Heterogeneity in Risk Attitudes across Domains: A Bivariate Random Preference Approach

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Abstract: In a series of field experiments, we elicit risk preferences for financial, life-duration, and environmental domains using sequential multiple price-list auctions. We intentionally oversample subjects who frequently engage in activities that increase their mortality risk. We analyze the data using a bivariate Random Preference approach. Under the assumption that subjects are Rank Dependent Utility maximizers, we estimate the joint distribution of the CRRA and probability weighting coefficients. We find that the experienced risk takers are less likely than the student control group to overweight small probability, extreme events in their decision making. This is true in all three domains. We find that the tendency of women to be more risk averse in the financial domain than men arises from probability weighting rather than differences in the utility function. Finally, we show that a significant minority of subjects deviate from the type of s-inverse probability weighting typically observed in experiments.

I. INTRODUCTION

Risk is a central component of human choice. Many of the economic decisions we make in our lifetime, from choosing our career path, updating our asset portfolios, or choosing medical treatment options, depend on our preferences over risk and our perceptions of the riskiness of different activities. Until recently, economists have primarily focused their efforts on understanding how people make choices concerning financial risks. However, economists are increasingly interested in risky choice outside the financial domain, delving into questions about how people make decisions to invest in uncertain medical treatments or choosing to support environmental policies and programs with uncertain costs and benefits.

Economists have typically assumed that risk preferences outside the financial domain will closely mirror financial risk preferences. Yet recent work calls that assumption into question (Einav et al. 2012, Dohmen et al. 2011, Weber Blais and Betz 2002). These studies generally conclude that financial risk preferences are correlated, but not perfectly correlated, with preferences in other domains. Although insightful, these studies share one clear limitation: the choices they consider are not defined by fixed probabilities and outcomes so that subjects may have different perceptions of the probability and expected consequences of the choice.[1]

Differing perceptions of the riskiness of different activities may influence a subject's stated or actual propensity to take risks. If subjects are grading their risk tolerance or making choices based on different underlying risk perceptions, then models that seek to estimate risk preferences may suffer from considerable measurement error. In support of this, Weber, Blais

[1] Einav et al. (2012) use actual choices for retirement accounts, insurance, and other financial instruments and have no information on the subject's perceptions of the riskiness of the products. Dohmen et al. (2011) uses a self-reported risk propensity score and does not collect data on perceived risk of the activities. Weber, Blais and Betz (2002) use a psychometric risk measure where perceived risk is measured on a 5-point ordinal scale rather than a probability or percentage.

and Betz (2002) find that most domain variation can be attributed to different perceptions of the risks and benefits of the activities rather than risk preferences *per se*. Thus, estimates of risk preference functions must carefully control for perceptions of both probabilities and outcomes.

The obvious solution to the problem of confounding risk attitudes and perceptions is to estimate an expected utility (EU) model defined over fixed outcomes and probabilities. However, research spanning the last two decades makes clear that one must pay special attention to how probabilities and outcomes are combined to form a coherent preference function. Numerous studies have shown that people tend to overemphasize extreme events in their financial decision making relative to the predictions of EU theory (for example Tversky and Kahneman 1992, Quiggin 1993, Rabin 1998, Starmer 2000, Bruhin, Fehr-Duda and Epper 2010). Cumulative prospect (CP) theory and rank dependent utility (RDU) theory allow probability weights to replace probabilities in the EU function and often better explain choices over risky financial prospects.

The observation that preferences vary as a result of inherent attitudes about risk (reflected in the utility function) as well as understanding of probabilities [reflected in the probability weighting function (PWF)] points to two sources of variation in preferences across domains. Preferences in the financial and life-duration domains, for example, may differ because people are more likely to emphasize extreme events in the decision concerning life-duration than in decisions concerning financial risks. Alternatively, variation may arise from differing intrinsic attitudes about risk expressed as variation in the curvature of the utility function. Thus, it is clear that any comparison of risk preferences across domains must acknowledge the distinction between attitudes about changes in outcomes (risk attitudes) and beliefs about probabilities (probability weighting).[2]

To date, two studies have compared probability weighting and risk attitude in the financial domain to that of the life-duration domain (Wakker and Deneffe 1996, Bleichrodt and Pinto 2000). Both studies conclude that subjects exhibit more probability weighting in the life-duration domain. Although interesting, both studies have small, student samples making it difficult to generalize the results outside of this relatively educated, younger demographic. Moreover, they use non-parametric modelling approaches that offer little insight into heterogeneity in the preference functions in the different domains.

The purpose of this article is to investigate the causes of variation in risk preferences between the environmental, financial, and life-duration domains. We use data from field experiments that elicit responses to switching multiple-price list (sMPL) choice sets defined over each of the domains. We assume RDU preferences based on the one-parameter CRRA utility function and the one-parameter PWF described by Prelec (1998). We estimate unique functional forms for each risk domain, allowing for heterogeneity between subjects for a given domain and within subjects across domains. Because the sMPL experiments fix outcomes and probabilities, the data has substantial advantages over self-reported risk attitudes and psychometric risk measures because it eliminates problems with confounding risk attitudes with risk perceptions that previous studies have suffered from.

One of the strengths of this study is that we use a convenience sample that intentionally oversamples subjects who regularly engage in risky activities: scuba divers, rock climbers, and

[2] In the remainder of the paper, we make a careful semantic distinction between attitudes about probability and attitudes about changes in utility. When referring to the former, we use the term probability weighting. The term "risk attitude" will be reserved for the utility function i.e. a subject's risk attitude is risk averse if their utility function is concave for the domain under consideration. The term "risk preference" will refer to aggregate effect of probability weighting and risk attitude on risky choice.

amateur auto racers. We also collect data from a student control group. Thus, one of the aims of the study is to determine whether subjects who frequently engage in activities that elevate their mortality risk have preference functions that are significantly different from the control group and also to determine the source of those differences.[3] The sample also offers significant preference heterogeneity that would likely not be found in small, student-only samples.

Several recent studies, including Tanaka, Camerer and Nguyen (2010), Liu (2013), Riddel (2012), and Riddel and Kolstoe (2013) use two sMPL series to estimate intervals for the risk aversion and probability weighting parameters. Responses to each of the series define a set of parameter pairs that are consistent with the switch points. Approximate values for the two parameters are obtained by intersecting the two sets. While innovative and conceptually straightforward for the subjects, the approach is not without its problems. For one, the method for obtaining the two parameter values can only be seen as a rough approximation, implying that the variables used in the analysis are certainly measured with error. More importantly, the approach throws away a significant amount of information that can be used to improve the precision of the parameter estimates.

In this study, we set out to improve on these estimation approaches by jointly estimating the parameters of the utility function and PWF in each domain. The model we propose is the

[3] Data from the same survey has been used in two prior papers. Riddel and Kolstoe (2013) estimate probability-weighting functions in the environmental and financial domains assuming RDU preferences. They find that subjects are more probabilistically risk averse in the environmental domain than the financial domain. Riddel (2012) examines how preferences of risky recreationists differ from those of the control group in the life-duration domain. She finds that risky recreationists are less subject to distortions in probability weighting than the control group. The current study is both deeper and broader than these previous papers. For one, we estimate and compare risk attitudes and attitudes about probabilities in each of the three domains. Second, the econometric model in the current paper is a substantial improvement over the previous papers since it offers more information about the source and magnitude of variation within and across domains.

Bivariate Random Preference (BRP) model. The principle underlying the BRP is that each pair of responses to the two series corresponds to an irregularly-shaped region defined over the risk-aversion and probability-weighting parameters. The estimation procedure is based on finding the probability mass within this irregularly-shaped region. The two parameters are described by distributions with moments varying by risky group and demographic characteristics of the subjects. This allows us to explore how the entire distribution of risk preferences shifts with changes in demographic variables or group membership in each domain. Since the BRP approach allows the estimation of distributions, we can estimate the percentage of our subjects who are risk averse, risk neutral, and risk loving in each domain. Similarly, we can distinguish subjects who tend to overweight small probability events from those who overweight high-probability events in their decision making. The joint modelling avoids measurement error and gives more efficient estimates of the model parameters than the approximation approach used by Tanaka, Camerer and Nguyen (2010) and others.

We find that there is considerable heterogeneity in preferences within subjects across domains. For example, we find that subjects are more likely to be risk averse in the life-duration and financial domains than the environmental domain. Our findings indicate that subjects in our sample are less likely to be EU maximizers in the financial domain than the other two domains, where probability weighting is less prevalent.

We also find significant heterogeneity between subjects in the same domain. Probably the most striking result is that the experienced risk takers are generally more likely to rationally weigh small and large probability events in their decision making than the control group. This is true in all three domains. Another intriguing finding is that gender differences in choices in the financial domain arise primarily from women’s tendency to overweight low probability outcomes rather than any intrinsic risk aversion.

II. LITERATURE REVIEW

2.1 Probability Weighted Preferences and Elicitation

The independence axiom requires that the outcomes of a lottery are independent of their corresponding probability and, consequently, the expected marginal utility of a change in probability is constant (Starmer 2000). Contrary to the independence axiom, behavioral experiments consistently find that people tend to place more mental weight on extreme outcomes in their decision process (Abdellaoui 2000; Diecidue and Wakker 2001, Starmer 2000, Bleichrodt and Pinto 2000, Prelec 1998, Rabin 1998, Wu and Gonzalez 1996, Tversky and Kahneman 1992).

Non-expected utility models, including CP theory of Tversky and Kahneman (1992) and Quiggin’s (1993) RDU theory, allow for violations of the independence axiom by transforming objective probabilities into decision weights using a probability-weighting function. Most estimates of the probability-weighting function for the financial domain suggest an s-inverse shape that is concave for low probabilities and convex for higher probabilities for the average subject. This shape represents “probabilistic risk aversion” as people place more weight on low-probability extreme outcomes relative to a reference point (Abdellaoui 2000; Diecidue and Wakker 2001, Starmer 2000, Wu and Gonzalez 1996, Tversky and Kahneman 1992, Camerer and Ho 1994, Bleichrodt and Pinto 2000, Prelec 1998). Numerous methods have been proposed for eliciting data relevant to CP and RDU preference functions including probability tradeoff methods, certainty equivalent methods, multiple price list and sMPL approaches. Also, a number of estimation techniques have been proposed for the different types of data (see Harrison and Rutström (2008) for an excellent review of these elicitation procedures and estimation methods). It is beyond the scope of this paper to explain all of these estimation and elicitation procedures. Instead, we highlight some papers that are relevant to our methods and results.

Three recent studies estimate finite mixture models that allow classification of subjects as EU or RDU types in the financial domain. Using a series of experiments that elicited certainty equivalents over gains and losses, Bruhin, Fehr Duda, and Epper (2010) find that roughly 20% of subjects exhibit no probability weighting and are essentially risk neutral over financial gains and losses. Accordingly, these subjects are best characterized as expected value maximizers. The remaining 80% of subjects exhibit significant probability weighting and are thus labeled CP types.

Conte, Hey, and Moffat (2011) also use a finite mixture model to categorize subjects into either EU types or RDU types using data from choices over financial gambles. They add a Fechnerian error to account for subjects being noisy in their choice behavior as well as a tremble to account for the possibility that choices are made randomly for some subjects. Despite the difference in approaches, Conte, Hey and Moffatt (2011), like Bruhin, Fehr-Duda, and Epper (2010), find that about 20% of their subjects exhibit no significant probability weighting. In a similar study based a slightly different specification of the finite mixture model, Harrison and Rutström (2009) conclude that 55% of subjects are EU maximizers with the remaining 45% better characterized as having CP preferences.

In recent years, the sMPL method has become a popular method for eliciting risk preferences. Like certainty equivalent and single lottery elicitation methods, it has the advantage that it allows for estimation of a preferences function where both the outcomes and the probability of the outcomes are controlled by the experimenter. Thus, unlike self-reported or psychometric risk measures, the resulting function is a description of preferences that are not confounded with perceptions. Andersen et al. (2006) argues that sMPL has additional advantages over simple lotteries and certainty equivalent methods because it is comparatively simple for subjects to master and it forces monotonicity in preferences.

In the simplest form of the sMPL elicitation scheme, subjects are offered a series of lottery pairs, A and B. The sequences for each of the two tasks are defined so that E[A]-E[B] decreases and eventually becomes negative. Subjects are asked to state their choice between lotteries A and B. The analyst notes where the subject switches from preferring lottery A to preferring lottery B. Later switch points indicate higher levels of risk aversion. Given the switch point, researchers typically estimate an EU function based on a single-parameter utility function such as CRRA. The switch points define a range for the risk-aversion parameter. A point estimate of the risk-aversion parameter can either be inferred using the midpoint of the range, or estimated using maximum-likelihood techniques (Harrison and Rutström 2008).[4]

Extensions of the sMPL approach support estimation of non-EU preference functions with multiple parameters. The elicitation approach in the current study is the one proposed by Tanaka, Camerer and Nguyen (2010) and used subsequently by Liu (2013), Riddel (2012), and Riddel and Kolstoe (2013). Subjects face two different sMPL lotteries. Typically, researchers

[4] Holt and Laury (2002) use an interval data model defined over the range for the coefficient. Harrison and Rutström (2008) present several variations on structural models based on direct estimation of the expected utility function. They define a latent index which is the difference between the expected utility of the lottery pairs. A link function, such as logit or probit is used to define the probability that the subject selected one of the two lotteries. Harrison and Rutström (2008) describe extensions to the model to allow for noisiness in the choice task using either a Luce or Fechner error term.

assume a one-parameter PWF like that proposed by Prelec (1998) together with the one-parameter CRRA utility function. The selections in the two lotteries define two inequalities, which then define a set of parameters pairs that are consistent with the switch point. Thus, for each switch point there is a region defined in (α, σ) space that is consistent with the corresponding inequality. Point estimates are obtained by overlapping the two sets and rounding the parameters estimates to the nearest 0.05. Given the point estimates, researchers use linear models to investigate variation in the parameters arising from demographic or other variables.

Although analytically simple, the approximation results in potentially significant measurement error that could bias coefficients in the linear models leading to incorrect inference about heterogeneity in preferences. Perhaps more importantly, the parameters are not estimated jointly, so a significant amount of information is lost and the precision of the parameter estimates is compromised. The BRP approach detailed below addresses both of these issues since it jointly estimates parameter values without introducing rounding and approximation error. And, like the finite mixture models Bruhin, Fehr-Duda, and Epper (2010), it allows us to estimate the proportion of subjects who have EU or RDU preferences while at the same time investigating the sources of heterogeneity within and between the different domains.

2.2 Domain-Specific Preference

To date, much of the work comparing risk preferences over domains is based on self-reported or psychometric risk measures. Soane and Chmiel (2005) examine domain heterogeneity for choices involving work, health and personal finance using self-reported preferences for taking or avoiding risk. Risk preference is measured on a 5-point Likert scale. They find that the majority of subjects (roughly 85%) display significant domain heterogeneity.

Dohmen et al. (2011) analyze subjects' willingness to take risks over five domains including driving automobiles, financial matters, sports and leisure, career, and health. They analyze two measures of risk: a self-reported willingness to take risk in each domain gleaned from a large survey (n=22,000) of the German population and a smaller dataset involving a field experiment with choices over real-stakes, money-denominated lotteries. They find that the self-reported risk measures are good predictors of the choices over lotteries. They also find that the risk measures across the different domains are highly, but not perfectly correlated. Moreover, they find that the domain-specific risk measures are good predictors of actual risk taking within the domain. For example, the best predictor of smoking is the subjective willingness to take health risks while the best predictor of self-employment (representing risk taking in the career domain) is willingness to take career risks.

Rather than self-reported measures, Einav et al. (2010) examine actual choices about 401(k) allocations, disability insurance, and insurance for health drug and dental expenditures. Their measure of risk preference is in each domain is a subject's willingness to take a risk relative to their peers. Their main interest is in determining whether a subject's willingness to take risk in one domain is a good predictor of willingness to take risk in other domains. They find that preferences are highly correlated across domains. This is perhaps not a definitive as other studies measuring domain variation since the risks they compare are all dollar denominated. Nevertheless, they find that risk preference in one domain is a far better predictor of preferences in other domains than demographic characteristics such as age, gender, income, ethnicity, job tenure, or union membership.

Soane and Chmiel (2005), Dohmen et al. (2011), and Einav et al. (2010) suffer from a common shortcoming: they do not recognize that variations in the perceived riskiness of an activity may affect self-reported risk measures and actual choices. A study by Weber, Blais and Betz (2002) makes clear that this may be a real problem. They find that variation in risk taking across domains arises from variation in the perception of the activities' benefits and risk, rather than variation in risk attitudes.[5] Thus, studies that don't carefully control for perceived riskiness of activities may confound risk attitudes with risk perceptions. Still, Weber, Blais and Betz (2002) approach is quite simple since their psychometric measure is a linear function of perceived risk, perceived benefit, and risk attitudes. Consequently, their measure gives little insight into probability weighting.

Only a few papers have looked at domain specificity by estimating subject-specific risk-preference functions that fix the probabilities of the outcomes while explicitly recognizing probability weighting. Verhoef et al. (1994) study risk attitudes for gambles in the life-duration domain with the goal of determining whether probability weighting is a significant factor in life-duration decision making. Using a sample of 30 females, they elicit certainty equivalents for life-duration gambles. They find support for an s-inverse PWF similar to that observed for financial gambles. Wakker and Deneffe (1996) use a gamble-tradeoff method that allows for elicitation of life-duration utility functions for a small sample of university student subjects. They find that students are typically more risk averse over life-duration than financial gambles, which they attribute to more extreme probability weighting in the life-duration domain. Bleichrodt and Pinto (2000) elicit the utility function and PWF over life-duration gambles for 51 student subjects. Like Verhoef et al. (1994) and Wakker and Deneffe (1996) they conclude that life-duration risk preferences are best modeled using an s-inverse PWF.

[5] The domains studied are financial, health/safety, recreational, ethical, and social risks.

By fixing outcomes and probabilities in their lottery choices, these studies avoid the pitfall of confounding risk and probability attitudes that come with psychometric risk measures. However, their samples are small and only student subjects are considered. In contrast, Riddel and Kolstoe (2013) conduct a series of field experiments aimed at understanding risk preferences in the life-duration domain using subjects who are likely to display significant variation in risk attitudes including SCUBA divers, rock climbers, amateur auto racers, as well as a student sample. They find significant s-inverse probability weighting in the life-duration domain. In a companion paper that addresses only the PWF, Riddel (2012) finds that subjects are more likely to overweight small probabilities in the environmental than the financial domain. She concludes that the domain differences arise from the PWF rather than the utility function.

The current study is based on the same dataset used in Riddel and Kolstoe (2013) and Riddel (2012). However, the current study is both deeper and broader in its investigation. First, we estimate RDU preference functions in all three domains as a function of the group (racer, scuba diver, rock climber, or student control group) and demographic variables. Second, the BRP corrects for statistical issues that were not addressed in the previous papers while offering a rich set of results that allow us to distinguish heterogeneity in risk aversion arising from curvature in the utility function from that related to the probability weighting function.

2.3. Heterogeneity in Risk Preferences

The extant research suggests that there is significant heterogeneity in financial risk preferences. Older, more educated subjects have been found to be more risk averse for financial gambles than their younger, less educated counterparts (Harrison, Lau, and Rutström 2007, Tanaka, Camerer, and Nguyen 2010, Dohmen et al. 2011). The findings on gender and risk preferences are mixed. Early studies find that women tend to be more risk averse than men in the financial domain (Jianakoplos and Bernasek 1998, Eckel and Grossman 2008), but more recent studies have not observed any variation in risk preferences across gender (Harrison, Lau, and Rutström 2007, Tanaka, Camerer, and Nguyen 2010).

Others have studied whether income affects preferences over financial risks. Harrison, Lau, and Rutström (2007) find that household income does not affect the risk preferences of Danish households. Tanaka, Camerer, and Nguyen (2010) study risk preferences of Vietnamese farmers, concluding that mean village income significantly affects risk preferences, with residents of wealthier villages exhibiting more risk tolerance, all else equal. They do not find a statistically significant relationship between risk preferences and household income. Dohmen et al. (2011) do not find a significant relationship between their self-reported risk measure and income in any domain.

Some recent studies examine heterogeneity in risk preferences outside the financial domain. Riddel and Kolstoe (2013) find that female and older subjects are more susceptible to probability weighting in the life-duration domain than their male or younger counterparts. Interestingly, gender and age do not affect risk preferences in the life-duration domain. They also find that wealthier subjects are more life-duration risk averse, but income does not influence probability weighting in that domain. Riddel (2012) compares the PWF in the environmental domain to that of the financial domain. She finds that older subjects exhibit more extreme curvature in the environmental PWF than in the financial PWF. Higher income subjects have more pronounced curvature in the financial PWF than the environmental PWF.

III. THE EXPERIMENTS

The experiments are based on the sMPL elicitation approach described in detail in Riddel (2012) and Riddel and Kolstoe (2013). We briefly recount the approach here. For each domain, subjects are offered two series of lottery pairs (See Appendix Tables 1-3 for these series for each domain.) Subjects are asked to state their choice between lotteries A and B for the sequence of lotteries in series 1. The sequence is defined so that E[A]-E[B] decreases and eventually becomes negative. In the financial and environmental domain, the data consist of 28 choices over the lottery pairs. In the life-duration domain, the data consist of 24 choices. Gambles in the environmental and life-duration domains are monotonic transformations of the financial-domain gambles.

All subjects completed a questionnaire that contained the sMPL questions, a set of demographic questions, and whether the subject participates in a set of risky behaviors such as smoking or not regularly wearing a seatbelt. Subjects in the field experiments engaged in the risky recreational activities also completed an additional section that queried them specifically about their participation in the risky activity.

Experiments based on sMPL questions in the financial domain typically include some mechanism, such as paying off one of the randomly-chosen hypothetical gambles, to ensure incentive compatibility. It is clear that incentive compatible experiments are impossible to design and implement in the life-duration or environmental domains. If the tasks are incentive compatible in only one domain, then it would be impossible to differentiate domain variation from incentive effects. For this reason, our experiments do not offer any real payouts in any of the gambles. Still, it is not likely that our results are inordinately influenced by incentive compatibility. Several studies directed at understanding the role of incentives in experiments have concluded that this is less of a problem in experiments that involve lotteries such as those used here (Camerer and Hogarth 1999, Tversky and Kahneman 1992, Beattie and Loomes 1997).

Each domain had text describing the choice task. In the life-duration domain, gambles are stated in terms of years of life gained from treating a fatal disease. The choice task was described in the experiment booklet as follows:

Hypothetical Health Risk*: Assume you have been diagnosed with a disease that will certainly be fatal in a year without treatment. There are two treatments, but neither is usually effective 100% of the time. Assume the costs of the treatment are the same, and neither treatment has side effects. Remember: THERE ARE NO CORRECT ANSWERS. YOUR ANSWERS MAY BE DIFFERENT THAN WHEN MONEY IS AT STAKE.*

In the environmental domain, lotteries are stated in terms of two different oil-spill mitigation technologies that have different levels of effectiveness. For example, gamble A may be a 30% chance of 20 sq. miles cleaned up and 70% chance of 5 sq. miles cleaned up whereas gamble B has a 10% chance of 34.5 sq. miles cleaned up and 90% chance of 2.5 sq. miles cleaned up. Note that clean-up constitutes a "good" rather than a "bad," so that gambles are comparable across domains. The choice task was described in the experiment booklet as follows:

In the previous two tasks, you were asked to make choices first about money lotteries then about risks associated with medical treatments. Now we turn to choices for environmental risks. ***Hypothetical Environmental Risk:*** *Here, assume that there has been a large offshore oil spill and an oil slick covers a large area in the Gulf of Mexico. The slick is 10 miles off the coast of* *the US. The oil spill has potential to destroy endangered species habitat and commercial fisheries. If it reaches shore, it will cover popular tourist beaches. There are two cleanup options, but the success rate of the two options is different because of the way the treatments are affected by weather, temperature, and ocean currents. More to the point, the number of square miles of the oil spill that is cleaned up is different for the two treatment options. Assume the costs of the cleanup options are the same. Remember: THERE ARE NO CORRECT ANSWERS. YOUR ANSWERS MAY BE DIFFERENT THAN WHEN MONEY OR HEALTH IS AT STAKE.*

3.1 The Subjects

Amateur auto enthusiasts were contacted at two of the Porsche Club of America (PCA) quarterly track events, one held at Spring Mountain Motorsports Ranch in December, 2010 and the second held at Buttonwillow Raceway in California in Spring 2011. Subjects were given a lunch ticket worth $10 for completing the experiment. The track event consists of a driver's education school and a formal PCA race. The driver's education school includes everyone from novice to experienced drivers. Novice drivers are given classroom and track instruction and with instructors in the car. Novices are allowed to go "solo" on the track when deemed ready by an instructor. For intermediate and advanced drivers, there are open-lapping events where cars are driven at speeds in excess of 120 mph. Passing zones are limited to avoid accidents. The driver's education component is intended for training and no formal racing takes place. The race component involves wheel-to-wheel racing on the track. Racers must have a PCA racing license. Licenses are limited to drivers who have several years of track experience, typically gained through attending multiple driver's education events. Racers must pass a physical and be approved by the regional chief driving instructor. Racing involves more skill and danger than the open-lapping events related to the driver's education component. Speeds are higher and passing is allowed anywhere on the track. Accidents are common, but fatalities are rare. Of the roughly 160 people at these track events, 58 completed the experiment.

Rock climbers were contacted at the Red Rock Rendezvous in Red Rock Canyon near Las Vegas, NV in March, 2011. The annual meeting attracts people from all skill levels, giving the opportunity for novice climbers to meet with world-renowned climbers and mountaineers. Clinics in different aspects of climbing and mountaineering are offered and the evening social events are quite popular. Climbers who completed the experiment were entered into a drawing for two climbing ropes, worth about $210 a piece, and two belay devices worth about $70 a piece. Eighty five of the roughly 300 people at the event completed the experiment. Elite climbers were identified by the hardest grade of route they had climbed. On a scale from 5.4 to 5.15 (where the 5 indicates that a rope and safety gear is generally required on the climb), elite climbers climbed at least 5.13.

The SCUBA divers contacted consist of all levels of recreational sports divers (depth limit 130 feet) and technical divers (diving requiring use of decompression tables). They were contacted in February 2011 at the monthly meeting of a Las Vegas dive club, GR8 Divin. The group itself has a regular raffle to encourage attendance, therefore no further incentive was offered to complete the experiment. Everyone at the meeting completed the experiment giving a total of 42 SCUBA divers.

The laboratory subjects consisted of graduate and undergraduate students at the University of Nevada, Las Vegas. They completed the experiments during the Fall 2010 and Spring 2011 semesters. Students were given extra credit for completing the experiment. Three-hundred and three students completed the experiment, giving a total sample size for the field and laboratory experiments to 490. Thirteen subjects did not complete the demographic sections of the booklet and were therefore dropped from the analysis. Thus the total sample size for estimation is 477.

IV. THE BIVARIATE RANDOM PREFERENCE MODEL WITH IMPORTANCE SAMPLING

In every domain, subject i, i=1,…,n, faces two price lists, L=1,2. Each list comprises T^L rows indexed by t. Each row displays two lotteries, lottery $A^{L,t}$ and lottery $B^{L,t}$, $t=1,\dots,T^L$.

Let us denote the two outcomes of lottery $A^{L,t}$ as $a_1^{L,t}$ and $a_2^{L,t}$, with $a_1^{L,t} > a_2^{L,t}$, occurring with probability $p^{L,t}$ and $1-p^{L,t}$, respectively. Similarly, the two outcomes of lottery $B^{L,t}$, are denoted as $b_1^{L,t}$ and $b_2^{L,t}$, with $b_1^{L,t} > b_2^{L,t}$, occurring with probability $q^{L,t}$ and $1-q^{L,t}$, respectively.

We assume that subjects are Rank Dependent Utility (RDU) maximisers. Therefore, subject i evaluates the two lotteries, $A^{L,t}$ and $B^{L,t}$, as follows:

$$(1)\ V_i(A^{L,t}) = w_i(p^{L,t})u_i\left(a_1^{L,t}\right) + [1-w_i(p^{L,t})]u_i\left(a_2^{L,t}\right)$$

$$V_i(B^{L,t}) = w_i(q^{L,t})u_i\left(b_1^{L,t}\right) + [1-w_i(q^{L,t})]u_i\left(b_2^{L,t}\right)$$

Here, the function $u_i\left(z\right)$ is a utility function, where z is the lottery outcome, and the function $w_i\left(r\right)$ is a probability-weighting function, where r is the true probability. For the utility function, we adopt the CRRA functional form, $u_i\left(z\right)=z^{\alpha_i}$. The coefficient $\alpha_i > 0$ is less than 1 for risk-averse agents, equal to 1 for risk-neutral agents, and greater than 1 for risk-loving agents.

The probability weighting function is assumed to take on the functional form proposed by Prelec (1998): $w_i(r) = exp[-(-ln(r))^{\gamma i}]$. The PWF coefficient $\gamma_i > 0$ determines the shape of the weighting function. When $\gamma_i = 1$, there is no probability distortion and the model reduces to the EU model. As $\gamma_i \rightarrow 0, w_i(r)$ becomes a step function, that is flat everywhere except the endpoints of the probability interval (Prelec, 1998). When $0 < \gamma_i < 1$, the PWF takes on an inverse-s shape. In this case, subjects overemphasize low probability outcomes and underemphasize high probability outcomes in their decision making relative to EU theory. When $\gamma_i > 1$, the PWF takes on an s-shape, so that, relatively to an EU decision maker, subject *i* overvalues high probability outcomes and undervalues low probability outcomes.

The two parameters of the choice model are assumed to follow a bivariate lognormal distribution, that is:

$$(2) \quad \begin{pmatrix} \ln(\alpha_i) \\ \ln(\gamma_i) \end{pmatrix} = \mathrm{N}\left(\begin{pmatrix} \mu_\alpha \\ \mu_\gamma \end{pmatrix}, \begin{pmatrix} \sigma_\alpha^2 & \rho\sigma_\alpha\sigma_\gamma \\ \rho\sigma_\alpha\sigma_\gamma & \sigma_\gamma^2 \end{pmatrix} \right)$$

Here, $\mu_.$ indicates the mean, $\sigma_.$ the standard deviation and ρ the correlation coefficient. The bivariate lognormal density function evaluated at (α_i, γ_i) is denoted as $f(\alpha_i, \gamma_i; \mu_\alpha, \sigma_\alpha, \mu_\gamma, \sigma_\gamma, \rho)$.

For each price list, subjects *i* is asked to state his/her choice between the two lotteries by reporting at which row of the list he/she intends to switch from lottery A^L to lottery B^L. The switch points in the two series define two inequalities which identify a region of (α-γ) space in which the values for the risk attitude coefficient and the PWF coefficient and must lie. Assume that subject i switches from A^L to B^L in row s_i^L, L=1,2. If the subject does not switch at all on list L, this is because $s_i^L > T^L$. For subject i, the values of α_i and γ_i have to jointly satisfy two sets of conditions C.1 and C.2, defined as follows. For L=1,2, conditions C.L are :

$$\text{(C.L)} \qquad \begin{aligned} & s_i^L = 1 \Leftrightarrow V_i\left(B^{L,1}\right) > V_i\left(A^{L,1}\right) \\ & 1 < s_i^L \le T^L \Leftrightarrow V_i\left(B^{L,s_i^L}\right) > V_i\left(A^{L,s_i^L}\right) > V_i\left(B^{L,s_i^L-1}\right) \\ & s_i^L > T^L \Leftrightarrow V_i\left(A^{L,T^L}\right) > V_i\left(B^{L,T^L}\right) \end{aligned}$$

This exercise produces a graph similar to the one depicted in Fig. 1. In our tasks, C.1 define the upward sloping lines and C.2 define the downward sloping lines. The higher the lines the earlier in the sequence the subject switches to lottery B. This holds for both MPLs in each domain. For example, if subject i switches in row 1 in sequence *1*, then the values of α_i and γ_i which are compatible with i's choice lie in the area above the highest upward sloping line; if i switches in row 2, then his/her α_i and γ_i lie between the highest and the second highest upward sloping lines, and so on. It is worth noting that those lines are neither straight nor parallel, and, for each combination of switch points, define irregular areas which are of different sizes and shapes.[6] The graph also makes clear that the estimation of one of the two coefficients cannot be separated from the estimation of the other. Hence, any estimation strategy that incorporates all available information must be one in which the two coefficients are modelled jointly. Hence, the information provided by this graph concerning location and dimension of each area is crucial in order to make inference, and we exploit it in the following way.

Given our distributional assumptions (2), we can define the probability of switching at s_i^1 in sequence *1* and at s_i^2 in sequence *2* as

[6] Had those lines been both straight and parallel, we could have twisted the axes and estimated the parameters of interest using bivariate interval regression.

$$(3)\ Prob(s_i^1 \cap s_i^2) = \iint_0^{\infty} \mathbf{1}[C.1(s_i^1;\alpha,\gamma) \cap C.2(s_i^2;\alpha,\gamma)] f\big(\alpha,\gamma;\mu_\alpha,\sigma_\alpha,\mu_\gamma,\sigma_\gamma,\rho\big) d\alpha d\gamma,$$

where **1**(.) is an indicator function taking the value 1 if the condition in brackets is true, 0 otherwise.

Integrating out α and γ may appear rather straightforwardly accomplishable by means of one of the numerous Monte Carlo integration techniques, but it becomes immediately clear by looking at Fig. 1 how small the probability of sampling, for example, from the (6,3) curvilinear quadrilateral is.[7] Similar situations are acknowledged in the literature on Monte Carlo simulations as rare event sampling cases [see, for example, Rubinstein and Kroese (2007)]. These are often studied and discussed in the analysis of dynamical systems, in Physics, Computer Physics, Engineering and Biology applications, among others. The goal is that of computing very small probabilities with great accuracy, but, at the same time, trying to keep the number of simulated draws per subject rather small.

There is not a unique solution to similar problems. In the specific of our application, we can make good use of the information provided by Fig. 1. In fact, for each combination of switch points, that figure enables us to identify exactly where the two parameters of interest lie and, consequently, to circumscribe the area from which we need to sample.

Let us consider, for example, the case displayed in Fig. 2, which magnifies the curvilinear quadrilateral from Fig. 1 that encloses all combinations of α and γ which are compatible with

[7] For example, using the most common crude frequency simulator, this integration would require that, at each stage of the Maximum Simulated Likelihood procedure, at least one of the simulated draws hit that particular area. This would not be guaranteed even by allowing a number of simulated draws per subject in the order of billions. More sophisticated sampling techniques, unless adapted, do not guarantee this for the same reasons.

the choice of switching at row 6 and 3 in sequence 1 and 2, respectively. The importance sampling technique (for a detailed description, see Gourieroux and Monfort (1996), among others) allows us to sample from a bivariate distribution (a relatively straightforward procedure) whose support is concentrated over the rectangle defined by pairs of vertical and horizontal lines, drawn at the lower and upper limits of the curvilinear quadrilateral from which we ultimately want to sample. Another way of viewing this rectangle is as the smallest rectangle drawn with vertical and horizontal sides that completely contains the curvilinear quadrilateral. Finally, we just need to apply an importance weight.

In the specific case of Fig. 2, we proceed as follows. We want to simulate a value for α and a value for γ from $f(\alpha_i, \gamma_i; \mu_\alpha, \sigma_\alpha, \mu_\gamma, \sigma_\gamma, \rho)$ in the space delimited by a_l and a_u on the horizontal axis and b_l and b_u on the vertical axis. We draw, say, $\widehat{\alpha_r}$ and $\widehat{\gamma_r}$ from a pre-specified function $g(\alpha, \gamma; \boldsymbol{\theta})$, that depends on some given parameters $\boldsymbol{\theta}$, truncated in the area a_l-a_u for $\hat{\alpha}$ and b_l-b_u for $\hat{\gamma}$. Given such draws, we then calculate $\mathbf{1}[C.1(s_i^1; \widehat{\alpha_r}, \widehat{\gamma_r}) \cap C.2(s_i^2; \widehat{\alpha_r}, \widehat{\gamma_r})]$ and the sampling weight $w(\widehat{\alpha_r}, \widehat{\gamma_r}) = f(\widehat{\alpha_r}, \widehat{\gamma_r}; \mu_\alpha, \sigma_\alpha, \mu_\gamma, \sigma_\gamma, \rho)/g(\widehat{\alpha_r}, \widehat{\gamma_r}; \boldsymbol{\theta})$. This procedure is repeated for a number R of draws of $\widehat{\alpha_r}$ and $\widehat{\gamma_r}$. An importance sampling estimate of $Prob(s_i^1 = 6 \cap s_i^2 = 3)$ is given by

(4) $Prob(s_i^1 = 6 \cap s_i^2 = 3) = \frac{1}{R}\sum_{r=1}^{R} \mathbf{1}[C.1(s_i^1 = 6; \widehat{\alpha_r}, \widehat{\gamma_r}) \cap C.2(s_i^2 = 3; \widehat{\alpha_r}, \widehat{\gamma_r})] w(\widehat{\alpha_r}, \widehat{\gamma_r})$

This procedure can be followed for each area defined by a combination of switch points. In all the cases in which the switch point in sequence II is 1, a_u and b_u are ∞.

Hence, the contribution to the likelihood for any given subject i, $i=1,\ldots,n$, is as given in (3). The overall log-likelihood for our sample is just the sum of the natural logarithm of (3) over all n subjects. Estimation proceeds by Maximum Simulated Likelihood according to the procedure described in this section. For each subject, we use a sequence of 500 Halton draws.[8] In our application, as a sampling distribution for α and γ, $g(\alpha, \gamma; \boldsymbol{\theta})$, we use two independent normal distributions appropriately truncated in the intervals of interest. The parameters for the two normal distributions, $\boldsymbol{\theta}$, have been chosen so that the truncated normal distributions, both with left-truncation point at 0, where those parameters roughly represent the marginal distributions of the real observations.[9] The estimation is carried out separately for each domain.

V. RESULTS

Table 1 gives the results of the models for the three domains, with the top section of the table giving the coefficients of μ_α and the middle section giving the coefficients of μ_γ. The estimated standard deviations of the distributions of α and γ are at the bottom of the table. As modelled, variation in the group and demographic variables induce changes in μ_α and μ_γ, which change both the mean and the variance of the distribution.[10] Consequently, negative values of the model coefficients for the risk aversion parameter μ_α cause the mean to shift to the left and the variance to fall, indicating a higher proportion of risk-averse subjects. Similarly, negative values for the coefficients in the model for μ_γ correspond to a higher proportion of subjects with an s-inverse PWF.

[8] The program is written in Stata.
[9] The results that we obtain are rather robust to changes in $\boldsymbol{\theta}$, as it should be, since it can be shown that weighted draws from *g*(.) are equivalent to draws from *f*(.). For a demonstration, see, for example, Train (2009).
[10] The standard deviations for each coefficient do not vary with demographic or group variables.

5.1 Comparing the Distributions of the Parameters Across Domains

Our first analysis examines variation for the average sample subject across domains. Accordingly, for each domain and each subject, we calculate the predicted of $\hat{\mu}_{\alpha i}$ and $\hat{\mu}_{\gamma i}$ as a function of the group and demographic variables using the results reported in Table 1. We then take the sample average of each of these and use these, together with the standard deviations, to plot the distributions for the average subject in the sample. The distributions are given in Figures 3 and 4.

First, consider the distribution of the risk aversion parameters in Figure 3. The distributions of the financial and life-duration parameters are very similar, with a mean of roughly 0.65. Thus, the average subject's is risk averse in both domains. This is still true within the environmental domain, but is less pronounced. Roughly 82 percent of the subjects are have a risk-aversion coefficient of less than 1 in the financial and life-duration domains, meaning that the remaining 18 percent of subjects are either risk neutral or risk loving. The percentage of risk-loving subjects in the environmental domain is somewhat higher at 21 percent.

Figure 4 gives the distributions for the probability-weighting parameters. The plots indicate that there is substantial variation in probability weighting with most subjects having an s-inverse PWF, but a sizable minority having a s-shaped pdf. The mean of the distributions for the environmental and life-duration domains are essentially the same (0.81 and 0.79, respectively), indicating that the average subject is displays s-inverse type PWF tending to over-weight low probability extreme events in their decision making. The mean is significantly smaller in the financial domain, and at an estimated value of 0.69, suggests that the average subject is more subject to biases from probability weighting in that domain.

About 33 percent of the subjects have a probability-weighting coefficient larger than 1 in the financial domain. That figure is larger in the life-duration domain (38 percent) and larger yet in the environmental domain (43 percent). For these subjects, there is no distortion in probabilities for values of γ close to 1. As γ increases, the PWF becomes increasingly s-shaped indicating that these subjects place extra emphasis on high-probability outcomes in their decision-making than warranted by EU theory. They also undervalue low probability events relative to the predictions of EU.

5.2 Heterogeneity in Risk Attitude

The results in Table 1 indicate that demographic variables account for heterogeneity in risk attitude. On average, women are more risk averse in the life-domain than men, but there is no significant gender variation in either the financial or environmental domains. Risk aversion is decreasing in income, but only in the financial domain. Risk attitudes do not vary with the age of the subject in any of the domains. There is no demographic variation in risk attitude in the environmental domain.

There is also domain variation in risk attitude arising from risky group membership. On average, rock climbers are more risk-averse in the life-duration domain than other subjects, however they are not significantly different from the average subject in the other domains. The average elite rock climber is significantly more risk averse than others in the financial domain. What is more, they are significantly more risk averse in the financial domain than the other domains. The distributions for smokers, racers, and scuba divers are not different from the control group in any of the domains. Risk aversion does not vary by group in the environmental domain.

Figure 5 plots the lognormal distributions for the risk-aversion parameters based on the average μ_α for each domain and group. The shapes of the distributions for the control group are quite similar across domains, with the mean of the environmental distribution shifted slightly to the right of that of the financial and life-duration distributions. This indicates that control-group subjects are, on average, modestly more tolerant of environmental risks than financial or life-duration risks. On balance, the distributions for the other groups are very similar to the control group with the average risk aversion coefficients roughly equal to 0.73+/-0.3. However, there are a few interesting exceptions. Racers are more risk-tolerant in the life-duration domain than in the other domains whereas, climbers are the least risk tolerant in that domain. Scuba divers are the most risk averse in the financial domain.

5.3 *Heterogeneity in Probability Weighting*

According to Table 1, the group variables induce substantial variation in probability weighting both within and across domains. On average, scuba divers are less subject to biases from probability weighting than other recreationists and the control group in all three domains. The average rock climber displays less probability weighting than the average control-group subject or other risky recreationists in the environmental domain, but is not different from the control group in the financial and life-duration domains. Elite climbers are not different from their less-skilled counterparts in this respect. The average racer has a larger probability-weighting coefficient than the control group or climbers (indicating less probability weighting) in the financial and life-duration domains, but the result is only marginally statistically significant in the life-duration domains (*p*-values 0.11). They are not different from the control group in the environmental domain.

Demographic variation in the sample also induces heterogeneity in probability weighting with most of the effect seen in the financial domain. On average, females display more probability weighting in the financial domain. However, there are no gender differences in the other two domains. Similarly, probability weighting is decreasing in income financial domain, but not the environmental or life-duration domains. Subjects display more financial probability weighting as they age, but the effect does not carry over into the other two domains.

Figure 6 plots the lognormal distributions of the probability-weighting parameters by group and by domain. Probably the most striking feature of the distributions is that the risky recreationists exhibit less probability weighting than the control group in almost every domain. The sole exception is rock climbers, who display more probability weighting in the financial domain. Indeed, for most of the groups and domains, the average subject's coefficient is near 1, implying no probability weighting and therefore EU preferences. In the environmental domain, the average is roughly 1.2 for scuba divers and rock climbers. In contrast with the s-inverse shape typically observed in experimental studies, the PWF for the risky groups are more likely to be S shaped, so that these subjects would tend to overweight high probability events and underweight low probability events in the decision making.

VI. DISCUSSION AND CONLUDING REMARKS

The main focus of the current research is to examine heterogeneity in risk preferences from several angles. To assure a wide swathe of risk preferences, we intentionally oversample subjects who frequently engage in risky activities. First, we seek to determine whether differences in preferences across domains arise primarily from variation in the risk aversion coefficient, variation in the subjective weighting of probabilities, or both. Moreover, this study jointly estimates distributions for the risk aversion and probability-weighting parameters that vary with the group and demographic characteristics of the subject. This enables us to estimate the proportion of the subjects in the sample or within one of the recreational groups that are risk loving or risk averse or have s-inverse versus s-shaped probability-weighting functions.

Considering the student control group, we find that preferences are very similar in the financial and life-duration domains with the average student subject displaying risk aversion and modest probability weighting in those domains. Control subjects are slightly less risk averse in the environmental domain than the other domains.

The other groups were quite dissimilar from the control group and each other in their average preferences. With a couple exceptions, the risky groups tend to be closer to EU maximizers than the control group, on balance eschewing probability weighting in their decision making in all three domains. Perhaps counterintuitively, the average racer is nearly an expected value maximizer in the life-duration domain: they judge probabilities accurately and are nearly risk neutral. The reasons for this stark difference between the ostensibly risk taking groups and the control groups are not clear. One explanation is that these people engage in these risky activities *because* they are not deterred by fears of small probability, bad outcomes. Alternatively, engaging in risky activities may have helped them improve their decision making over time i.e. they evolve into rational decision makers as they gain experience. As designed, this study cannot distinguish between these two hypotheses. Future studies that more carefully control for experience may be helpful.

Past research has found that experimental subjects have s-inverse PWF in the life-duration and financial domains tending to overweight (underweight) small (large) probabilities relative to an EU maximizer (Bleichrodt and Pinto 2000, Wakker and Deneffe 1996, Tversky and

Kahneman 1992). The PWF of most rock climbers and scuba divers in the current study is the reverse in the environmental domain: large probabilities are over weighted indicating that they tend to have a stronger preference for options that have a high probability of cleanup, all else equal. Rock climbers and scuba divers enjoy their sports in the outdoors. Outdoor recreationists may be more interested in and familiar with environmental concerns, with these beliefs carrying over into their choices over uncertain environmental cleanup.

One of the key findings of this research is that the distributions of the probability-weighting parameters exhibit considerable right skew in all of the domains. For our control group, we find that the average subject has the standard s-inverse PWF but there is a significant minority (35 – 40% depending on the domain) that has an s-shaped PWF which is convex over the lower portion and concave over the upper portion. The distributions for the racers and scuba divers have even more mass in the right tail: in all domains, more than 45% of subjects have s-shaped or nearly linear PWFs. The distributions of the probability-weighting parameters for climbers look much like that of the control group in the financial and health domains, but more closely match that of their fellow risky recreationists in the environmental domain.

We also find variation in the preference function arising from demographic variables. Higher income subjects are less risk averse with less probability weighting in the financial domain, but this is not true in the other domains. Thus, as income increases subjects become increasingly likely to engage in gambles for two reasons. First, their risk premium falls so that they have to be compensated less for taking risks. Second, they are less likely to be averse to small probability large losses. This contrasts with previous studies that find that the CRRA risk-aversion coefficient in the financial domain is independent of income (Tanaka, Camerer and Nguyen 2012, Dohmen et al. 2011, Harrison, Lau, and Rutström 2007). The difference may well be a result of differences in the samples: these previous studies have been based on large sample surveys of Europeans (Danish citizens in the case of Harrison Lau and Rutström 2007, German citizens in Dohmen et al. 2011) or a field experiment of Vietnamese farmers (Tanaka, Camerer and Nguyen 2010).

Our results show that the average woman is more risk averse than men in the life-duration domain but not the financial domain or environmental domains. Furthermore, we find that women display more marked s-inverse probability weighting than men in the financial domain. At first, this seems to be at odds with the body of research that finds that women are more risk averse in the financial domain (Jiankoplos and Bernasek 1996, Croson and Gneezy 2009). Indeed, our results show that the financial-risk aversion observed in other studies may in fact be coming from the probability-weighting function. If women tend to overemphasize small probability losses in the financial domain, studies that don't carefully control for probability weighting may erroneously conclude that women are more risk averse.

The BRP approach gives key insights into the sources of heterogeneity within and between risky domains. Nevertheless, there are some limitations to the approach. For one, we intentionally oversampled subjects who engage in risky activities. Thus, our results are not immediately generalizable to the US adult population. The experimental design also does not lead to causal inference about the source of heterogeneity. For example, we cannot determine whether the risk-taking group suffers less from probability-weighting biases than the control group because they are used to taking risks or of the reverse is true.

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Table 1. Mixture Model Coefficients for the Risk Attitude Parameter, α , and Probability-weighting Parameter, γ .

Domain	Financial		Life Duration		Environmental	
parameter	μ_α		μ_α		μ_α	
variable	coeff.	p-value	coeff.	p-val	coeff.	p-val.
scuba	-0.1376	0.3780	0.0666	0.6730	-0.1114	0.4260
rockclimbers	0.0976	0.3500	-0.2220	0.0390	0.0040	0.9660
racer	0.0170	0.9280	0.2500	0.1810	-0.1368	0.4070
elite climber	-1.4914	0.0000	-0.0738	0.7940	-0.2822	0.2260
age	-0.0036	0.3150	-0.0015	0.6800	0.0012	0.7100
female	-0.0093	0.8980	-0.1335	0.0730	-0.0225	0.7300
income (thous)	0.0011	0.1060	0.0004	0.5220	0.0006	0.3200
smoke	0.0614	0.5020	0.0104	0.9110	-0.0857	0.3030
c	-0.6062	0.0000	-0.5950	0.0000	-0.5587	0.0000
parameter	μ_γ		μ_γ		μ_γ	
variable	coeff.	p-value	coeff.	p-value	coeff.	p-value
scuba	0.6554	0.0000	0.4320	0.0060	0.5955	0.0180
rockclimbers	0.0106	0.9310	0.1029	0.3570	0.5126	0.0040
racer	0.5798	0.0070	0.3137	0.1130	0.3142	0.3130
elite climber	0.2733	0.3570	0.1267	0.6410	-0.3968	0.3730
age	-0.0143	0.0010	-0.0016	0.6770	-0.0070	0.2460
female	-0.1434	0.0900	0.0341	0.6610	-0.0304	0.8030
income (thous)	0.0014	0.0650	0.0007	0.2980	0.0006	0.5770
smoke	-0.0786	0.4600	-0.0339	0.7280	-0.0062	0.9680
c	-0.4192	0.0010	-0.6139	0.0000	-0.9187	0.0000
	coeff.	p-value	coeff.	p-value	coeff.	p-value
St. Dev. α	0.7401	0.0000	0.7395	0.0000	0.6576	0.0000
St. Dev. γ	0.8603	0.0000	0.7777	0.0000	1.2215	0.0000
rho	-0.0009	0.847	0.0430	0.431	-0.0695	0.1800

Figures

Fig. 1 Areas Defined by *C*.1 and *C*.2. The numbers in brackets indicate the row in the first and second sequence in which a subject must switch for his/her coefficients to lie in that particular area of the graph. *ns* indicates the "no switch" cases.

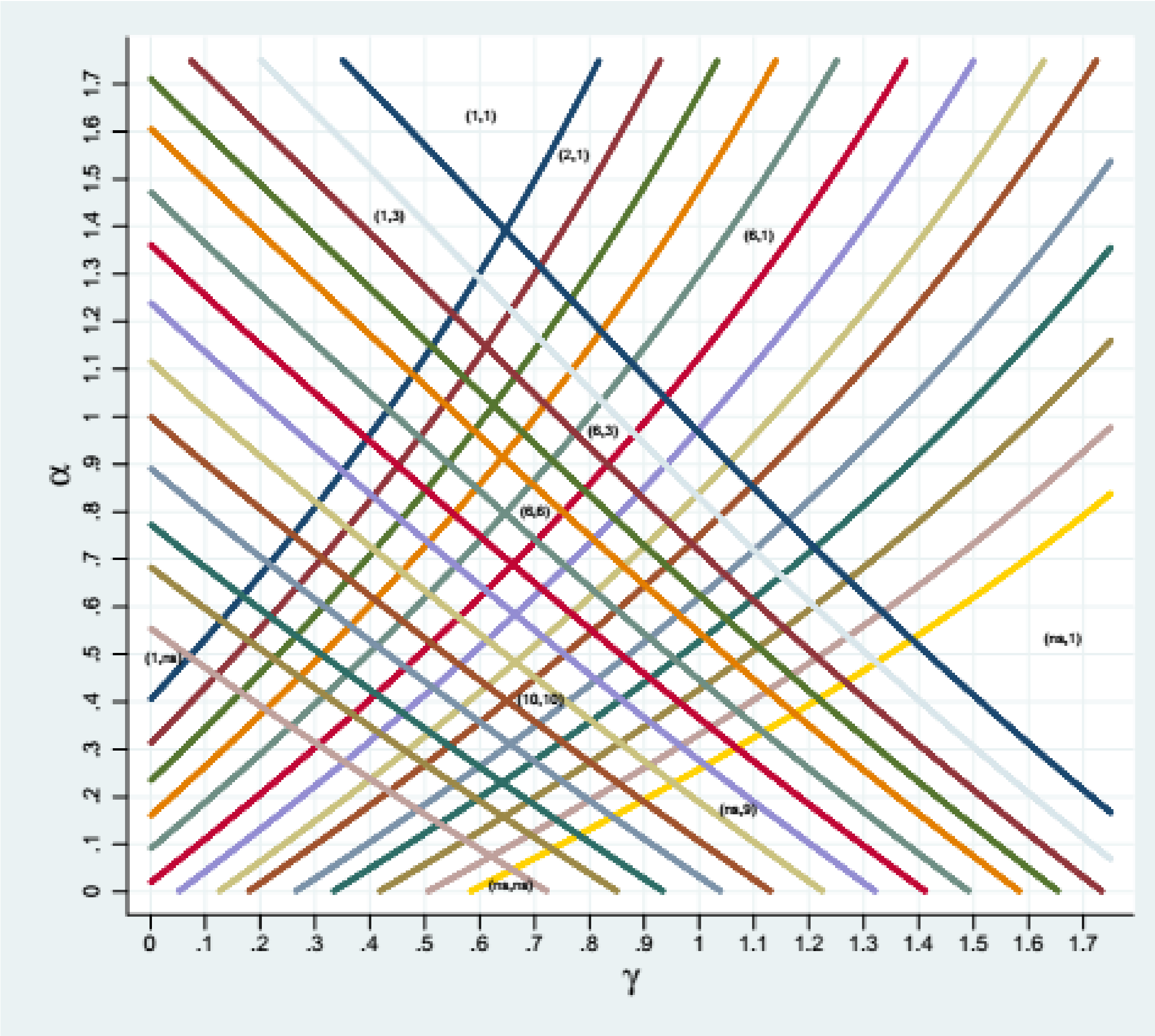


Fig. 2 This figure magnifies the area in Fig. 1 where the parameters α and γ lie if in sequence 1 and sequence 2 subjects switch at row 6 and 3, respectively.

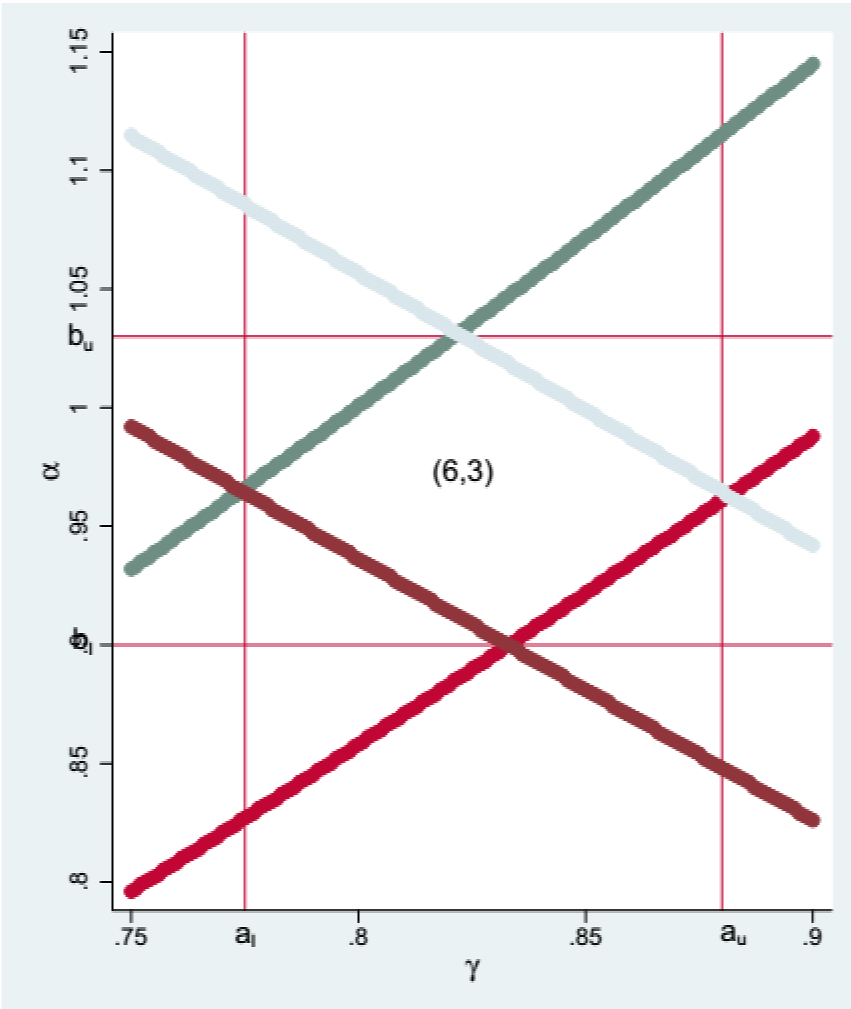


Figure 3. Lognormal Density Function for Risk Attitude Parameter α

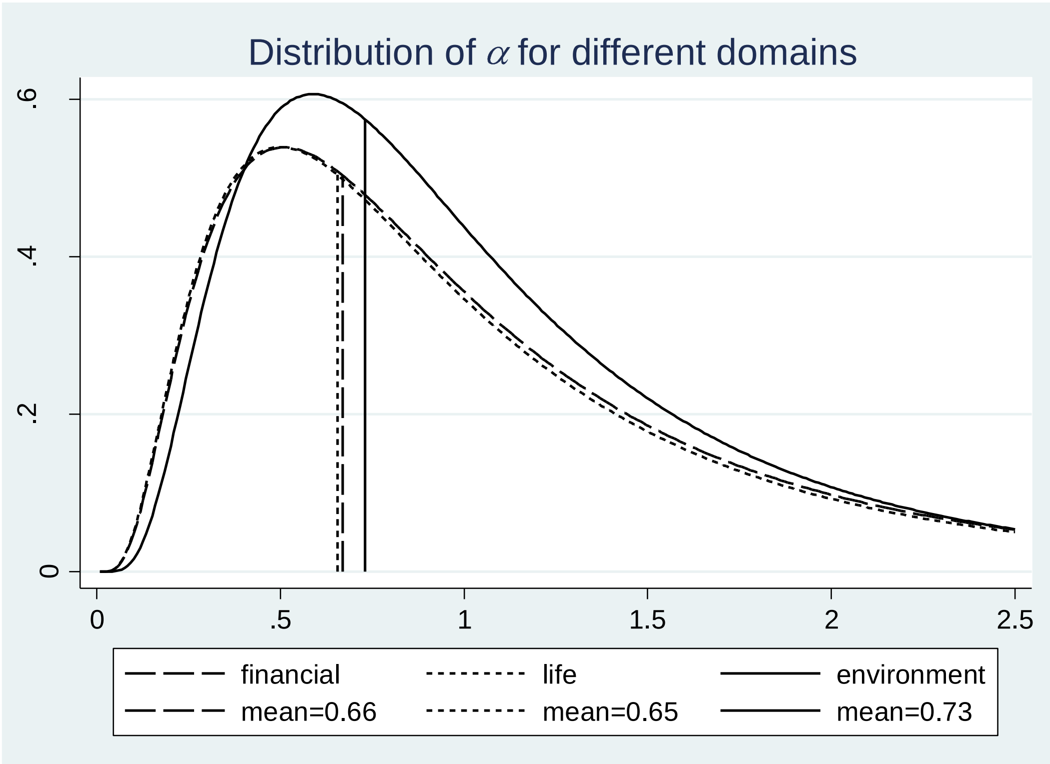


Figure 4. Lognormal Density Function for the Probability Weighting Parameter γ

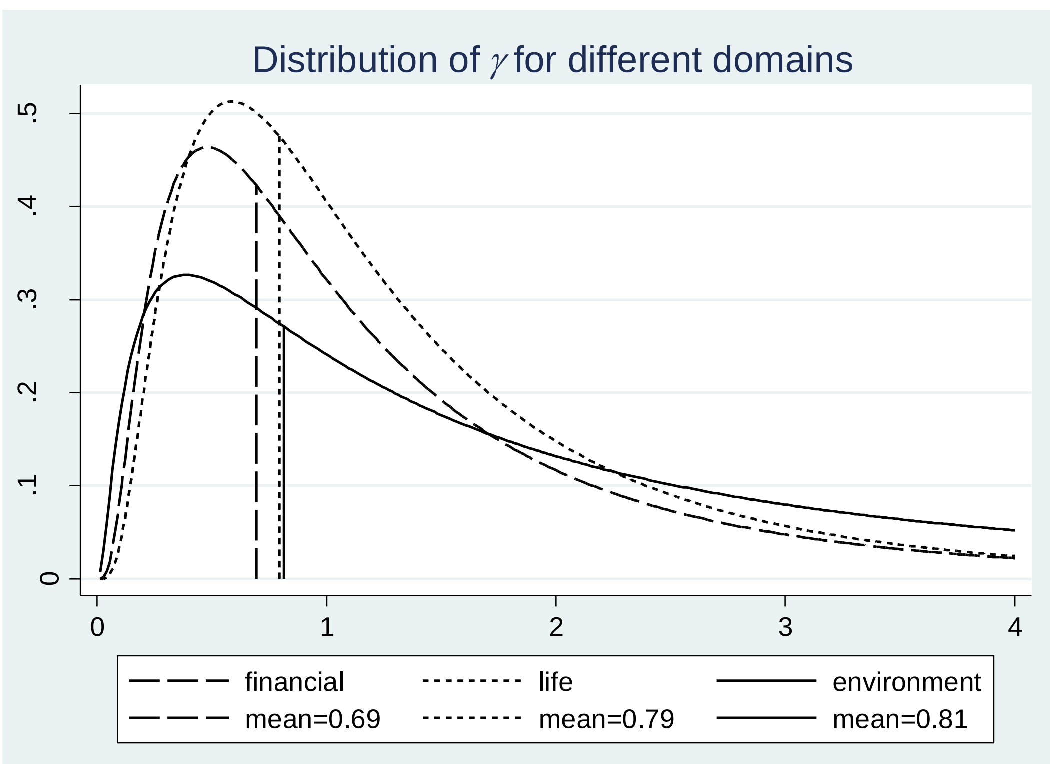


Figure 5. Lognormal Distributions of Risk Aversion Parameters by Group

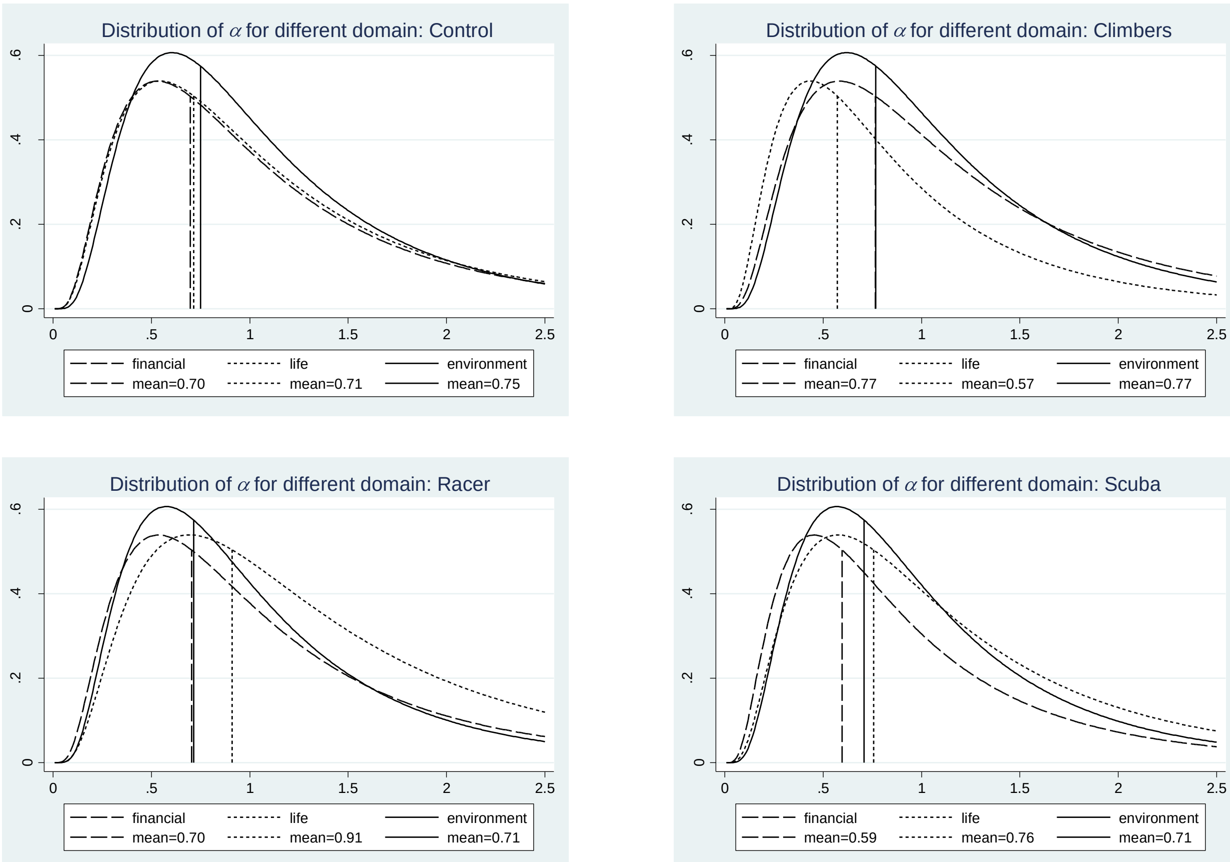
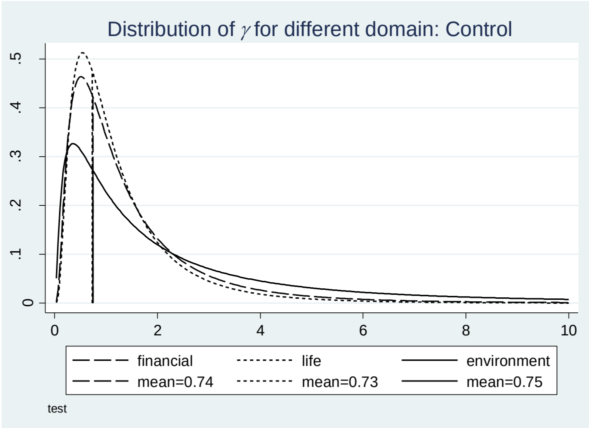
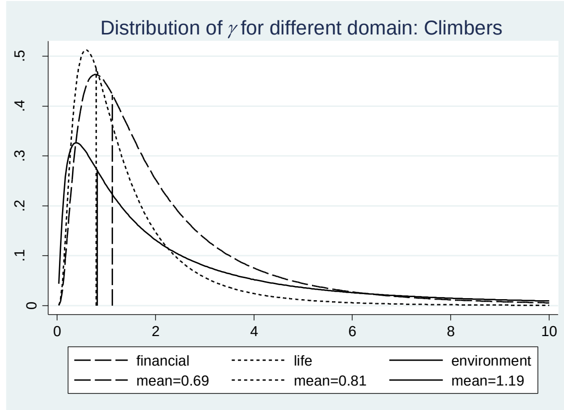
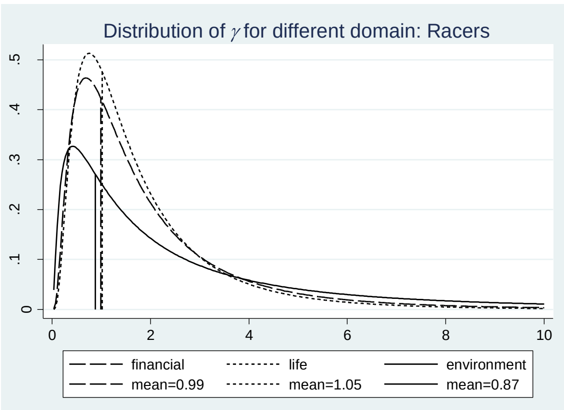
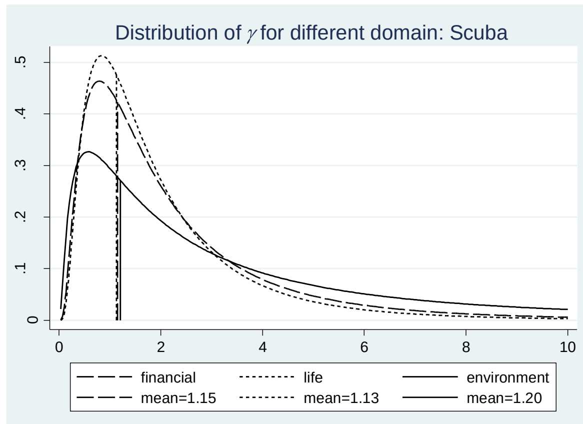


Figure 6. Lognormal Distributions of Probability Weighting Parameters by Group









Appendix A1. sMPL Lottery Choices in Financial Domain

	Lottery A				Lottery B				Please Circle EITHER A or B Stop when First B Circled	
Row	probability ($400)	Payoff	probability ($100)	Payoff	probability ($?)	Payoff	probability ($50)	Payoff	Choose A	Choose B
1	0.3	$400	0.7	$100	0.1	$680	0.9	$50	A	B
2	0.3	$400	0.7	$100	0.1	$750	0.9	$50	A	B
3	0.3	$400	0.7	$100	0.1	$830	0.9	$50	A	B
4	0.3	$400	0.7	$100	0.1	$930	0.9	$50	A	B
5	0.3	$400	0.7	$100	0.1	$1,060	0.9	$50	A	B
6	0.3	$400	0.7	$100	0.1	$1,250	0.9	$50	A	B
7	0.3	$400	0.7	$100	0.1	$1,500	0.9	$50	A	B
8	0.3	$400	0.7	$100	0.1	$1,850	0.9	$50	A	B
9	0.3	$400	0.7	$100	0.1	$2,200	0.9	$50	A	B
10	0.3	$400	0.7	$100	0.1	$3,000	0.9	$50	A	B
11	0.3	$400	0.7	$100	0.1	$4,000	0.9	$50	A	B
12	0.3	$400	0.7	$100	0.1	$6,000	0.9	$50	A	B
13	0.3	$400	0.7	$100	0.1	$10,000	0.9	$50	A	B
14	0.3	$400	0.7	$100	0.1	$17,000	0.9	$50	A	B

	Lottery A				Lottery B				Please Circle EITHER A or B Stop when First B Circled	
Row	probability ($400)	Payoff	probability ($300)	Payoff	probability ($?)	Payoff	probability ($50)	Payoff	Choose A	Choose B
1	0.9	$400	0.1	$300	0.7	$540	0.3	$50	A	B
2	0.9	$400	0.1	$300	0.7	$560	0.3	$50	A	B
3	0.9	$400	0.1	$300	0.7	$580	0.3	$50	A	B
4	0.9	$400	0.1	$300	0.7	$600	0.3	$50	A	B
5	0.9	$400	0.1	$300	0.7	$620	0.3	$50	A	B
6	0.9	$400	0.1	$300	0.7	$650	0.3	$50	A	B
7	0.9	$400	0.1	$300	0.7	$680	0.3	$50	A	B
8	0.9	$400	0.1	$300	0.7	$720	0.3	$50	A	B
9	0.9	$400	0.1	$300	0.7	$770	0.3	$50	A	B
10	0.9	$400	0.1	$300	0.7	$830	0.3	$50	A	B
11	0.9	$400	0.1	$300	0.7	$900	0.3	$50	A	B
12	0.9	$400	0.1	$300	0.7	$1,000	0.3	$50	A	B
13	0.9	$400	0.1	$300	0.7	$1,100	0.3	$50	A	B
14	0.9	$400	0.1	$300	0.7	$1,300	0.3	$50	A	B

Appendix A2. sMPL Choices in Life-Duration Domain

	Treatment A				Treatment B				Please Circle EITHER A or B Stop when First B Circled	
Row	probability (8 Years)	Years	probability (2 Years)	Years	probability (? Years)	Years	probability (1 Year)	Year	Choose A	Choose B
1	0.3	8 Years	0.7	2 Years	0.1	13.5 Years	0.9	1 Year	A	B
2	0.3	8 Years	0.7	2 Years	0.1	15 Years	0.9	1 Year	A	B
3	0.3	8 Years	0.7	2 Years	0.1	16.5 Years	0.9	1 Year	A	B
4	0.3	8 Years	0.7	2 Years	0.1	18.5 Years	0.9	1 Year	A	B
5	0.3	8 Years	0.7	2 Years	0.1	21 Years	0.9	1 Year	A	B
6	0.3	8 Years	0.7	2 Years	0.1	25 Years	0.9	1 Year	A	B
7	0.3	8 Years	0.7	2 Years	0.1	30 Years	0.9	1 Year	A	B
8	0.3	8 Years	0.7	2 Years	0.1	37 Years	0.9	1 Year	A	B
9	0.3	8 Years	0.7	2 Years	0.1	44 Years	0.9	1 Year	A	B
10	0.3	8 Years	0.7	2 Years	0.1	60 Years	0.9	1 Year	A	B

	Treatment A				Treatment B				Please Circle EITHER A or B Stop when First B Circled	
Row	probability (8 Years)	Years	probability (6 Years)	Years	probability (? Years)	Years	probability (1 Year)	Year	Choose A	Choose B
1	0.9	8 Years	0.1	6 Years	0.7	10.5 Years	0.3	1 Year	A	B
2	0.9	8 Years	0.1	6 Years	0.7	11 Years	0.3	1 Year	A	B
3	0.9	8 Years	0.1	6 Years	0.7	11.5 Years	0.3	1 Year	A	B
4	0.9	8 Years	0.1	6 Years	0.7	12 Years	0.3	1 Year	A	B
5	0.9	8 Years	0.1	6 Years	0.7	12.5 Years	0.3	1 Year	A	B
6	0.9	8 Years	0.1	6 Years	0.7	13 Years	0.3	1 Year	A	B
7	0.9	8 Years	0.1	6 Years	0.7	13.5 Years	0.3	1 Year	A	B
8	0.9	8 Years	0.1	6 Years	0.7	14.5 Years	0.3	1 Year	A	B
9	0.9	8 Years	0.1	6 Years	0.7	15.5 Years	0.3	1 Year	A	B
10	0.9	8 Years	0.1	6 Years	0.7	16.5 Years	0.3	1 Year	A	B
11	0.9	8 Years	0.1	6 Years	0.7	18 Years	0.3	1 Year	A	B
12	0.9	8 Years	0.1	6 Years	0.7	20 Years	0.3	1 Year	A	B
13	0.9	8 Years	0.1	6 Years	0.7	22 Years	0.3	1 Year	A	B
14	0.9	8 Years	0.1	6 Years	0.7	26 Years	0.3	1 Year	A	B

Appendix A3. sMPL Lottery Choices in Environmental Domain

	Cleanup Option A				Cleanup Option B				Please Circle EITHER A or B Stop when First B Circled	
Row	probability (20 sq miles)	Square Miles Cleaned	probability (15 sq miles)	Square Miles Cleaned	probability	Square Miles Cleaned	probability (2.5 sq miles)	Square Miles Cleaned	Choose A	Choose B
1	0.9	20 sq miles	0.1	15 sq miles	0.7	27 sq miles	0.3	2.5 sq miles	A	B
2	0.9	20 sq miles	0.1	15 sq miles	0.7	28 sq miles	0.3	2.5 sq miles	A	B
3	0.9	20 sq miles	0.1	15 sq miles	0.7	29 sq miles	0.3	2.5 sq miles	A	B
4	0.9	20 sq miles	0.1	15 sq miles	0.7	30 sq miles	0.3	2.5 sq miles	A	B
5	0.9	20 sq miles	0.1	15 sq miles	0.7	31 sq miles	0.3	2.5 sq miles	A	B
6	0.9	20 sq miles	0.1	15 sq miles	0.7	32.5 sq miles	0.3	2.5 sq miles	A	B
7	0.9	20 sq miles	0.1	15 sq miles	0.7	34 sq miles	0.3	2.5 sq miles	A	B
8	0.9	20 sq miles	0.1	15 sq miles	0.7	36 sq miles	0.3	2.5 sq miles	A	B
9	0.9	20 sq miles	0.1	15 sq miles	0.7	38.5 sq miles	0.3	2.5 sq miles	A	B
10	0.9	20 sq miles	0.1	15 sq miles	0.7	41.5 sq miles	0.3	2.5 sq miles	A	B
11	0.9	20 sq miles	0.1	15 sq miles	0.7	45 sq miles	0.3	2.5 sq miles	A	B
12	0.9	20 sq miles	0.1	15 sq miles	0.7	50 sq miles	0.3	2.5 sq miles	A	B
13	0.9	20 sq miles	0.1	15 sq miles	0.7	55 sq miles	0.3	2.5 sq miles	A	B
14	0.9	20 sq miles	0.1	15 sq miles	0.7	65 sq miles	0.3	2.5 sq miles	A	B

	Cleanup Option A				Cleanup Option B				Please Circle EITHER A or B Stop when First B Circled	
Row	probability (20 sq miles)	Square Miles Cleaned	probability (5 sq miles)	Square Miles Cleaned	probability (? sq miles)	Square Miles Cleaned	probability (2.5 sq miles)	Square Miles Cleaned	Choose A	Choose B
1	0.3	20 sq miles	0.7	5 sq miles	0.1	34 sq miles	0.9	2.5 sq miles	A	B
2	0.3	20 sq miles	0.7	5 sq miles	0.1	37.5 sq miles	0.9	2.5 sq miles	A	B
3	0.3	20 sq miles	0.7	5 sq miles	0.1	41.5 sq miles	0.9	2.5 sq miles	A	B
4	0.3	20 sq miles	0.7	5 sq miles	0.1	46.5 sq miles	0.9	2.5 sq miles	A	B
5	0.3	20 sq miles	0.7	5 sq miles	0.1	53 sq miles	0.9	2.5 sq miles	A	B
6	0.3	20 sq miles	0.7	5 sq miles	0.1	62.5 sq miles	0.9	2.5 sq miles	A	B
7	0.3	20 sq miles	0.7	5 sq miles	0.1	75 sq miles	0.9	2.5 sq miles	A	B
8	0.3	20 sq miles	0.7	5 sq miles	0.1	92.5 sq miles	0.9	2.5 sq miles	A	B
9	0.3	20 sq miles	0.7	5 sq miles	0.1	110 sq miles	0.9	2.5 sq miles	A	B
10	0.3	20 sq miles	0.7	5 sq miles	0.1	150 sq miles	0.9	2.5 sq miles	A	B
11	0.3	20 sq miles	0.7	5 sq miles	0.1	200 sq miles	0.9	2.5 sq miles	A	B
12	0.3	20 sq miles	0.7	5 sq miles	0.1	300 sq miles	0.9	2.5 sq miles	A	B
13	0.3	20 sq miles	0.7	5 sq miles	0.1	500 sq miles	0.9	2.5 sq miles	A	B
14	0.3	20 sq miles	0.7	5 sq miles	0.1	850 sq miles	0.9	2.5 sq miles	A	B