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Can Personality Type Explain Heterogeneity in Probability Distortions?

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Abstract

There are two regularities we have learned from experimental studies of choice under risk. The first is that the majority of people weigh objective probabilities non-linearly. The second regularity, although less commonly acknowledged, is that there is a large amount of heterogeneity in how people distort probabilities. Despite of this, little effort has been made to identify the source of heterogeneity. In this paper, we explore the possibility that personality type is linked to probability distortions. Using validated psychological questionnaires, we clustered participants into distinct personality types: motivated, impulsive, and affective. We found that the motivated viewed gambling more attractive, whereas the impulsive were the most capable of discriminating non-extreme probabilities. Our results suggest that the observed heterogeneity in probability distortions may be explained by personality profiles, which can be elicited through standard psychological questionnaires.

Keywords

choice under risk; personality; experiments; probability weighting function

There are two regularities that we have learned from experimental studies of choice under risk. The first is that the majority of people weigh objective probabilities non-linearly, challenging the view from traditional economics that expected utility is linear in probability. In particular, several studies suggest that people overweight small probabilities of a gain or loss and underweigh medium and large probabilities, and the “typical” probability weighting function has an inverse S-shape as depicted below (see Latimore, Baker & Witte 1992; Tversky & Kahneman, 1992; Camerer & Ho, 1994; Abdellaoui, 2000; Starmer, 2000). The

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second regularity, although less commonly acknowledged, is that there is a large amount of heterogeneity in how people distort probabilities (Berns et al., 2007; Bleichrodt & Pinto, 2000; Bruhin, Fehr-Duda & Epper, 2010; Fehr-Duda & Epper, 2012; Gonzalez & Wu, 1999; Wu & Gonzalez, 1999; Wu & Gonzalez, 1996). Indeed, although in most of the above-mentioned studies the authors report close median estimates of the probability weights (as shown in Figure 1), heterogeneity in the subject-specific estimates is seldom explained.

Interestingly, these regularities (i.e., inverse-shaped median probability weighting functions and large heterogeneity) seem to hold when choices are defined over gains or losses, and when outcomes are monetary or nonmonetary. For example, allowing for heterogeneity in preferences, Bleichrodt and Pinto (2000) proposed non-parametric elicitation of individuals' utility and probability weighting functions for hypothetical gains and losses. They found significant evidence of inverse S-shaped probability weighting both at the aggregate and the individual level. In Berns et al. (2007), we used electric shocks to induce real and negative outcomes in choice under risk. We found median estimated probability distortion parameters similar to the above-mentioned. In addition, we found that, 46% of the subjects distorted probabilities in an inverse S-shape manner, as predicted by Prospect Theory or Rank-dependent Utility Theory; 14% did not distort probabilities and could be classified as Expected Utility Theory (EUT) subjects, whereas 16% could not be classified at all with existing theories of choice under risk. Finally, using parametric and non-parametric estimation of the probability weighting function, Gonzalez and Wu (1999) – henceforth G&W – found that sub-certainty (the tendency of subjective probabilities to add to a number less than 1) failed to hold in 40% of the subjects. The implication of G&W's result is that *some* people may overestimate a larger set of probabilities than it is customarily believed.

Although little effort has been made to identify the determinants of such heterogeneity, existing research suggests there are two possible explanations. First, differences in estimated values of probability weighting may be due to differences in participants' ability and experience in processing probability. For example, Piaget and Inhelder (1975) showed that 4-year old children had a step-like function. Young children seemed to understand when a sure thing would happen and when something would not happen, but they treated all other probabilities equally. This suggests that very young children have flat probability weighting functions. More recently, in a large-scale experiment, Dohmen et al. (2011) found that lower cognitive ability was associated with greater risk aversion.

A second possible explanation comes from the emotional response to the task. Rottenstreich and Hsee's (2001) experiments, for example, showed that the weighting function depended on affective reactions, which were influenced by the description of the outcome. They found that affect-rich prizes, such as a trip to the Caribbean, revealed weighting functions with jumps at the ends of the probability scale and low marginal sensitivity over a wide range of probabilities in the middle (i.e., child-like weighting functions). However, even in affect-poor environments, people distort probability in surprisingly different ways, as mentioned above.

Given the important modulatory role of personality on behavior, motivation, emotion and cognition, we investigate the impact of personality on risky choices. Specifically, we explore the possibility that the personality "type" of the decision maker is linked to probability distortions. We choose to study personality type rather than personality traits, because an individual's personality consists of many dimensions. An individual may possess a set of contradictory traits (i.e., score high in extraversion, inhibition, and neuroticism), but is best described by a dominant personality trait or type that he or she shares with other people. Thus, here, we identify how groups of subjects, who differ in their personality types, differ with respect to their probability and utility weights.

There are several reasons for why we believe that personality influences probability weights. First, personality mediates emotion. Individuals who rank high in neuroticism, for example, tend to experience feelings such as anxiety, anger, and depressed mood. Previous studies on the effect of affect on choice under risk suggest that induced positive affect decreased the perceived frequency of negative outcomes (see Johnson & Tversky, 1983). Secondly, personality reflects generally stable patterns in behavior, motivation, and cognition (Borghans et al., 2009; Zillig, Hemenover & Dienstbier, 2002). Borghans, Golsteyn, Heckman and Meijers (2009) conducted an experiment on a sample of 347 Dutch high school students; they showed that the differences in cognitive and non-cognitive personality traits, such as IQ, the Big Five (openness, conscientiousness, extraversion, agreeableness, neuroticism), and self-control accounted for the differences in preference parameters. Zuckerman (2007) also found that differences in sensation-seeking personality traits (i.e. impulsivity, motivation, and extraversion) were strongly related to a broad range of risky behaviors, such as extreme sports, substance use and abuse (i.e. smoking, drinking, drugs), unprotected sex, violence, and criminal behavior. Finally, voxel-based morphometry (e.g., Blankstein, et al., 2009; DeYoung et al., 2010; Omura et al., 2005) and diffusion tensor imaging (Cohen et al., 2008) studies have identified neuroanatomical correlates of individual differences in personality traits. Furthermore, functional imaging studies have demonstrated significant modulation of neural correlates of emotional reactivity (e.g., Mobbs et al., 2005; Canli et al., 2002) and functional connectivity (Adelstein et al., 2011) by personality trait. Together, results from Personality Neuroscience underline the modulatory role of personality traits in brain-behavior relationships.

In order to explore the link between personality and probability distortions, we designed an experiment that consisted of two parts. In the first, participants responded to several psychological questionnaires¹ that included the Eysenck Personality Questionnaire Revised Version (EPQ-R; Eysenck et al., 1985), the Behavioral inhibition and behavioral activation systems scale BIS/BAS Scales (Carver & White, 1994), the Barratt Impulsiveness Scale, Version 11 (BIS-11; Patton et al., 1995), and the Regulatory Focus Questionnaire (RFQ; Higgins et al., 2001). Unlike the Big Five questionnaire, which is more widely recognized, our chosen psychological questionnaires provide validated measures of sensation-seeking personality traits that are shown to strongly correlate with risk preference (Zuckerman, 2007; Harlow & Brown, 1990). We used the personality scores obtained from these four questionnaires to cluster people into heterogeneous personality types. We did this to identify how groups of individuals that exhibited differing categorizations of dominant traits distorted probabilities and outcomes.

In the second part, participants made a series of binary choices between a fixed amount of sure bet and a chance of winning a larger amount. To estimate probability weighting and the curvature of the utility function for each participant, we assumed a power utility function, and a two-parameter probability weighting function as in Lattimore, Baker and Witte (1992), Tversky and Wakker (1995), and Gonzalez and Wu (1999). Unlike one-parameter probability functions, the two-parameter weighting function allowed us to identify heterogeneity in distortions that were due to discriminability (i.e., a measure of curvature that captures the idea that people are more sensitive to changes in probabilities as they move away from certainty), or due to attractiveness (i.e., a measure of elevation that captures how appealing gambling is to the decision maker). To approximate an individual's value of a lottery or certainty equivalent (CE), we used a modified version of the parameter estimation by sequential testing (PEST) procedure (Luce, 2000; Cho, Luce & von Winterfeld, 1994).

¹In personality studies, it is customary to include a large set of questions to better capture the complete personality profile of the participants; not all questions capture the same attribute (see Cicchetti, 1994 for a discussion of guidelines and criteria for assessment instruments in Psychology).

We found that heterogeneous types of personality traits are associated with different risk characteristics. In particular, the motivated viewed gambling more attractive, while the impulsive were most capable of discriminating non-extreme probabilities. The remainder of the paper is organized as follows. We begin by describing the experiment. Then we analyze the experimental data, and finally, we discuss the implications of our experiment.

Experimental Design and Procedures

We recruited a total of 48 healthy participants (32 females) for this study. All participants were students or staff members at Emory University. The average age was 23.40 with a standard deviation of 5.36 years. All participants gave written informed consent to participate. The experiment took about 2 hours to complete, and included a one-hour brain scan, parts of which are reported elsewhere (Engelmann et al., 2009, 2012). Earnings ranged between \$44.50 and \$76 with an average of \$60.51.

The sequence of experimental procedures was as follows. First, subjects were asked to respond to a pre-survey consisting of a set of psychological questionnaires including the EPQ-R and BIS/BAS². After completing all psychological surveys, participants were asked to make a series of choices between a sure win and lotteries providing ex-ante probabilities of winning a comparatively higher payoff denominated in experimental currency (Yen), or not winning anything. For every decision, the higher payoff was always 1,000 Yen and the probability of winning the 1,000 Yen prize varied across conditions (0.01, 0.1, 0.2, 0.37, 0.8, 0.9, and 0.99). The sure win amount was adjusted according to participant's choices on previous trials using an iterative staircase algorithm (PEST) that is outlined in detail in the next section. Figure 2 depicts an example of the lottery choices in two different trials.

A typical trial consisted of a decision-making period, followed by a feedback period that provided confirmatory information about which option was selected by the participant, but not about how much the subject made in that trial. In order to control for wealth effects, one of the trials was selected randomly to count towards payment at the end of the session. The decision made on the selected trial determined payment as follows: if the sure win was chosen on the selected trial, the respective amount was paid to the subject; if the lottery was chosen, a "computerized coin" was tossed, giving subjects a chance to win 1,000 laboratory Yen at the probability indicated in the lottery. Finally, an exchange rate of 1,000 laboratory Yen = 16 USD was established at the beginning of the experiment. At the beginning of the experiment subjects were fully informed of the payment plan and the exchange rate.

Certainty Equivalents and Structural Estimation

We were interested in identifying each individual's certainty equivalents (CE) for the lotteries. To do this, we used a modified version of the Parameter Estimation by Sequential Testing (PEST) introduced by Cho, Luce and von Winterfeld (1994), which is a procedure that relies on a staircase algorithm to identify the CE of a lottery. With PEST, the CE of a lottery is found by sequentially adjusting the value of the sure win according to decisions made by the subject. In our version of PEST, the algorithm started with a random offer that depended on the probability condition. When the probability of winning the prize was between 0.1 and 0.37 (i.e. low probability conditions), the sure win was between 0 and 500 Yen. In contrast, offers started between 500 and 1,000 Yen in the high probability conditions (i.e., 0.8–0.99). In order to create choice switches between sure wins and lotteries, amounts for sure wins were adjusted as follows: whenever the subject chose the sure win, the amount offered on the next trial was decreased by step-size, ϵ . Whenever the subject chose the

²We provide a more detailed explanation of the personality surveys in the "Psychological Questionnaires" section.

lottery, the amount of the sure win offered on the next trial was increased by ε . The magnitude of ε was determined by the following 4 rules adapted from Luce (2000) and Cho, Luce and von Winterfeld (1994): (1) the initial step-size was set to 1/5 of the difference between the maximum and minimum possible payoffs ($\varepsilon = 200$ Yen); (2) at each choice switch ε was halved; (3) ε was doubled after three successive choices of the same item; (4) values were bounded at the maximum (1,000 Yen) and the minimum payoffs (0 Yen). This was done within each probability condition, which we presented in random order. The staircase algorithm terminated when the threshold step-size for a given probability condition was reached. This threshold was set to 25 Yen for all conditions, except for 0.01, 0.37 and 0.99, for which the threshold was set to 12.5 Yen.

The PEST procedure allowed us to generate CEs relatively fast for many pairs of different lotteries³. This is important because we are interested in estimating individual-level probability weighting and utility function parameters. For this, many observations of decisions for each subject were needed. In addition, the PEST procedure is a choice task, not a valuation task, and previous literature has suggested that choice mode may be less “biased” than valuation mode (see Cox & Grether, 1996). Thus, for our purposes, the PEST procedure is preferred over alternative value elicitation mechanisms, such as auction mechanisms and the Becker-deGroot-Marschak (BDM) procedure.

After collecting all the data from subjects’ binary decisions (lottery or sure win), we estimated each participant’s probability weighting and utility functions using Gonzalez and Wu (1999)’s probability weighting form and power utility function. In each trial, the subject had a choice between a sure win (sw) and a lottery that paid a fixed amount π with probability p . The probability of choosing the lottery (P_l) was estimated using a logistic regression specification:

$$P_l = \frac{e^{\phi}}{1 + e^{\phi}}$$

where ϕ represented the difference in utility between the lottery and the sure win in each trial; that is,

$$\phi = w(p)\pi^{\sigma} - sw^{\sigma}$$

The parameter σ captures the curvature of the utility function, and the subjective probability of winning the lottery was given by:

$$w(p) = \frac{\delta p^{\gamma}}{\delta p^{\gamma} + (1 - p)^{\gamma}}$$

where parameters γ and δ control the curvature (discriminability) and the elevation (attractiveness) of the probability weighting function, respectively.

Figure 3 shows shapes of the probability weighting for a few of our subjects. On the top panel, subject S8 and subject S13 share very similar estimated δ (elevation), but different estimated γ (discriminability). Subject S13 discriminates intermediate probabilities more

³The staircase algorithm terminated as soon as a threshold was reached - so there was no set number of trials; the longer the algorithm would take, the more trials there were. Most subjects participated in more than 50 trials.

than S8, whose $w(p)$ at the extremes is very steep. On the bottom panel, subjects S35 and S37 share similar γ parameters, but differ in their estimated δ , resulting in S35's $w(p)$ that lies above the 45° line and S37's $w(p)$ that lies below the 45° line. In our study, we estimated the three risk parameters jointly for each individual using Matlab.

Psychological Questionnaires

According to psychologists, personality reflects the characteristic patterns of thoughts, feelings, and behaviors that make a person unique. It originates within the individual and remains fairly consistent throughout life (Borghans et al., 2009). To psychologists, personality is an area of study that deals with complex human behavior, including emotions, actions, and cognitive (thought) processes. As early as in the 90s, researchers like Harlow and Brown (1990) studied the role of certain biological and personality traits in the formation of economic preferences. To test the statistical relations between various measures, they separated male and female subjects into subgroups within each gender group, based on measures of subjects' neurochemical activities, and their scores on sensation-seeking scale and introversion scale. They found that individuals with a high level of "sensation-seeking" personality traits (i.e. extraversion and impulsivity) exhibited a willingness to accept economic risk. Recent studies have shown that sensation-seeking personality traits are linked to risk taking behaviors, such as extreme sports, substance use and abuse (i.e. smoking, drinking, drugs), unprotected sex, violence, and criminal behavior (see Zuckerman, 2007 for a review).

To measure sensation-seeking personality traits, we used well-established psychological questionnaires/scales including the EPQ-R, the BAS/BIS, the BIS-11, and the RFQ. The EPQ-R contains 100 Yes/No questions assessing biologically-based categories of temperament including Extraversion/Introversion, Neuroticism/Stability, Psychoticism/Socialisation, and Lie. Extraversion is characterized by being outgoing, talkative, high on positive affect (feeling good), and in need of external stimulation. Neuroticism is characterized by having high levels of negative affect such as anger, depression, and anxiety. Psychoticism is associated not only with the liability to have a psychotic episode (or break with reality), but also with aggression. Last but not the least, Lie scale measures the tendency of lying when lying makes one socially better off. The second questionnaire (BAS/BIS) contains behavioral questions. According to Gray (1981, 1982) two general motivational systems underlie behavior and affect: a behavioral inhibition system (BIS) and a behavioral activation system (BAS). A behavioral activation system (BAS) is believed to regulate appetitive motives, in which the goal is to move toward something desired. A behavioral inhibition system (BIS) is said to regulate aversive motives, in which the goal is to move away from something unpleasant. The BIS/BAS scales assess individual differences in the sensitivity of these systems. The Barratt Impulsiveness Scale, Version 11 (BIS-11; Patton et al., 1995) is a 30 item self-report questionnaire designed to assess general impulsiveness, which includes attentional impulsiveness, motor impulsiveness, self-control, and planning impulsiveness. Finally, the RFQ is an 11 item self-report questionnaire designed to assess individuals' subjective histories of success or failure in promoting and preventing self-regulation. According to focus theory (Higgins, 1998), all goal-directed behavior is regulated by two distinct motivational systems. These two systems, termed promotion and prevention, each serve as a distinct survival function. The promotion system is concerned with obtaining nurturance (e.g. nourishing food) and underlies higher-level concerns with accomplishment and advancement. The promotion system's hedonic concerns relate to the pleasurable presence of positive outcomes and the painful absence of positive outcomes. In contrast, the prevention system is concerned with obtaining security and underlies higher-level concerns with safety and fulfillment of responsibilities. The

prevention system's hedonic concerns relate to the pleasurable absence of negative outcomes and the painful presence of negative outcomes.

Results

Table 1 displays a summary statistics of parameter estimates among the 48 subjects. The median estimates suggest an inverse-S probability weighting function similar to those reported in previous literature.

At the individual level, we observed a large variability in individual's estimated probability weighting parameters (see Chart A in the Appendix). To determine how personality profiles differed with respect to their probability and outcome distortions, we used clustering analysis⁴ to identify participants based on their responses to the four psychological questionnaires⁵. We used hierarchical clustering analysis (Complete Linkage method⁶) to classify 47 subjects⁷ into different clusters; we identified four distinct personality types. Personality Type 1 (henceforth PersType1) had a total of 9 subjects who, on average, were older and mostly women. PersType2 was comprised of 21 subjects, and had a higher proportion of males than the other groups. PersType3 had 16 subjects and the female/male ratio mirrored our participant population. Finally, PersType4 had 1 subject only. We excluded PersType4 from the rest of the analysis.

What kind of personality profiles do these clustered types have? To answer this question and label the types, we performed factor analysis (i.e. varimax rotation) and identified four factors with eigenvalues greater than one, which accounted for 68.3% of the variance. Table 2 shows the loadings and the uniqueness scores for each personality attribute. As the table suggests, Factor 1 is mainly defined by **impulsivity traits** (NP-BIS11; Mot-BIS-11; Cog-BIS-11; Psychoticism; BAS-funskg). Factor 2 is mainly defined by **affective traits** (Extraversion; Neuroticism; BIS). In contrast, Factor 3 is influenced by **motivational traits** (Reg-promote; BAS-drive; BAS-rewards). Finally, Factor 4 is defined by loss avoidance/prevention traits (Lie-all; Reg-prevent).

For each clustered type, we identified which factors had positive average scores. For PersType1, the average score of Factor 3 (motivation) was positive, the rest were negative. For PersType2, the average score for Factor 1 (impulsiveness) was positive, the rest were negative. For PersType3, only Factor 1's average score was negative, the rest positive.

We tested whether the factor scores among these three personality types were statistically different. PersType2 differed from the other two personality-types (PersTypes1 and 3) with respect to the Factor 1 (Median test $p=0.012$ and $p<0.001$, respectively), with PersType2 being relatively more impulsive. With respect to Factor 2, PersType3 was different from the two other personality types (Median test $p=0.001$ and $p<0.001$) with PersType3 being relatively more emotionally reactive, or more affective. In addition to these personality differences, we noticed that PersType1 were older and had relatively more females (see

⁴The criterion for classifying subjects into clustered personality types is the measure of traits similarity or distances (dissimilarity measures) between individual subjects. At each stage, it computes the distances between all the existing clusters to determine which clusters are the closest to each other. The closest clusters are combined to form a new, large cluster and the algorithm stops clustering whenever membership in clusters stabilizes. As a result, items within a cluster are similar, and/or the distance between them is small; and items in different clusters are dissimilar, and/or the distance between them is large.

⁵Although correlating personality to risk parameters without clustering the data may seem reasonable, this method hides the fact that the effect of a specific trait (e.g. extraversion) on preferences is conditional on the general personality profile of the individual. For example, more extraversion in an inhibited person has a contradictory effect compared to more extraversion in an impulsive one.

⁶We also tried out other clustering algorithms that apply different criteria to measure distances such as Single, Median, Centroid Linkage, and obtained the same results.

⁷One female subject didn't complete all the personality questionnaires, so this observation was excluded.

Table C in the Appendix for a summary of demographic variables by clustered type). The above results suggest that we could label three types in the following manner: PersType1 (9 subjects) were relatively more “Motivated”. PersType2 (21 subjects) were more “Impulsive”. Finally PersType3, which had 16 subjects, were more “Affective” (see Table B and C for further details).

Behavioral differences among Types

Table 3 presents summary statistics of the estimated risk parameters gamma, delta, and sigma by personality type (additional data are found in the appendix). We compared and contrasted the three different personality types with respect to the estimated probability weighting and utility functions parameters. Acknowledging the fact that we had three groups of multivariate data, we performed group comparison tests using non-parametric MANOVA⁸. We found noticeable overall differences among the three characteristic types (test statistics based on distances to centroids, $F=3.092$, $p=0.056$). In particular, PersType1 (Motivated) differed significantly from PersType3 (Affective) with regard to the three estimated risk parameters (test statistics based on distances to centroids, $t=2.521$, permutation $p\text{-value}=0.054$). With respect to comparisons between types, we found differences in attractiveness (i.e., a measure of elevation that captures how appealing gambling is to the decision maker) and discriminability (i.e., a measure of curvature of the probability weighting function that captures the idea that people are more sensitive to changes in probabilities as they move away from certainty). PersType1 (Motivated) subjects had different estimated delta values, as compared to PersType2 (Impulsive) and PersType3 (Affective) (MWT, $Z=1.924$, $p=0.054$; and $Z=1.981$, $p=0.048$, respectively). This suggests that the motivated viewed gambling significantly more attractive, PersType2 and PersType3 or the Impulsive vs. the Affective (but not impulsive) differed with respect to their estimated gamma values (MWT, $Z=2.115$, $p=0.034$) suggesting that the impulsive were the most capable of discriminating non-extreme probabilities. Finally with respect to sigma, PersType1 (Motivated) and PersType2 (Impulsive) differed significantly (MWT, $Z=-1.969$, $p=0.049$).

It's also interesting to study the gender effect on individual's risk preferences. Aggregating across all types (47 subjects), only with respect to the curvature of the utility function (sigma) did we observe significant differences between men and women (MWT, $Z=2.613$, $p=0.009$). This result is consistent with other works that have identified gender differences in risk attitudes (see Borghans et al., 2009). However, we did not observe statistically significant differences between men and women with respect to discriminability and elevation.

Discussion

Several studies of choice under risk that report individual parameter estimates show that there is a high level of heterogeneity in how people distort probabilities. Despite of this, little effort has been made to identify the source of this heterogeneity. In this paper, we put forward the idea that personality type is a determinant of choice under risk, and that different personality types exhibit different risk preferences. Using four widely utilized psychological tests, we were able to classify participants into three distinct personality types. We then compared these types with respect to their estimated risk parameters. PersType 1, or “motivated” individuals, who were controlled and emotionally stable, tended to be more

⁸Non-parametric MANOVA (Multivariate Analysis of Variance) is to test significant difference between two or more groups of multivariate data, based on any distance measure of choice (Anderson, 2001). In our analysis, we used Euclidean distances and performed 9999 permutations. Manly (1997) pointed out that for tests at an α -level of 0.05, at least 999 permutations should be used; for tests at an α -level of 0.01, at least 4999 permutations should be used.

risk averse as measured by the curvature of the utility function, but they were also more optimistic, as measured by the elevation of the probability weighting function. These results fit well with predictions from regulatory focus theory (RFT, Higgins, 1998) that people with a promotion focus have a heightened sensitivity for positive outcomes. It could be argued that motivated individuals by focusing on rewarding outcomes, they place a greater weight on payoff magnitude relative to payoff probability leading to more optimistic risk attitudes. PersType 2 or “impulsive” individuals were reward and fun seeking, and they tended to be less risk averse. Finally, PersType 3 or “affective” individuals were inhibited and neurotic, and they were shown to discriminate probabilities less around the middle and have curvier probability weighting functions around the reference points. Our results, thus, suggest that heterogeneity in probability weighting and more generally, in choice under risk may be explained by personality profiles, which can be elicited through standard psychological questionnaires. We also found that females were more risk averse than males, confirming previous findings.

Recent literature has shown that personality affects risk preferences (see Borghans et al., 2009). In addition, psychologists believe personality is a stable trait, but that personality also often interacts with the environment to produce a certain outcome (Weber et al., 2002). This can explain why risk preferences are stable when elicited through a single choice mode (Harrison & Rutström, 2000; Andersen, Harrison, Lau & Rutström, 2008), yet, may differ when elicited through valuation mechanisms (e.g., auction vs. lottery choice – see Eckel & Grossman, 2002; Berg, Dickhaut, & McCabe, 2005; Issac & James, 2000). Issac and James (2000), for example, showed that the estimated numerical values of individuals’ implied risk parameters were not stable within individuals across the BDM and first-price auction institutions. Furthermore, the rankings across subjects of the numerical values of risk were not preserved. In a more recent paper, Berg, Dickhaut and McCabe (2005) replicated these findings with an improved paradigm. They concluded by saying that “...there simply might not be such things as preferences (“they” ain’t nothing til we call em”). However, our study highlights the important role of personality type in explaining choices under risk, and it is the first step towards formulating the hypothesis that the observed instability of preferences may be due to an interaction between personality and the choice environment. Indeed, this could be an interesting path for future research.

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Appendix

Chart A

Estimates of individual risk parameters and demographics

Subject	Probability weighting		Utility	Gender	Age	Payment (USD)
	γ	δ	σ			
1	0.0853	1.2584	0.5319	F	25	63
2	0.3957	0.683	0.4908	F	25	65
3	0.4799	0.8599	0.4711	M	24	60
4	2.486	1	0.2042	F	22	63
5	0.5213	0.8688	0.5087	M	22	53.5
6	0.6797	0.549	0.4384	F	19	45
7	0.4468	0.7275	0.4583	F	22	54
8	0.3837	1.0797	1.1982	M	23	72.5
9	0.7624	0.5704	0.4435	M	20	60
10	0.8733	0.4662	0.5514	F	25	75
11	0.5	0.423	0.3203	M	20	70
12	0.9256	2.1918	2.1249	F	20	76
13	0.6497	1.0735	0.6437	M	22	72
14	2.5545	2.3059	0.5174	F	21	50
15	0.3752	0.8255	0.3904	F	21	45
16	0.4731	0.8646	0.3818	F	28	60.5
17	1.4804	1.7078	0.5141	F	21	63
18	1.5707	0.25	0.7073	F	22	65
19	2.0405	1	0.195	F	45	60.5
20	0.8703	1.8744	1.4863	M	18	44.5
21	3.9056	1	0.1971	F	21	62
22	0.7369	0.5405	0.4068	M	19	52
23	0.8854	1.5476	1.3497	M	20	49.5
24	0.2967	0.8436	0.4243	F	26	61
25	0.1007	1.4416	0.6182	F	19	60
26	0.322	0.4858	0.4132	F	28	69
27	0.5042	0.5529	0.4023	F	25	60
28	0.7625	0.5956	0.5099	F	20	47.4
29	0.3792	0.9213	0.4735	F	20	52.75
30	0.9842	1.5192	1.5306	M	28	60.48
31	1.9884	0.4115	1.3041	F	34	61
32	0.2693	0.7404	0.4328	F	21	76
33	0.9271	0.5443	0.5085	M	21	76
34	0.7157	0.5902	0.5337	F	21	60
35	0.9388	1.2865	1.2663	M	28	60
36	0.3772	0.5444	0.4234	F	25	51.84
37	1.0113	0.4968	0.4426	M	18	47
38	0.4277	1.0278	0.4483	F	21	60

Subject	Probability weighting		Utility	Gender	Age	Payment (USD)
	γ	δ	σ			
39	0.8149	0.4496	0.4087	F	18	60
40	0.9161	0.4595	0.5182	M	23	61
41	0.19	2.4983	0.2835	F	21	60
42	0.8443	0.7622	0.5592	M	20	62.25
43	1.0656	0.5107	0.5369	M	18	60
44	0.8914	1.0918	0.837	F	23	68
45	0.5135	0.6051	0.4884	M	28	76
46	0.4722	0.574	0.2462	F	36	59.93
47	1.63	2.8992	0.4218	F	36	66
48	1.1985	5	0.269	F	20	48

Table B

Description of Variables (47 Subjects)

Category	Variable Name	Description / Range of Values	Mean (Std)	Median	Mode	95% C. I.
	NP-BIS-11	Non-planning impulsiveness (a lack of “futuring” or planning). Values range from 13 to 29	21.09 (3.79)	21.00	21.00	(19.97, 22.20)
	Cog-BIS-11	Cognitive impulsiveness (i.e. making quick cognitive decisions). Values range from 11 to 26	17.17 (3.46)	18.00	18.00	(16.15, 18.19)
	Mot-BIS-11	Motor impulsiveness (i.e. acting without thinking). Values range from 13 to 32	21.13 (3.78)	21.00	20.00 23.00	(20.02, 22.24)
	Reg-promote	Promotion focused self-regulation to approach matches to desired end-states. Values range from 16 to 30	23.38 (3.22)	23.00	21.00 23.00 24.00	(22.44, 24.33)
	Reg-prevent	Prevention focused self-regulation to approach matches to desired end-states. Values range from 6 to 25	18.09 (4.18)	17.00	17.00	(16.86, 19.31)
Personality Traits	Psychoticism	Liability to have a psychotic episode (or break with reality), and aggression. Values range from 1 to 12	6.04 (2.65)	6.00	6.00	(5.27, 6.82)

Category	Variable Name	Description / Range of Values	Mean (Std)	Median	Mode	95% C. I.
	Extraversion	Being outgoing, talkative, high on positive affect (feeling good), and in need of external stimulation. Values range from 5 to 21	14.51 (4.88)	16.00	19.00	(13.08, 15.94)
	Neuroticism	Emotionality, characterized by high levels of negative affect such as depression and anxiety. Values range from 0 to 23	9.89 (5.51)	10.00	4.00 5.00	(8.27, 11.51)
	Lie-all	Tendency of lying when lying makes one socially better off. Values range from 2 to 14	8.15 (3.01)	8.00	7.00	(7.26, 9.03)
	BAS-drive	Behavioral activation sensitivity to driving motives. Values range from 6 to 16	10.94 (2.50)	11.00	11.00	(10. 20, 11.67)
	BAS-funskg	Behavioral activation sensitivity to fun-seeking motives. Values range from 5 to 16	11.30 (2.62)	11.00	14.00	(10. 53, 12. 07)
	BAS-reward	Behavioral activation sensitivity towards rewards. Values range from 13 to 20	17.53 (1.85)	18.00	18.00	(16. 99, 18.08)
	BIS	Behavioral inhibition sensitivity to unpleasantness. Values range from 13 to 28	19.96 (3.68)	20.00	20.00	(18. 88, 21.04)
	Factor1	Impulsivity traits, defined by Non-planning Impulsiveness, Cognitive Impulsiveness, Motor Impulsiveness, Psychoticism and BAS Fun-seeking. Values range from -1.71 to 3.08.	3.80E-09 (1.00)	-0.24	—	(-0.29, 0.29)
Four Factors	Factor2	Affective traits, defined by Extraversion, Neuroticism and BIS. Values range from -2.01 to 1.96.	4.29E-08 (1.00)	0.14	—	(-0.29, 0.29)
	Factor3	Motivational traits, defined by Regulatory-	-2.85E-08 (1.00)	-0.11	—	(-0.29, 0.29)

Category	Variable Name	Description / Range of Values	Mean (Std)	Median	Mode	95% C. I.
	Factor4	promotion, BAS-drive and BAS-reward. Values range from -2.33 to 2.36. Loss avoidance/prevention traits, defined by Regulatory-prevention and Lie-all. Values range from -2.37 to 1.83	1.80E-08 (1.00)	-0.06	—	(-0.29, 0.29)
Demographics	Male/Female	Sex of the student subjects. Dummy: 0 Male, 1 Female	0.64 (0.49)	1.00	1.00	(0.50, 0.78)
	Age	Age of the student subjects. Age ranges from 18 to 45.	23.47 (5.40)	22.00	21.00	(21.88, 25.05)
	Payment	Subject's earnings from the experiment. Maximum is 76, minimum is 44.5	60.18 (8.46)	60.00	60.00	(57.70, 62.67)
Estimated	Gamma-WG	The curvature of the probability weighting function. It measures how one discriminates probabilities. Maximum is 3.91, minimum is 0.085	0.89 (0.82)	0.74	—	(0.67, 1.10)
Parameters	Delta-WG	The elevation of the probability weighting function. It measures how attractive one views gambling. Maximum is 5, minimum is 0.25	1.03 (0.33)	0.83	1.00	(0.79, 1.27)
	Sigma-CU	The curvature of the CRRA utility function. Maximum is 1.53, minimum is 0.20	0.57 (0.33)	0.47	—	(0.41, 0.74)

Table C (i)

Summary Statistics by Personality Type (47 subjects)

	Type	Mean (Std)	Median	Maximum	Minimum	[95% Conf. Interval]
Factor1	1	-0.93 (0.47)	-1.00	-0.30	-1.59	(-1.29, -0.57)
	2	0.56 (0.74)	.59	1.60	-1.18	(0.22, 0.89)
	3	-0.40 (0.68)	-.49	0.79	-1.71	(-.76, -0.04)
	4	3.08 (0.00)	3.08	—	—	—
	Total	3.80E-09 (1.00)	-0.24	3.08	-1.71	(-0.29, 0.29)

	Type	Mean (Std)	Median	Maximum	Minimum	[95% Conf. Interval]
Factor2	1	-1.06 (0.69)	-1.35	0.21	-1.98	(-1.59, -0.53)
	2	-0.30 (0.71)	-.31	0.81	-2.01	(-0.62, 0.03)
	3	0.91 (0.58)	.91	1.96	-0.03	(0.60, 1.21)
	4	1.35 (0.00)	1.35	—	—	—
	Total	4.29E-08 (1.00)	0.14	1.96	-2.01	(-0.29, 0.29)
Factor3	1	0.22 (0.83)	.19	1.55	-1.13	(-0.42, 0.87)
	2	-0.48 (0.79)	-.45	0.55	-2.33	(-0.83, -0.12)
	3	0.42 (1.11)	.31	2.36	-1.50	(-0.17, 1.01)
	4	1.27 (0.00)	1.27	—	—	—
	Total	-2.85E-08 (1.00)	-0.11	2.36	-2.33	(-0.29, 0.29)
Factor4	1	-0.07 (0.45)	-.15	0.60	-0.69	(-0.42, 0.28)
	2	-0.14 (1.06)	-.22	1.64	-2. 21	(-0.62, 0.34)
	3	0.26 (1.16)	.368	1.83	-2.37	(-0.36, 0.88)
	4	-0.59 (0.00)	-.59	—	—	—
	Total	1.80E-08 (1.00)	-0.06	1.83	-2.37	(-0.29, 0.29)
Gamma_WG	1	0.91 (0.69)	.48	2.04	0.09	(0.39, 1.44)
	2	1.06 (0.87)	.87	3.91	0.30	(0.67, 1.46)
	3	0.67 (0.51)	.50	1.99	0.10	(0.40, 0.94)
	4	0.5 (0.00)	.50	—	—	—
	Total	0.89 (0.82)	0.74	3.91	0.09	(0.67, 1.10)
Delta_WG	1	1.67 (1.43)	1.03	5.00	0.57	(0.57, 2.77)
	2	0.90 (0.50)	.73	2.31	0.46	(0.67, 1.13)
	3	0.87 (0.56)	.78	2.50	0. 25	(0.57, 1.17)
	4	0.42 (0.00)	.42	—	—	—
	Total	1.03 (0.33)	0.83	5.00	0.25	(0.79, 1.27)

Table C (ii)

	Type	Mean (Std)	Median	Maximum	Minimum	[95% Conf. Interval]
Sigma_CU	1	0.40 (0.13)	.45	0.53	0. 20	(0.30, 0.50)
	2	0.65 (0.39)	.52	1.53	0. 20	(0.47, 0.82)
	3	0.58 (0.31)	.44	1.35	0. 28	(0.41, 0.74)
	4	0.32 (0.00)	.32	—	—	—
	Total	0.57 (0.33)	0.47	1.53	0. 20	(0.47, 0.67)
Gender	1	0.89 (0.33)	1.00	1.00	0.00	(0.63, 1.15)
	2	0.52 (0.51)	1.00	1.00	0.00	(0.29, 0.76)
	3	0.69 (0.48)	1.00	1.00	0.00	(0.43, 0.94)
	4	0 (0.00)	0.00	0.00	—	—
	Total	0.64 (0.49)	1.00	1.00	0.00	(0.50, 0.78)

Table C (ii)

	Type	Mean (Std)	Median	Maximum	Minimum	[95% Conf. Interval]
Age	1	28.11 (8.75)	25.00	45.00	20.00	(21.38, 34.84)
	2	22.43 (3.19)	22.00	28.00	18.00	(20.98, 23.88)
	3	22.44 (4.30)	21.00	34.00	18.00	(20.14, 24.73)
	4	20 (0.00)	20.00	20.00	—	—
	Total	23.47 (5.40)	22.00	45.00	18.00	(21.88, 25.05)
Payment	1	60.60 (5.24)	60.50	66.00	48.00	(56.57, 64.63)
	2	60.48 (9.48)	60.48	76.00	44.50	(56.17, 64.80)
	3	58.94 (8.78)	60.00	76.00	45.00	(54.27, 63.62)
	4	70 (0.00)	70.00	60.00	—	—
	Total	60.18 (8.46)	60.00	76.00	44.50	(57.70, 62.67)

Figure 1. Typical one-parameter probability weighting functions $w(p) = \frac{\delta p^\gamma}{\delta p^\gamma + (1-p)^\gamma}$

Subjective probability weights $[w(p)]$ representing how individuals perceive objective probabilities throughout the $[0, 1]$ interval. Under the Expected Utility Theory (EUT), there is no probability distortion, as presented by the 45-degree straight line. However, several studies suggest that people overweigh small probabilities of a gain, and underweigh medium and large probabilities; the “typical” probability weighting function has an inverse S-shape (i.e. Latimore, Baker & Witte 1992; Tversky & Kahneman, 1992; Camerer & Ho, 1994; Abdellaoui, 2000; Starmer, 2000). In addition, many studies also report that there is a large amount of heterogeneity in how people distort probabilities (Berns et al., 2007; Bleichrodt & Pinto, 2000; Bruhin, Fehr-Duda & Epper, 2010; Fehr-Duda & Epper, 2012; Gonzalez & Wu, 1999; Wu & Gonzalez, 1996).

Figure 2. Examples of Lottery Choices

In each trial, participants were asked to make a choice between a sure win and a lottery providing ex-ante probabilities of winning a comparatively higher payoff denominated in experimental currency (Yen), or not winning anything. For every decision, the higher payoff was always 1,000 Yen and the probability of winning the 1,000 Yen prize varied across conditions (0.01, 0.1, 0.2, 0.37, 0.8, 0.9, and 0.99). The sure win amount was adjusted according to participant's choices on previous trials using an iterative staircase algorithm (PEST). The decision made on the selected trial determined payment as follows: if the sure win was chosen on the selected trial, the respective amount was paid to the subject; if the lottery was chosen, a "computerized coin" was tossed, giving subjects a chance to win 1,000 laboratory Yen at the probability indicated in the lottery.

Figure 3. Examples of subjects with different curvature (top) and elevation (bottom)

Shapes of the probability weighting for a few of our subjects.

On the top panel, subject S8 and subject S13 share very similar estimated δ (elevation=1.07~1.08), but different estimated γ (discriminability=0.38, and 0.65, respectively).

On the bottom panel, subjects S35 and S37 share similar γ parameters (discriminability=0.93~1.02), but different estimated δ (elevation=1.29, and 0.50, respectively).

Table 1

Population Estimates

Statistics	Probability weighting		Utility
	Discriminability (γ)	Attractiveness (δ)	Curvature (σ)
Mean	0.888	1.052	0.601
SE	0.104	0.120	0.057
Median	0.750	0.835	0.481

Note. Table 1 displays a summary statistics of parameter estimates among the 48 subjects. The median estimates suggest an inverse-S probability weighting function similar to those reported in previous literature.

Table 2

Factor Loadings and Uniqueness Scores

Variable	Factor1 Impulsivity	Factor2 Emotional Reactivity	Factor3 Approach Motivation	Factor4 Loss Avoidance /Prevention	Uniqueness
NP-BIS-11	0.7377	0.1058	-0.3183	-0.0734	0.3379
Cog-BIS-11	0.5483	0.4701	-0.0864	0.0798	0.4646
Mot-BIS-11	0.8017	-0.0941	0.0300	-0.1255	0.3317
Reg-promote	-0.3350	-0.2232	0.6944	0.2662	0.2848
Reg-prevent	-0.4416	0.0191	-0.1432	0.7109	0.2788
Psychoticism	0.6744	-0.1415	0.1212	-0.2413	0.4522
Extraversion	0.3885	-0.5098	0.4913	0.1610	0.3219
Neuroticism	0.0451	0.9149	0.0099	-0.0761	0.1550
Lie-all	0.0067	-0.1266	0.1321	0.8585	0.2294
BAS-drive	0.2735	-0.0178	0.6239	0.0186	0.5353
BAS-funskg	0.5972	-0.2760	0.4609	-0.1293	0.3380
BAS-rewards	-0.0253	0.2050	0.8292	-0.0882	0.2619
BIS	-0.0982	0.9248	0.0202	-0.0266	0.1340

Note. NP-BIS-11, Cog-BIS-11 and Mot-BIS-11 are indicators of impulsiveness, obtained from the Barratt Impulsiveness Scale, Version 11. Reg-promote and Reg-prevent assess individuals' levels of self-regulation, given by the RFQ questionnaire. Psychoticism, Extraversion, Neuroticism and Lie-all belong to categories of the EPQ-R questionnaire, measuring different aspects of temperament. BAS-drive, BAS-funskg, BAS-rewards and BIS are components of the BAS/BIS scales that assess two motivational systems underlie behavior and affect. For a more detailed description of trait variables, see Table B in the Appendix.

Table 3

Summary Statistics of Estimated Mean and Median Risk Parameters by PersType

PersType	Dominant Personality Traits	Discriminability γ Mean (std) Median	Attractiveness δ Mean (std) Median	Curvature σ Mean (std) Median
1	Motivated	.912 (.685) .480	1.668 (1.435) 1.028	.399 (.127) .448
2	Impulsive	1.062 (.867) .870	.900 (.495) .728	.646 (.387) .517
3	Affective	.668 (.510) .497	.874 (.563) .783	.577 (.312) .443
All	---	.896 (.732) .750	1.041 (.824) .835	.574 (.332) .481

Note. Table 3 presents summary statistics of the estimated risk parameters gamma, delta, and sigma by personality type (additional data are in the appendix).