be worth 2 million yuan."

Respondents' willingness to pay are then elicited with a table that can be found in the appendix. Correspondingly, the treatment group is:

Scenario 1 (treatment group): You are considering buying an apartment. If housing price will be rising steadily in the next 3 years, the property will be worth 4 million yuan in 3 years; if housing price depreciation happens, the property will be worth 1 million yuan in 3 years; otherwise 2 million yuan (no other possibilities). Now, a reliable private information source releases the following information to you: "The property will be worth 4 million yuan in 3 years with a probability of 10%, 1 million yuan in 3 years with a probability of 10%, otherwise it will be worth 2 million yuan."

Because all the responses we received from the survey study are answers to hypothetical questions, it would be important to study how people respond to the presence of adverse outcome under real incentives. We then designed a laboratory experiment to simulate the same idea in an economic laboratory.

2.2 Laboratory Experiment

This experiment is designed to examine how possible adverse outcome affects risk attitudes towards risky prospects. We employed *both* within–subject and between–subject design in our experiment for two reasons. Firstly, within–subject design allows us to control for individual characteristics. However, such design allows the subjects to use different strategies for different treatments. Secondly, there is a major drawback of using within–subject design: decision makers almost never come across the questions described in different treatments either simultaneously or consecutively in reality. Hence, it is necessary to compare the results from the within–subject sessions with the between–subject sessions to observe the gap between theory and reality.

We define the four different treatments in this paper. A *simple gain prospect*(SGP) is a simple lottery $(x, p; 0, 1-p)$ that wins amount x with probability p and nothing with probability $1-p$; a *simple mixed prospect*(SMP) is a lottery $(x, p; -y, q; 0, 1-p-q)$ that wins amount x with probability p, loses amount y with probability q and nothing with probability $1-p-q$. A *compound gain prospect*(CGP) shares the same form with the *simple gain prospect* except that it adds another layer on top of it. There is a $\frac{1}{3}$ chance of playing the lottery $(x, p-r; 0, 1-p+r)$, $\frac{1}{3}$ chance of playing $(x, p; 0, 1-p)$ and another $\frac{1}{3}$ chance of playing $(x, p+r; 0, 1-p-r)$. The *compound mixed prospect*(CMP) is defined in a similar way. Participants have $\frac{1}{3}$ chance to play $(x, p-r; -y, q; 0, 1-p+r)$, $\frac{1}{3}$ chance to play $(x, p; -y, q; 0, 1-p-q)$ and $\frac{1}{3}$ chance of playing $(x, p+r; -y, q; 0, 1-p-r)$. x and y are positive dollar amounts. p, q, and r are probabilities so $0 \leq p, q, r \leq 1$. In each treatment of our experiment, we divide the probability range from 0 to 1 into 10 equal intervals and p takes the values $p_1 = 0.1$, $p_2 = 0.2$, $\ldots p_9 = 0.9$; $q_1 = q_2 = \ldots = q_9 = q = 0.1$. Again Panel A of Table 1 shows all the treatments we had in both the within–subject sessions and between–subject sessions. The mixed prospects (SMP and CMP) are designed to examine the effect of possible negative outcome. The compound lotteries are designed to test the linear probability assumption in EUT. Note that the between–subject design only applies to the comparison between SGP and SMP as well as CGP and CMP because T1 is always paired with T3 while T2 is always paired with T4.

All the experimental sessions are conducted at a national university in Beijing with undergraduate students as main subject pool. In each treatment of the experiment (SGP, SMP, CGP, or CMP), there are 9 different lottery tickets. Subjects were asked to reveal their certainty equivalents through the iterative Multiple Price List (iMPL) method (Andersen et al., 2006). For each different amount, subjects simply indicate a “yes” or “no” answer. Based on the answers in the first iteration, the computer program further divides the interval into smaller intervals and subjects answer the “yes/no” questions again in the second iteration. For example, if a subject indicates that she chooses the lottery ticket over \$2 but chooses the fixed payment of \$3 over the lottery, the computer program further asks if she would choose the lottery ticket or the fixed amount for ten different amounts between \$2 and \$3[4]. One of the displayed amounts was then randomly drawn by a participant. Answers to that particular amount was implemented (i.e. if lottery ticket was chosen, then the lottery would be played out; if the fixed amount was chosen, the subject would receive the dollar amount). Subjects were also told that only one randomly selected lottery would be played out but they should treat each one as if it was chosen. Details can be found in the appendix.

The experiment consists two waves. In the first wave, the within–subject design was employed. Participants were asked to complete all four treatments in a random order within a single session. After each treatment, a lottery ticket was randomly selected to be played out and subjects were informed their earnings in the treatment. They then completed some survey questions before proceeding to the next treatment. In the second wave, the between–subject design was used. In a single session, subjects only completed two treatments (either SGP and CGP, or SMP and CMP). This was to make the difference between prospects without negative outcome and prospects with negative outcome less salient to subjects. Of course, one cannot make individual level comparisons with these data.

Experimental participants were recruited through emails and posters. When participants arrived at the laboratory, they were firstly directed to a preparation room where the instructor carefully went through the instruction with Microsoft PowerPoint and answered any question the participants might have. Participants were told not to talk with each other during the experiment before they were assigned to separated computer stations. The experimenter then started the session and participants made their decisions at their own pace[5].

3 Results

In this section, we firstly present results from the survey study. Then we follow the literature to analyze our experimental data. In the last subsection, we discuss risk preference in the context of EUT and fit our experimental data to different specifications of the utility function.

Following Kechelmeier and Shehata (1992), we calculate the ratio of a

[4]The ten different amounts increase at \$0.1.

[5]For the reason of determining earnings, participants still needed to move into the next treatment simultaneously.

subject's certainty equivalent for a particular lottery to the same lottery's expected value as a non–parametric measure of risk preference. For example, an individual is indifferent between a lottery ticket that has 50% probability of winning 20 *yuan* and a fixed amount of 8 *yuan*, then the calculated ratio is 8/(20*50%)=0.8 in this case.

3.1 Regression results using survey data

Table 2 presents the simple descriptives for the respondents' willingness to pay in different housing baseline values and risky prospects. It can be shown from the data that the respondents did not make sufficient downward adjustments when the odd of an adverse outcome is present (i.e., the SMP case). Such phenomenon is especially pronounced for the relatively lower housing value.

Figure 1 shows the ratios by different risky prospects and baseline housing values in the survey study. For the two groups with a relatively lower baseline housing value (2 million *yuan*), the ratios for the observations with mixed prospects are dominantly higher than the observations with simple gain prospects under all probabilities. In addition, the SMP group exhibits risk loving patterns under smaller probabilities (0.1, 0.2, 0.3, 0.4 and 0.5). In the two groups with a relatively higher baseline housing value (5 million *yuan*), the respondents are more risk averse on average as indicated by the lower ratios. This is consistent with the literature that higher wealth level is associated with higher risk aversion. Similar to the groups with lower housing values, the ratios for the observations with mixed prospects are higher than the observations with simple gain prospects, with smaller gaps though.

With the collected survey data, we run a simple linear regression. The detailed specification can be found in Equation 1.

$$\begin{aligned}(CE/EV)^i_{jk} =& \alpha_{SMP} D^i_{SMP} + \beta_j Probability_j + \gamma_{SMP,j} D^i_{SMP} \times Probability_j \\ &+ \delta_k Value_k + \eta_{SMP,k} D^i_{SMP} \times Value_k + Constant + \epsilon^i_{jk} \qquad (1)\end{aligned}$$

where i denotes individual survey respondent, j denotes the price scenario in the survey question, and k denotes the value of the target house. D_{SMP} is a treatment dummy variable. Its value equals 1 for respondents in the treated group. $Probability$ is the probability that the house's market value will appreciate. $Value$ is the baseline housing price. ϵ is an error term that follows a normal distribution.

Table 3 shows the survey study results using regression analysis. We regress the ratios and the log ratios of certainty equivalent to expected values on a dummy for the SMP group, dummies for each probability (p=0.1 as the baseline group), an interaction between the SMP dummy and each probability, the baseline housing value (2 million or 5 million), and an interaction between housing value and the SMP dummy. The coefficient on SMP dummy is significantly positive, indicating that the respondents in the SMP group are significantly more risk loving than the SGP group. Such significant difference is especially pronounced for small probabilities, as indicated from the significantly positive interaction terms between SMP and small probabilities (p=0.2, 0.3 and 0.5). In addition, higher housing value is significantly associated with higher risk aversion, especially for the group with mixed prospects.

3.2 Regression results using lab data

Table 4 presents the simple descriptives for the subjects' certainty equivalents for different prospects in different treatments. One can tell from the table that subjects did not make sufficient downward adjustments when a loss became possible (i.e., the SMP and CMP cases). This pattern is consistent with what we observed from the survey data. Figure 2 shows the ratios from the four different treatments in our laboratory experiment. The top panel plots results from the within–subject sessions while the bottom panel plots the between–subject sessions. Points above the reference line represent risk loving and points below reference line are risk averse. One immediate observation is that the degree of risk aversion increases along with the increment in probability of winning. Second observation is that SMP is the least risk averse treatment especially under smaller probabilities. We also conduct the following linear regression that is similar to Equation 1.

$$\begin{aligned}(CE/EV)_j^i = &\alpha_{SMP} D^i_{SMP} + \alpha_{CGP} D^i_{CGP} + \alpha_{CMP} D^i_{CMP} + \beta_j Probability_j + \\ &\gamma_{SMP,j} D^i_{SMP} \times Probability_j + \gamma_{CGP,j} D^i_{CGP} \times Probability_j + \\ &\gamma_{CMP,j} D^i_{CMP} \times Probability_j + Constant + \epsilon^i_j \end{aligned} \tag{2}$$

The rule of notation is the same as in the regression equation for the survey data except that we have more treatment dummy variables for the laboratory data.

Table 5 shows regression results from random–effects model to further examine these patterns[6]. It is worth noting that the presence of possible negative outcome on risk preference only exists for small probabilities[7]. This can be observed from both Figure 2 and Table 5. This result is similar to the ones documented in Kechelmeier and Shehata (1992) except that we are examining the effect of presenting a possible negative outcome to subjects. It is also important to emphasize that we employed the iMPL method as Holt and Laury (2002) while Kechelmeier and Shehata (1992) used Willingness To Accept (WTA) values as the certainty equivalents. WTA values has long been associated with the endowment effects (Kahneman et al., 1990; Thaler, 1980) which could possibly bias the certainty equivalents[8]. Therefore, we believe that our elicitation method is more of a neutral environment and is less vulnerable to bias induced by endowment effects.

It is also worth noting that the difference in CE/EV ratios with and without possible negative outcome only exists in small probabilities (i.e. p=0.1, 0.2). As the probability of the positive outcome increases, the gap between the ratios diminishes. It should not be surprising that the difference in risk preference becomes more prominent when the probability of a positive outcome is small. When the probability of positive outcome is large enough, the CE values are also large, so the downward adjustment in the presence of negative outcome becomes proportionally smaller.

3.3 Structural analysis

Most of the analyses of risk preference are conducted under the EUT framework. In other words, the expected utility are assumed to be linear in probabilities and any risk preference is explained by the curvature of the Bernoulli utility function. In this subsection, we follow the literature to estimate two structural models in the EUT family and show that we cannot solely rely on them to explain the observed risk preferences. Before ending the section, we

[6] We conduct Hausman test to confirm the appropriateness of using the random–effects model. The test resulted in a p value of 1 suggesting that a random–effects model is appropriate.

[7] For the within–subject sessions, F test on the regression coefficients result in p value of 0.0054 and 0.1630 when the probabilities of winning are 10% and 20% respectively. For the between–subject sessions, the two p values are 0.0000 and 0.0309

[8] There are theories that can reconcile the WTA–WTP difference while explaining risk preference such as prospect theory. We do not discuss them here.

conduct a simple hypothesis testing to demonstrate that EUT may fail to explain risk preference in a broader sense.

One of the two models we estimate has the Constant Relative Risk Aversion (CRRA) utility function that many employ in empirical work (shown in Equation 3). The second model features the Expo–power utility function which is more flexible and incorporates the first one as a special case (Saha, 1993) (shown in Equation 4).

$$u(x) = x^{1-r} \tag{3}$$

$$u(x) = \frac{1 - e^{-\alpha x^{1-r}}}{\alpha} \tag{4}$$

Depending on the values of the parameters, the Expo–power utility function can be of increasing, constant or decreasing absolute/relative risk aversion. Regarding relative risk aversion,

$$\frac{-u''(x)x}{u'(x)} = r + \alpha(1-r)x^{1-r} \tag{5}$$

It is easy to see that it reduces to CRRA when $\alpha \to 0$ and to Constant Absolute Risk Aversion(CARA) when $r \to 0$. Combining the Expo–power utility function and linearity in probability, we can then derive the decision rules for our experimental subjects.

$$pu(w+x) + qu(w-y) + (1-p-q)u(w) = u(w+CE) \tag{6}$$

where p is the probability of positive outcome while q is the probability of negative outcome. Note that w is defined as initial wealth level in EUT but in most of previous studies especially experiment studies, researchers used income as the argument of the utility function. We argue that, given our experimental design, $w = 10$ which was the fixed payment given to all subjects at the beginning of the experiment[9]. Although we elicited the values of certainty equivalents in this study, we still follow the estimation technique used by Holt and Laury (2002). This better facilitates any comparison with existing literature. In particular, we restructured the dataset to form pairwise binary choices. Because we used iMPL elicitation technique, each pair is just the lottery on the left and a fixed amount on the right. For the same

[9]We cannot let subjects lose money in the experiment so their overall expected payoffs from any experimental session were always positive.

probability, the lottery on the left hand side does not change while the certain amount on the right hand side varies. Subjects choose either the left (lottery) or right (certain amount) option in each pair.

To form the likelihood function, a stochastic term is needed in the econometric model and the Luce error form is employed here. In Equation 7, μ represents the error term so the representative agent can deviate from the prediction made by the model. $U(\cdot)$ is the expected utility.

$$Pr(ChooseLeft) = \frac{U_{Left}^{1/\mu}}{U_{Left}^{1/\mu} + U_{Right}^{1/\mu}} \tag{7}$$

Estimated structural parameters from maximum likelihood estimation are shown in Table 6. Column (1) is the result from the CRRA model while column (2) is the result from the Expo–power model. Contrary to the results in the reduced–form analysis, with CRRA model, decisions on the mixed prospects show a higher level of risk aversion. This result suggests a possible incorrect specification. For a more straightforward examination of the estimation results, Figure 3 plot the utility functions implied by the estimated parameters with top panel being the CRRA utility function while bottom panel being the Expo–power utility function. With both CRRA and Expo–power functions, the parameters estimated from GP treatments and MP treatments are different from each other. This suggests that the presence of possible negative outcome does alter the risk preference within EUT framework. Admittedly, both CRRA and Expo–power are just two special functional forms of the Bernoulli utility function, but in terms of making predictions, even the most flexible functional form we could find in literature fails to provide a satisfactory solution.

Now, let's assume a general Bernoulli utility function $u(\cdot)$ with $u' > 0, u'' \leq 0$. Decision rules under EUT in SGP and SMP can be expressed in Equation 8. With $q = 0$, it represents the case of SGP and represents SMP when $q \neq 0$[10].

$$u(w + CE) = pu(w + x) + qu(w - y) + (1 - p - q)u(w) \tag{8}$$

Given that $u'' \leq 0$, it is easy to see that

[10] We shall discuss the cases of CGP and CMP later.

$$CE_{SGP} - CE_{SMP} \geq \frac{u(w + CE_{SGP}) - u(w + CE_{SMP})}{u'(w)}$$
$$= \frac{q[u(w) - u(w - y)]}{u'(w)} \geq qy$$

This simple prediction provides a testable hypothesis:

H1 The differences between Certainty Equivalents(CE) elicited from SGP subjects and CE elicited from SMP subjects are greater than the differences in Expected Values(EV)

By examining Table 4, one can notice that **H1** is generally not supported [11]. This is another even stronger evidence that is against the EUT explanation of risk preference. We discuss some possible explanations of this phenomenon in the next section.

4 Discussions

4.1 Gender differences

In the next step, we are interested in the potential heterogeneity by different demographic groups. As surveyed in Eckel and Grossman (2008), females are generally more risk averse than males. Therefore, we interact a dummy for gender (1 if male) with all the regressors in Equation 1. Table 7 shows the survey results. Interestingly, the coefficients on "male" dummy is positive and significant at the 0.1 level. The result suggests that males are more risk loving on average which is consistent with the literature about the gender differences in risk preference. In addition, the interaction of male and the dummy for "SMP" tends to be negative but insignificant. Such negative sign is in line with the previous findings that female is likely to be less rational in decision making. Table 8 further displays the results from the lab experiments. It turns out that gender does not play a significant role in determining the certainty equivalent to expected value ratio. However, the

[11] For the within-subject design, this hypothesis is rejected under one probability. For the between-subject design, this hypothesis is rejected under four probabilities with a significance level of 10%.

signs on gender-related coefficients are expected in most of the regressions. For example, three out of four coefficients on "male" have positive coefficients, suggesting that male respondents are on average more risk loving than female respondents, statistically insignificant though. In addition, three out of four coefficients for the interaction term between "SMP" and "male" are negative, indicating that female respondents display more risk loving with negative risk prospect.

4.2 External validity

Due to practical constraints, we were not able to use working professionals for the laboratory experiment. However, to better understand the external validity of our lab findings, it would be interesting to examine whether working professionals behave differently than university students. Since our survey sample consists both students and working professionals, we generate a dummy for students and interact the dummy with the variables on the right hand side of Equation 1. Table 9 shows the results. Neither the main effect of the "student dummy", nor the interaction term of SMP and the student dummy is significant, indicating that students and working professionals behave indifferently in terms of risk preference in different risk prospects. Therefore, it is likely that the findings in lab experiment can be generalized to a broader cohort.

4.3 Behavioral explanation

The observed change in risk preference from both the reduced form analysis and structural estimation seems unresolvable within the EUT framework. There are, however, well established behavioral explanations that might be consistent with the observations. Considering the cumulative version of prospect theory (Tversky and Kahneman, 1992), value of the four different prospects from the four different treatments can be calculated as in Equation 9.

$$
\begin{aligned}
V_{SGP} &= \pi^{+}(p)v(x) \\
V_{SMP} &= \pi^{+}(p)v(x) + \pi^{-}(q)v(-y) \\
V_{CGP} &= [\pi^{+}(\frac{1}{3}(p-r)) + \pi^{+}(\frac{1}{3}p) + \pi^{+}(\frac{1}{3}(p+r))]v(x) \\
V_{CMP} &= [\pi^{+}(\frac{1}{3}(p-r)) + \pi^{+}(\frac{1}{3}p) + \pi^{+}(\frac{1}{3}(p+r))]v(x) + \pi^{-}(q)v(-y)
\end{aligned} \tag{9}
$$

V represents the value of a specific prospect and v is the value function in prospect theory. $\pi^+(\cdot)$ and $\pi^-(\cdot)$ are the probability weighting functions in the gain and loss domains respectively. Note, for V_{CGP} and V_{CMP}, we assume no combining process[12]. Our main focus is the different between V_{SMP} and V_{SGP} which is $\pi^-(q)v(-y)$. Because the probability weighting function has an inversed S–shaped curve, $\pi^-(0.1) > 0.1$. Hence, the difference between SMP and SGP can only be explained by the curvature of $v(\cdot)$. Because $-y$ represents a loss and $v(\cdot)$ is a convex function in the loss domain, it must be that $v(-10) < -10$[13].

When we turn to the comparison between simple and compound prospects, we notice that when r is small, $V_{CGP} > V_{SGP}$ if the probability weighting function is a strictly concave function and vice verse. That is, $\lim_{r \to 0} V_{CGP} \geq V_{SGP}$. When r is not small enough, we cannot infer a definite relation between the two values.

5 Conclusion

This paper presents results from a survey study and a controlled laboratory experiment. In both tasks subjects were requested to provide certainty equivalents to different risky prospects. The study design allows us to identify the role of risk preference in valuing different risky prospects. Both studies show that people are less risk averse when a possible adverse outcome is in presence. This observation suggests that people hold different risk preferences when valuing prospects with and without adverse outcome(s). It further suggests that one set of parameters of the Bernoulli utility function cannot simultaneously explain behavior in both scenarios. By reviewing the literature, especially prospect theory, we argue this phenomenon can be explained by the curvature of value function in prospect theory. That is, people are risk seeking in losses.

We believe that this result has important policy implications. Researchers and policy makers often attribute bubbles in the housing or financial market to risk misperception and hence believe that better informed individuals are capable to make better decisions. However, if decision makers' intrinsic risk preferences are different when valuing gain only prospects and mixed

[12]Otherwise, we would have $V_{CGP} = V_{SGP}$ and $V_{CMP} = V_{SMP}$

[13]Utility or value is normalized.

prospects, they may naturally fail to adjust their strategies in buying or investing decisions.

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Figure 1: Certainty Equivalent to Expected Value Ratios in Survey Study

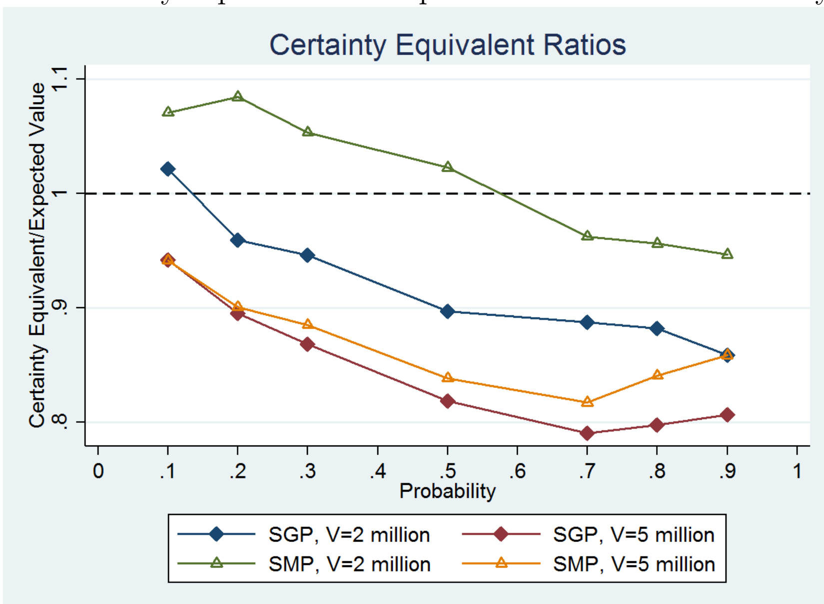


Figure 2: Certainty Equivalent to Expected Value Ratios in Lab Experiment

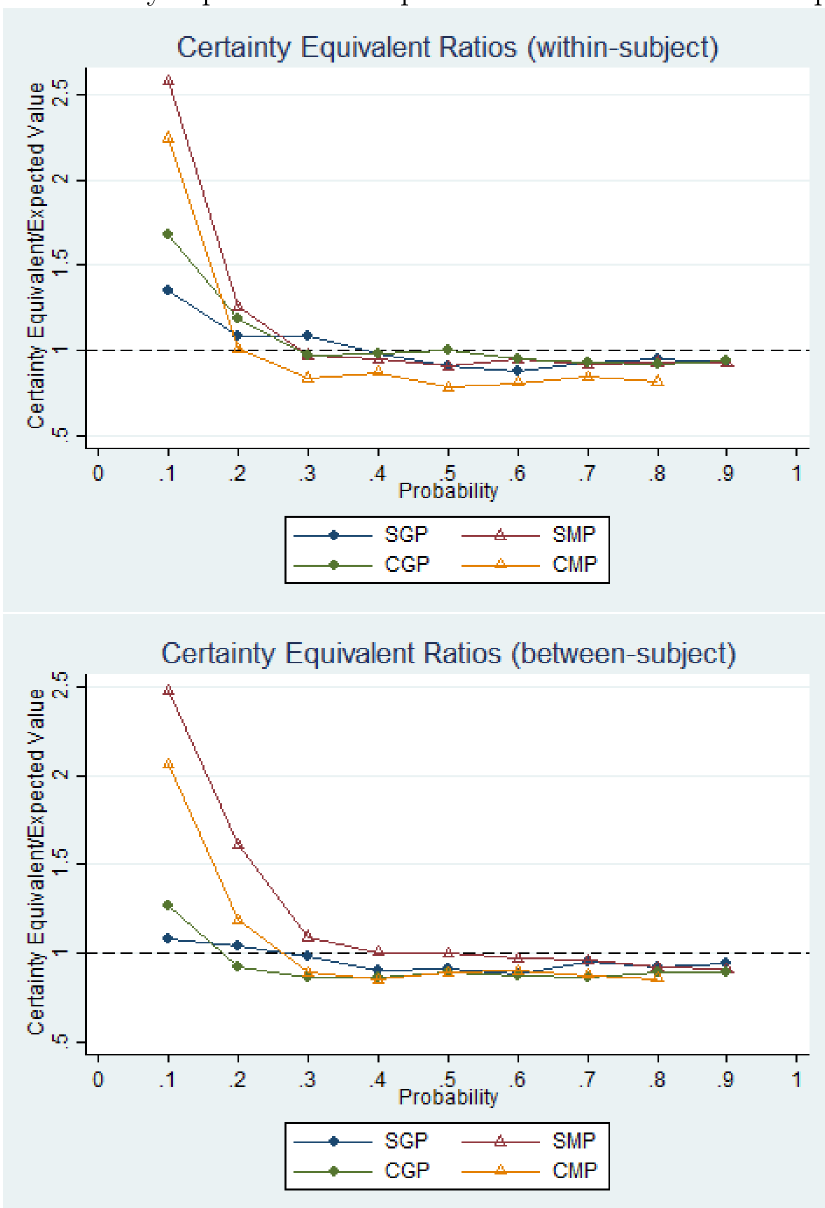
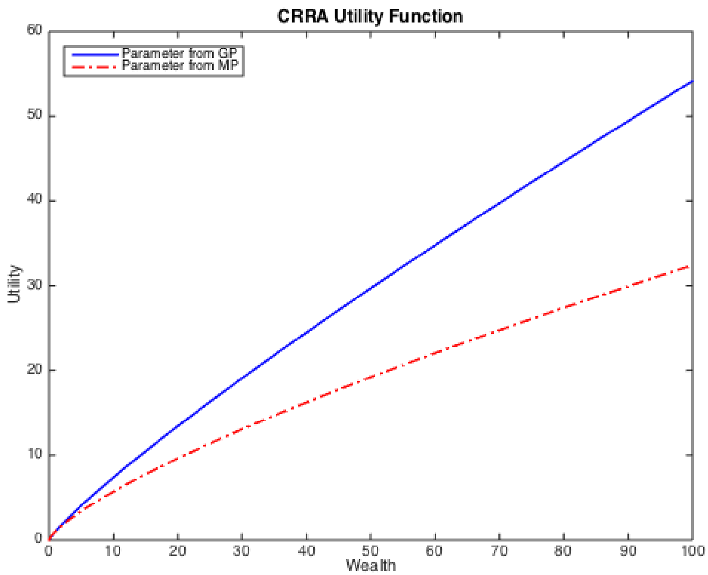


Figure 3: Utility Functions Implied by Parameters Estimated from Experimental Data



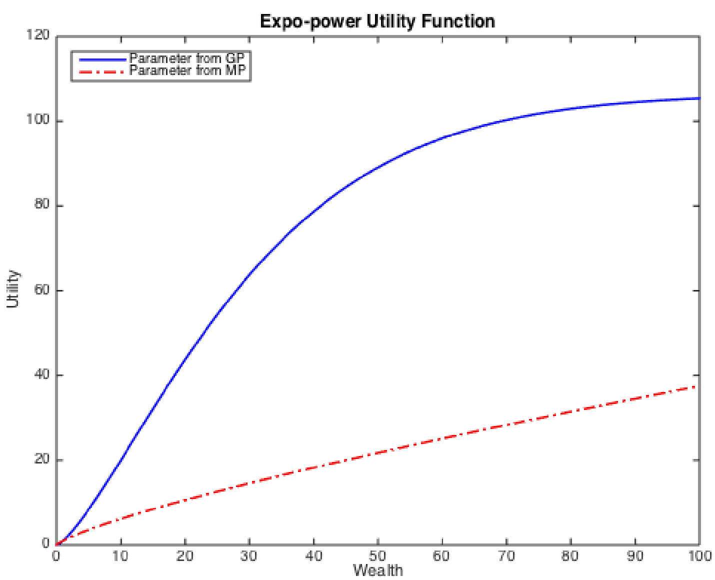


Table 1: Summary of Treatments

Treatment	No. of subject	Possible gain (*yuan*)	Possible loss (*yuan*)
	Panel A: incentivized lab experiment		
Within-subject design			
T1: simple gain prospect (SGP)	40	20	0
T2: simple mixed prospect (SMP)	40	20	10
T3: compound gain prospect (CGP)	40	20	0
T4: compound mixed prospects (CMP)	40	20	10
Between-subject design (T1 paired with T3 and T2 paired with T4)			
T1: simple gain prospect (SGP)	40	20	0
T2: simple mixed prospect (SMP)	40	20	10
T3: compound gain prospect (CGP)	40	20	0
T4: compound mixed prospects (CMP)	39	20	10
	Panel B: randomized field survey (hypothetical)		
Between-subject design–2 million property value			
T1: simple gain prospect (SGP)	132	2 million	0
T2: simple mixed prospect (SMP)	136	2 million	1 million
Between-subject design–5 million property value			
T1: simple gain prospect (SGP)	132	5 million	0
T2: simple mixed prospect (SMP)	136	5 million	2.5 million

Table 2: Mean and Standard Errors of Willingness To Pay from Survey Responses

	Value = 2M			Value = 5M		
Probability	EV	SGP	SMP	EV	SGP	SMP
0.1	220; 210	224.773	203.419	550; 525	517.955	447.206
		(4.739)	(4.328)		(11.384)	(12.426)
0.2	240; 230	230.265	227.684	600; 575	537.273	472.868
		(5.121)	(4.779)		(11.048)	(12.233)
0.3	260; 250	245.909	242.279	650; 625	564.242	508.971
		(5.887)	(5.243)		(12.831)	(12.462)
0.5	300; 290	269.015	276.103	750; 725	614.091	565.956
		(6.091)	(5.462)		(14.012)	(11.547)
0.7	340; 330	301.629	298.309	850; 825	671.894	633.382
		(6.719)	(6.023)		(14.590)	(14.604)
0.8	360; 350	317.614	315.478	900; 875	718.182	693.750
		(6.777)	(5.972)		(15.963)	(16.418)
0.9	380; 370	326.326	331.250	950; 925	766.212	751.324
		(6.895)	(6.092)		(15.657)	(17.439)

Notes: SGP and SMP are Willingness To Pay for gain prospect and mixed prospect respectively. EV is expected value of the gain prospect(before semi–colon) and mixed prospect(after semi–colon). Probability is the odd that housing price will be doubled. For mixed prospects, there is a 10% probability that the housing price will be half. Standard errors of means are in parentheses.

Table 3: Explaining Risk Preference (Certainty Equivalent/Expected Value) in Survey Study

	(1) CE/EV		(2) Log(CE/EV)	
SMP	0.104***	(0.0347)	0.0839**	(0.0421)
P=0.2	-0.0543***	(0.00746)	-0.0606***	(0.00689)
P=0.3	-0.0748***	(0.00962)	-0.0872***	(0.00929)
P=0.5	-0.124***	(0.0108)	-0.143***	(0.0112)
P=0.7	-0.143***	(0.0125)	-0.166***	(0.0136)
P=0.8	-0.142***	(0.0139)	-0.166***	(0.0154)
P=0.9	-0.149***	(0.0158)	-0.171***	(0.0174)
(P=0.2) X SMP	0.0407**	(0.0126)	0.0615**	(0.0190)
(P=0.3) X SMP	0.0380**	(0.0170)	0.0597**	(0.0239)
(P=0.5) X SMP	0.0484**	(0.0189)	0.0747***	(0.0242)
(P=0.7) X SMP	0.0266	(0.0212)	0.0484*	(0.0264)
(P=0.8) X SMP	0.0340	(0.0233)	0.0641**	(0.0292)
(P=0.9) X SMP	0.0456	(0.0257)	0.0751**	(0.0323)
Value	-0.000254***	(0.0000382)	-0.000254***	(0.0000470)
Value X SMP	-0.000229***	(0.0000587)	-0.000204***	(0.0000686)
Constant	1.071***	(0.0237)	0.0436	(0.0281)
Observations	3752		3723	

Notes: Random effects model with standard error clustered by respondents. Standard errors in parentheses. *p<0.1, **p<0.05, ***p<0.01

Table 4: Mean and Standard Errors of Certainty Equivalents from Laboratory Experiments

Probability	EV	SGP	SMP	CGP	CMP
			Within–Subject		
0.1	2; 1	2.713	2.590	3.356	2.273
		(0.507)	(0.626)	(0.516)	(0.563)
0.2	4; 3	4.340	3.770	4.718	3.063
		(0.384)	(0.516)	(0.510)	(0.598)
0.3	6; 5	6.508	4.845	5.805	4.220
		(0.543)	(0.368)	(0.419)	(0.563)
0.4	8; 7	7.790	6.615	7.838	6.100
		(0.449)	(0.497)	(0.436)	(0.585)
0.5	10; 9	9.080	8.130	9.938	7.033
		(0.422)	(0.406)	(0.422)	(0.428)
0.6	12; 11	10.483	10.388	11.349	8.888
		(0.467)	(0.483)	(0.373)	(0.556)
0.7	14; 13	12.945	11.915	12.933	10.915
		(0.414)	(0.432)	(0.333)	(0.542)
0.8	16; 15	15.183	13.933	14.723	12.220
		(0.337)	(0.463)	(0.550)	(0.676)
0.9	18; 17	16.758	15.725		
		(0.408)	(0.480)		
			Between–Subject		
0.1	2; 1	2.165	2.563	2.636	2.208

		(0.263)	(0.339)	(0.462)	(0.560)
0.2	4; 3	4.200	3.710	4.897	3.603
		(0.392)	(0.292)	(0.640)	(0.461)
0.3	6; 5	5.875	5.205	5.487	4.487
		(0.427)	(0.312)	(0.553)	(0.409)
0.4	8; 7	7.248	6.930	7.051	5.982
		(0.323)	(0.316)	(0.567)	(0.422)
0.5	10; 9	9.105	8.910	8.954	8.013
		(0.426)	(0.379)	(0.420)	(0.432)
0.6	12; 11	10.610	10.430	10.656	9.890
		(0.442)	(0.395)	(0.547)	(0.574)
0.7	14; 13	13.353	12.098	12.413	11.380
		(0.494)	(0.517)	(0.609)	(0.586)
0.8	16; 15	14.670	14.200	13.772	12.818
		(0.501)	(0.610)	(0.657)	(0.672)
0.9	18; 17	16.918	16.060		
		(0.489)	(0.623)		

Notes: SGP, SMP, CGP, and CMP are certainty equivalents of simple gain prospect, simple mixed prospect, compound gain prospect, and compound mixed prospect respectively. EV is expected value of the gain prospect(before semi–colon) and mixed prospect(after semi–colon). Probability is the odd of winning 20 *yuan*. For mixed prospects, there is always a 10% odd to lose 10 *yuan*. Standard errors of means are in parentheses.

Table 5: Explaining Risk Preference (Certainty Equivalent/Expected Value) in Lab Experiment

	Within–Subject				Between–Subject			
	(1) CE/EV		(2) Log(CE/EV)		(3) CE/EV		(4) Log(CE/EV)	
SMP	1.234***	(0.444)	0.233	(0.223)	1.480***	(0.259)	0.712***	(0.134)
CGP	0.308*	(0.171)	0.218	(0.135)	0.235	(0.268)	0.190	(0.216)
CMP	0.916**	(0.403)	0.349	(0.236)	1.125*	(0.579)	0.522**	(0.257)
P=0.2	-0.271	(0.178)	-0.0312	(0.116)	-0.0325	(0.117)	0.113	(0.0884)
P=0.3	-0.272	(0.237)	0.0320	(0.136)	-0.103	(0.130)	0.0696	(0.110)
P=0.4	-0.383*	(0.217)	0.00177	(0.131)	-0.177	(0.114)	0.00241	(0.0948)
P=0.5	-0.448*	(0.234)	-0.0513	(0.154)	-0.172	(0.110)	0.0138	(0.103)
P=0.6	-0.483**	(0.239)	-0.0866	(0.153)	-0.198	(0.124)	-0.0252	(0.115)
P=0.7	-0.432*	(0.244)	-0.00701	(0.153)	-0.129	(0.121)	0.107	(0.112)
P=0.8	-0.407	(0.249)	0.0326	(0.157)	-0.166	(0.127)	0.0552	(0.112)
P=0.9	-0.425*	(0.256)	0.0107	(0.167)	-0.143	(0.130)	0.109	(0.120)
(P=0.2) X SMP	-1.062***	(0.366)	-0.148	(0.182)	-1.293***	(0.252)	-0.545***	(0.141)
(P=0.2) X CGP	-0.227	(0.160)	-0.111	(0.122)	-0.0611	(0.174)	-0.134	(0.151)
(P=0.2) X CMP	-0.980***	(0.334)	-0.650***	(0.225)	-0.974**	(0.474)	-0.517***	(0.164)
(P=0.3) X SMP	-1.349***	(0.428)	-0.380*	(0.212)	-1.418***	(0.232)	-0.642***	(0.130)
(P=0.3) X CGP	-0.439**	(0.179)	-0.295**	(0.134)	-0.300	(0.221)	-0.282	(0.189)
(P=0.3) X CMP	-1.157***	(0.367)	-0.608**	(0.258)	-1.207**	(0.525)	-0.559***	(0.208)
(P=0.4) X SMP	-1.263***	(0.430)	-0.380*	(0.229)	-1.396***	(0.261)	-0.648***	(0.141)
(P=0.4) X CGP	-0.316*	(0.179)	-0.231*	(0.131)	-0.260	(0.226)	-0.174	(0.184)
(P=0.4) X CMP	-1.019***	(0.358)	-0.569**	(0.274)	-1.177**	(0.547)	-0.599***	(0.208)

(P=0.5) X SMP	-1.238***	(0.444)	-0.258	(0.232)	-1.400***	(0.265)	-0.601***	(0.137)
(P=0.5) X CGP	-0.236	(0.173)	-0.140	(0.142)	-0.251	(0.242)	-0.171	(0.189)
(P=0.5) X CMP	-1.043**	(0.415)	-0.567*	(0.304)	-1.145**	(0.566)	-0.533**	(0.231)
(P=0.6) X SMP	-1.163***	(0.444)	-0.163	(0.230)	-1.416***	(0.265)	-0.597***	(0.140)
(P=0.6) X CGP	-0.250	(0.167)	-0.148	(0.134)	-0.232	(0.262)	-0.142	(0.209)
(P=0.6) X CMP	-0.982**	(0.395)	-0.510**	(0.260)	-1.110**	(0.565)	-0.484**	(0.234)
(P=0.7) X SMP	-1.242***	(0.440)	-0.251	(0.224)	-1.503***	(0.256)	-0.767***	(0.140)
(P=0.7) X CGP	-0.323*	(0.169)	-0.239*	(0.140)	-0.303	(0.259)	-0.273	(0.205)
(P=0.7) X CMP	-1.001**	(0.396)	-0.491*	(0.256)	-1.204**	(0.569)	-0.631***	(0.234)
(P=0.8) X SMP	-1.254***	(0.444)	-0.271	(0.228)	-1.450***	(0.262)	-0.695***	(0.137)
(P=0.8) X CGP	-0.351*	(0.179)	-0.317*	(0.177)	-0.292	(0.260)	-0.249	(0.205)
(P=0.8) X CMP	-1.050***	(0.405)	-0.625**	(0.288)	-1.188**	(0.585)	-0.608**	(0.247)
(P=0.9) X SMP	-1.240***	(0.437)	-0.249	(0.225)	-1.475***	(0.261)	-0.737***	(0.143)
Constant	1.356***	(0.257)	-0.0967	(0.165)	1.083***	(0.132)	-0.196	(0.134)
Observations	1352		1330		1343		1313	

Notes: Random effects model with standard error clustered by subjects. Standard errors in parentheses. *p<0.1, **p<0.05, ***p<0.01

Table 6: Estimation of Structural Parameters

	(1)	(2)
	CRRA	Expo–power
r(GP)	0.1332	-0.3456
	(0.00001)	(0.0005)
r(MP)	0.2447	0.2132
	(0.000006)	(0.0002)
α(GP)		0.0094
		(0.0000002)
α(MP)		0.0000
		(0.000005)
μ	0.0846	0.0931
	(0.00002)	(0.00007)
Observations	572400	572400

Notes: Standard errors in parentheses. (GP) represents gain only prospects; (MP) represents mixed prospects.

Table 7: Explaining Risk Preference by Gender in Survey Study

	(1) CE/EV		(2) Log(CE/EV)	
SMP	0.124*	(0.049)	0.115	(0.060)
Male	0.0979*	(0.046)	0.126*	(0.052)
SMP X Male	-0.0439	(0.068)	-0.0717	(0.081)
P=0.2	-0.0614***	(0.010)	-0.0677***	(0.010)
P=0.3	-0.0774***	(0.014)	-0.0919***	(0.014)
P=0.5	-0.126***	(0.014)	-0.150***	(0.015)
P=0.7	-0.135***	(0.016)	-0.165***	(0.019)
P=0.8	-0.129***	(0.018)	-0.161***	(0.021)
P=0.9	-0.138***	(0.019)	-0.164***	(0.022)
Value	-0.000245***	(0.000)	-0.000230***	(0.000)
SMP X Value	-0.000289***	(0.000)	-0.000271**	(0.000)
Male X Value	-0.0000203	(0.000)	-0.0000577	(0.000)
Other Interaction Terms as Controls				
Constant	1.029***	(0.033)	-0.00985	(0.042)
Observations	3752		3723	

Notes: Random effects model with standard error clustered by respondents. Standard errors in parentheses. *p<0.1, **p<0.05, ***p<0.01

Table 8: Explaining Risk Preference by Gender in Lab Experiment

	Within–Subject				Between–Subject			
	(1) CE/EV		(2) Log(CE/EV)		(3) CE/EV		(4) Log(CE/EV)	
SMP	1.273***	(0.466)	0.265	(0.280)	1.830***	(0.444)	0.925***	(0.262)
CGP	0.429*	(0.237)	0.137	(0.165)	0.267	(0.359)	0.217	(0.316)
CMP	1.210***	(0.422)	0.524**	(0.241)	1.644*	(0.948)	0.577	(0.386)
Male	0.601	(0.714)	-0.000299	(0.381)	0.251	(0.211)	0.18	(0.207)
SMP X Male	0.119	(1.174)	-0.171	(0.515)	-0.636	(0.720)	-0.477	(0.444)
CGP X Male	-0.36	(0.357)	0.178	(0.304)	-0.0726	(0.463)	-0.14	(0.389)
CMP X Male	-0.603	(1.000)	-0.448	(0.452)	-1.076	(1.009)	-0.0601	(0.414)
P=0.2	-0.508	(0.499)	0.0221	(0.283)	-0.000198	(0.234)	-0.0294	(0.185)
P=0.3	-0.776	(0.638)	-0.0803	(0.318)	-0.176	(0.261)	-0.0497	(0.228)
P=0.4	-0.578	(0.616)	0.0375	(0.318)	-0.216	(0.224)	-0.122	(0.195)
P=0.5	-0.546	(0.642)	0.0942	(0.338)	-0.247	(0.218)	-0.168	(0.213)
P=0.6	-0.519	(0.657)	0.116	(0.343)	-0.227	(0.246)	-0.133	(0.233)
P=0.7	-0.548	(0.684)	0.0789	(0.357)	-0.236	(0.239)	-0.156	(0.226)
P=0.8	-0.575	(0.692)	0.0385	(0.367)	-0.275	(0.250)	-0.195	(0.232)
P=0.9	-0.581	(0.703)	0.0337	(0.377)	-0.319	(0.254)	-0.243	(0.235)
Other Interaction Terms as Controls								
Constant	1.106***	(0.171)	-0.0935	(0.165)	0.953***	(0.122)	-0.266	(0.168)
Observations	1258		1238		1284		1259	

Notes: Random effects model with standard error clustered by subjects. Standard errors in parentheses. *p<0.1, **p<0.05, ***p<0.01

Table 9: Test of External Validity with Survey data

	(1)		(2)	
	CE/EV		Log(CE/EV)	
SMP	0.0863**	(0.0400)	0.0493	(0.0462)
Student	-0.0680	(0.0666)	-0.114	(0.0900)
SMP X Student	0.0578	(0.0884)	0.118	(0.114)
P=0.2	-0.0530***	(0.00910)	-0.0583***	(0.00833)
P=0.3	-0.0714***	(0.0113)	-0.0830***	(0.0103)
P=0.5	-0.129***	(0.0123)	-0.147***	(0.0126)
P=0.7	-0.142***	(0.0141)	-0.162***	(0.0155)
P=0.8	-0.139***	(0.0162)	-0.159***	(0.0177)
P=0.9	-0.150***	(0.0177)	-0.169***	(0.0192)
(P=0.2) X SMP	0.0517***	(0.0146)	0.0728***	(0.0238)
(P=0.3) X SMP	0.0445**	(0.0201)	0.0701**	(0.0296)
(P=0.5) X SMP	0.0606***	(0.0212)	0.0958***	(0.0285)
(P=0.7) X SMP	0.0332	(0.0229)	0.0629**	(0.0294)
(P=0.8) X SMP	0.0405	(0.0250)	0.0764**	(0.0327)
(P=0.9) X SMP	0.0566**	(0.0275)	0.0943***	(0.0363)
Other Interaction Terms as Controls				
Constant	1.091***	(0.0255)	0.0765***	(0.0258)
Observations	3598		3573	

Notes: Random effects model with clustered standard error by respondents. Standard errors in parentheses. *p<0.1, **p<0.05, ***p<0.01