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Can Personality Type Explain Heterogeneity in Probability Distortions?

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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 nonlinearly. The second regularity, although less commonly acknowledged, is that there is a large amount of heterogeneity in how people distort probabilities. Despite this, little effort has been made to identify the source of heterogeneity. 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 participants viewed gambling as more attractive, whereas the impulsive participants 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 though standard psychological questionnaires.

Keywords: choice under risk, personality, experiments, probability weighting function

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 nonlinearly, challenging the view from traditional economics that expected utility is linear in probability. In particular, several studies suggest that people overweigh 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 in Figure 1 (see Abdellaoui, 2000; Camerer & Ho, 1994; Lattimore, Baker, & Witte, 1992; Starmer, 2000; Tversky & Kahneman, 1992). The second regularity, although less commonly acknowledged, is that there is a large amount of heterogeneity in how people distort probabilities (Berns, Capra, Moore, & Noussair, 2007; Bleichrodt & Pinto, 2000; Bruhin, Fehr-Duda, & Epper, 2010; Fehr-Duda & Epper, 2012; Gonzalez & Wu, 1999; Wu & Gonzalez, 1996, 1999). 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 S-shaped median probability weighting functions and large heterogeneity) seem to hold

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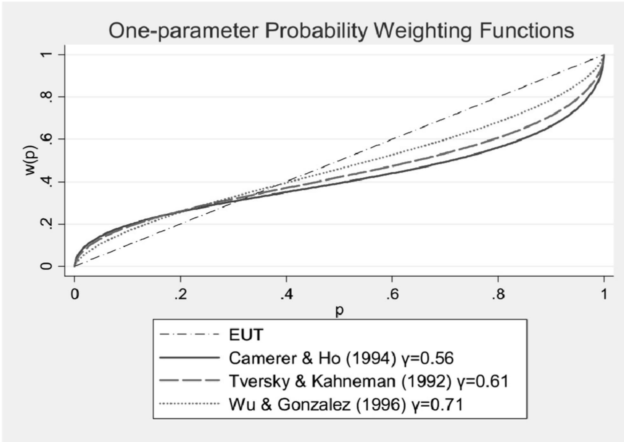

Figure 1. Typical one-parameter probability weighting functions $w(p) = \frac{\delta p^{\gamma}}{\delta p^{\gamma} + (1 - p)^{\gamma}}$. Subjective probability weights [$w(p)$] representing how individuals perceive objective probabilities throughout the [0, 1] interval. Under the expected utility theory, there is no probability distortion, as presented by the 45° 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 (see Abdellaoui, 2000; Camerer & Ho, 1994; Lattimore et al., 1992; Starmer, 2000; Tversky & Kahneman, 1992). 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 et al., 2010; Fehr-Duda & Epper, 2012; Gonzalez & Wu, 1999; Wu & Gonzalez, 1996).

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 those mentioned above. 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 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) found that subcertainty (the tendency of subjective probabilities to add to a number less than 1) failed to hold in 40% of the subjects. The implication of Gonzalez and Wu (1999)'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 that 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 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., childlike 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 in behavior, motivation, emotion, and cognition, we investigated the impact of personality on risky choices. Specifically, we explored the possibility that the personality "type" of the decision maker is linked to probability distortions. We chose 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., scores 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, we identified how groups of subjects who differed in their personality types differed 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). Second, personality reflects generally stable patterns in behavior, motivation, and cognition (Borghans, Golsteyn, Heckman, & Meijers, 2009; Zillig, Hemenover, & Dienstbier, 2002). Borghans et al. (2009) conducted an experiment on a sample of 347 Dutch high school students; they showed the differences in cognitive and noncognitive personality traits, such as IQ, the Big Five (openness, conscientiousness, extraversion, agreeableness, and neuroticism), and self-control accounted for the differences in preference parameters. Zuckerman (2007) also found 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, and drugs), unprotected sex, violence, and criminal behavior. Finally, voxel-based morphometry (e.g., Blankstein, Chen, Mincic, McGrath, & Davis, 2009; DeYoung et al., 2010; Omura, Todd Constable, & Canli, 2005) and diffusion tensor imaging (Cohen, Schoene-Bake, Elger, & Weber, 2009) 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, Hagan, Azim, Menon, & Reiss, 2005; Canli, Sivers, Whitfield, Gotlib, & Gabrieli, 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.

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 questionnaires that included the Eysenck Personality Questionnaire—Revised (EPQ–R; Eysenck, Eysenck, & Barrett, 1985), the behavioral inhibition and behavioral activation systems scales (BIS/BAS scales; Carver & White, 1994), the Barratt Impulsiveness Scale, Version 11 (BIS-11; Patton, Stanford, & Barratt, 1995), and the Regulatory Focus Questionnaire (RFQ; Higgins et al., 2001).[1] 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 (Harlow & Brown, 1990; Zuckerman, 2007). 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 different categorizations of dominant traits distorted probabilities and outcomes.

[1] In 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).

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 et al. (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 (Cho, Luce, & von Winterfeld, 1994; Luce, 2000).

We found that heterogeneous types of personality traits are associated with different risk characteristics. In particular, motivated individuals viewed gambling as more attractive, whereas impulsive individuals were most capable of discriminating non-extreme probabilities. The remainder of the article 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 Procedure

We recruited a total of 48 healthy participants (32 women) for this study. All participants were students or staff members at Emory University. The average age was 23.40 years ($SD = 5.36$). 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, Capra, Noussair, & Berns, 2009; Engelmann, Moore, Capra, & Berns, 2012). Participants earned between \$44.50 and \$76.00, 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/BAS.[2] 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 a participant's choices on previous trials using PEST, which 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. To control for wealth effects, we randomly selected one of the trials to count toward payment at the end of the session. The decision made on the selected trial determined payment as below: 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 U.S. dollars 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.

CEs and Structural Estimation

We were interested in identifying each individual's CEs for the lotteries. To do this, we used a modified version of PEST introduced by Cho et al. (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

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

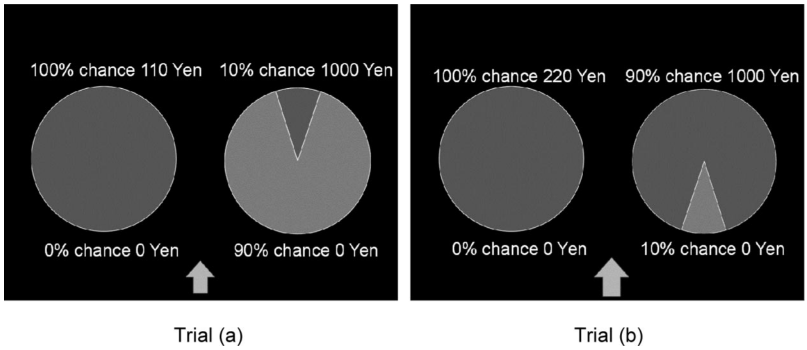

Figure 2. Examples of lottery choices. In each trial, participants were asked to make a choice between a sure win and a lottery providing ex-ante probabilities of winning a comparatively higher payoff denominated in experimental currency (Yen) or not winning anything. For every decision, the higher payoff 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 the participant's choices on previous trials using an iterative staircase algorithm. The decision made on the selected trial determined payment as below: 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.

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). To create choice switches between sure wins and lotteries, we adjusted amounts for sure wins 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 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 four rules adapted from Luce (2000) and Cho et al. (1994): (1) The initial step size was set to one fifth of the difference between the maximum and minimum possible payoffs (ε = 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 quickly for many pairs of different lotteries.[3] This is important because we were 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 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 probabil-

[3] The 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.

ity 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 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 1990s, researchers such as 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 a sensation-seeking scale and an 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, and 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/Socialization, 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 of having a psychotic episode (or break with reality), but also with aggression. Last but not the least, the Lie scale measures the tendency to lie when lying makes one socially better off.

The BAS/BIS scales contain 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 BAS is believed to regulate appetitive motives, in which the goal is to move toward something desired. A 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 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.

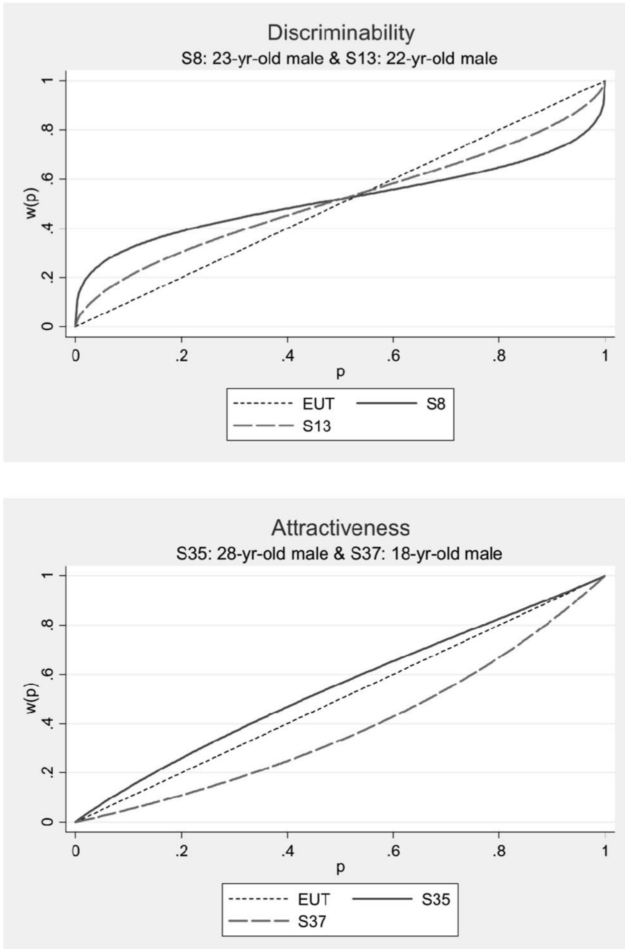

Figure 3. Examples of subjects with different curvature (top) and elevation (bottom). On the top panel, Subject S8 and Subject S13 share very similar estimated δ (elevation = 1.07~1.08), but different estimated γ (discriminability = 0.38, and 0.65, respectively). On the bottom panel, Subjects S35 and S37 share similar γ parameters (discriminability = 0.93~1.02), but different estimated δ (elevation = 1.29, and 0.50, respectively).

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 summary statistics of parameter estimates for the 48 subjects. The median estimates suggest an inverse S-shaped probability weighting function similar to those reported in previous literature.

Table 1
Summary Statistics of Parameter Estimates for the 48 Subjects

Statistic	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. The median estimates suggest an inverse S-shaped probability weighting function similar to those reported in previous literature.

At the individual level, we observed a large variability in individuals' 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 analysis to identify participants on the basis of their responses to the four psychological questionnaires.[4,5] We used hierarchical clustering analysis (complete linkage method) to classify 47 subjects into different clusters[6,7]; we identified four distinct personality types. Personality Type I (henceforth PersType1) had a total of nine subjects who, on average, were older and mostly women. PersType2 comprised 21 subjects, and had a higher proportion of men than the other groups. PersType3 had 16 subjects and the female/male ratio mirrored our participant population. Finally, PersType4 had one 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 1.00, 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 (Nonplanning Impulsiveness–BIS-11, Motor Impulsiveness–BIS-11, Cognitive Impulsiveness–BIS-11, Psychoticism, and BAS–Fun-seeking). Factor 2 is mainly defined by affective traits (Extraversion, Neuroticism, and BIS). In contrast, Factor 3 is influenced by motivational traits (promotion-focused self-regulation, BAS-drive, and BAS-rewards). Finally, Factor 4 is defined by loss avoidance/prevention traits (Lie-all, and prevention-focused self-regulation).

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 PerstType3, only Factor 1's average score was negative; the rest were positive.

We tested whether the factor scores among these three personality types were statistically different. PersType2 differed from the other two personality types (PersType1 and PersType 3) with respect to the Factor 1 (median test $p = .012$ and $p < .001$, respectively), with PersType2 being relatively more impulsive. With respect to Factor 2, PersType3 was different from the two other personality types (median test $p = .001$ and $p < .001$), with PersType3 being relatively more emotionally reactive or more affective. In addition to these personality differences, we noticed that PersType1 members were older and there were relatively more women (see Chart 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 (nine subjects) were relatively more "motivated." PersType2 (21 subjects) were more "impulsive". Finally PersType3, which had 16 subjects, were more "affective" (see Appendix Charts B and C for further details).

[4] The criterion for classifying subjects into clustered personality types is the measure of trait 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.

[5] Although 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 with more extraversion in an impulsive one.

[6] We also tried other clustering algorithms that apply different criteria to measure distances such as single, median, and centroid linkage, and obtained the same results.

[7] One female subject did not complete all the personality questionnaires, so this observation was excluded.

Table 2
Factor Loadings and Uniqueness Scores

Variable	Factor 1: Impulsivity	Factor 2: Emotional Reactivity	Factor 3: Approach Motivation	Factor 4: 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 (BIS-11). Reg-promote and Reg-prevent assess individuals' levels of self-regulation, given by the Regulatory Focus Questionnaire. Psychoticism, Extraversion, Neuroticism, and Lie-all belong to categories of the Eysenck Personality Questionnaire—Revised, measuring different aspects of temperament. BAS-drive, BAS-funskg, BAS-rewards, and BIS are components of the behavioral inhibition and behavioral activation systems that assess two motivational systems that underlie behavior and affect. For a more detailed description of trait variables, see Chart B in the Appendix.

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 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 multivariate analysis of variance.[8] We found noticeable overall differences among the three characteristic types (test statistics based on distances to centroids, $F(2, 43) = 3.092$, $p = .056$). In particular, PersType1 (motivated) differed significantly from PersType3 (affective) with regard to the three estimated risk parameters (test statistics based on distances to centroids, $t(23) = 2.521$, permutation p value $= .054$). 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, compared with PersType2 (impulsive) and PersType3 (affective) subjects (Mann-Whitney test, or MWT, $Z = 1.924$, $p = .054$, and $Z = 1.981$, $p = .048$, respectively). This suggests that the motivated subjects viewed gambling as significantly more attractive; PersType2 and PersType3 or the impulsive versus the affective subjects (but not impulsive) differed with respect to their estimated gamma values (MWT, $Z = 2.115$, $p = .034$), suggesting that the impulsive subjects were the most capable of discriminating non-extreme probabilities. Finally, with respect to sigma, PersType1 (motivated) and PersType2 (impulsive) subjects differed significantly (MWT, $Z = -1.969$, $p = .049$).

It is 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

[8] Non-parametric multivariate analysis of variance tests the 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 9,999 permutations. Manly (1997) pointed out that for tests at an α level of .05, at least 999 permutations should be used; for tests at an α level of .01, at least 4,999 permutations should be used.

Table 3
Summary Statistics of Estimated Mean and Median Risk Parameters by Personality Type

Personality type	Dominant personality trait	Discriminability γ			Attractiveness δ			Curvature σ		
		M	*SD*	*Mdn*	*M*	*SD*	*Mdn*	*M*	*SD*	*Mdn*
1	Motivated	0.912	0.685	0.480	1.668	1.435	1.028	0.399	0.127	0.448
2	Impulsive	1.062	0.867	0.870	0.900	0.495	0.728	0.646	0.387	0.517
3	Affective	0.668	0.510	0.497	0.874	0.563	0.783	0.577	0.312	0.443
All	—	0.896	0.732	0.750	1.041	0.824	0.783	0.574	0.332	0.481

women (MWT, $Z = 2.613$, $p = .009$). 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 there is a high level of heterogeneity in how people distort probabilities. Despite this, little effort has been made to identify the source of heterogeneity. In this article, 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 used 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 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 (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, placed a greater weight on payoff magnitude relative to payoff probability, leading to more optimistic risk attitudes. PersType 2 or "impulsive" individuals were reward-responsive 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 though standard psychological questionnaires. We also found that women were more risk averse than men, 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 it also often interacts with the environment to produce a certain outcome (Weber, Blais, & Betz, 2002). This can explain why risk preferences are stable when elicited through a single choice mode (Andersen, Harrison, Lau, & Rutström, 2008; Harrison & Rutström, 2000), yet may differ when elicited through valuation mechanisms (e.g., auction vs. lottery choice; see Berg, Dickhaut, & McCabe, 2005; Eckel & Grossman, 2002; Isaac & James, 2000). Isaac and James (2000), for example, showed that the estimated numerical values of individuals' implied risk parameters were not stable within individuals across the Becker–DeGroot-Marschak and first-price auction institutions. Furthermore, the ranking across subjects of the numerical values of risk was not preserved. In a more recent article, Berg et al. (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')" (p. 4213). However, our study highlights the important role of personality type in explaining choices under risk, and it is the first step toward 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

Charts

Chart A: Estimates of individual risk parameters and demographics

Subject	Probability weighting γ	Probability weighting δ	Utility σ	Gender	Age (years)	Payment (U.S. $)
1	0.0853	1.2584	0.5319	F	25	63.00
2	0.3957	0.6830	0.4908	F	25	65.00
3	0.4799	0.8599	0.4711	M	24	60.00
4	2.4860	1.0000	0.2042	F	22	63.00
5	0.5213	0.8688	0.5087	M	22	53.50
6	0.6797	0.549	0.4384	F	19	45.00
7	0.4468	0.7275	0.4583	F	22	54.00
8	0.3837	1.0797	1.1982	M	23	72.50
9	0.7624	0.5704	0.4435	M	20	60.00
10	0.8733	0.4662	0.5514	F	25	75.00
11	0.5000	0.4230	0.3203	M	20	70.00
12	0.9256	2.1918	2.1249	F	20	76.00
13	0.6497	1.0735	0.6437	M	22	72.00
14	2.5545	2.3059	0.5174	F	21	50.00
15	0.3752	0.8255	0.3904	F	21	45.00
16	0.4731	0.8646	0.3818	F	28	60.50
17	1.4804	1.7078	0.5141	F	21	63.00
18	1.5707	0.2500	0.7073	F	22	65.00
19	2.0405	1.0000	0.1950	F	45	60.50
20	0.8703	1.8744	1.4863	M	18	44.50
21	3.9056	1.0000	0.1971	F	21	62.00
22	0.7369	0.5405	0.4068	M	19	52.00
23	0.8854	1.5476	1.3497	M	20	49.50
24	0.2967	0.8436	0.4243	F	26	61.00
25	0.1007	1.4416	0.6182	F	19	60.00
26	0.3220	0.4858	0.4132	F	28	69.00
27	0.5042	0.5529	0.4023	F	25	60.00
28	0.7625	0.5956	0.5099	F	20	47.40
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	61.00
32	0.2693	0.7404	0.4328	F	21	76.00
33	0.9271	0.5443	0.5085	M	21	76.00
34	0.7157	0.5902	0.5337	F	21	60.00
35	0.9388	1.2865	1.2663	M	28	60.00
36	0.3772	0.5444	0.4234	F	25	51.84
37	1.0113	0.4968	0.4426	M	18	47.00
38	0.4277	1.0278	0.4483	F	21	60.00
39	0.8149	0.4496	0.4087	F	18	60.00
40	0.9161	0.4595	0.5182	M	23	61.00
41	0.1900	2.4983	0.2835	F	21	60.00
42	0.8443	0.7622	0.5592	M	20	62.25
43	1.0656	0.5107	0.5369	M	18	60.00
44	0.8914	1.0918	0.8370	F	23	68.00
45	0.5135	0.6051	0.4884	M	28	76.00
46	0.4722	0.5740	0.2462	F	36	59.93
47	1.6300	2.8992	0.4218	F	36	66.00
48	1.1985	5.0000	0.2690	F	20	48.00

(*Appendix continues*)

Chart B: Description of variables (47 subjects)

Category	Variable name	Description/range of values	Mean (*SD*)	*Mdn*	Mode	95% CI
Personality traits	NP-BIS-11	Nonplanning impulsiveness, i.e., 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 impulsivenes, 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 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 approach matches to desired end states. Values range from 6 to 25.	18.09 (4.18)	17.00	17.00	[16.86, 19.31]
	Psychoticism	Liability of having 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]
	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 to lie 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 toward rewards. Values range from 13 to 20.	17.53 (1.85)	18.00	18.00	[16.99, 18.08]

(*Appendix continues*)

	BIS	Behavioral inhibition sensitivity to unpleasantness. Values range from 13 to 28.	19.96 (3.68)	20.00	20.00	[18.88, 21.04]
Four factors	Factor 1	Impulsivity traits, defined by nonplanning 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]
	Factor 2	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]
	Factor 3	Motivational traits, defined by regulatory-promotion, BAS-drive, and BAS-reward. Values range from −2.33 to 2.36.	–2.85E-08 (1.00)	−0.11	—	[−0.29, 0.29]
	Factor 4	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	Gender	Gender of the subjects. Dummy: 0 = male, 1 = female.	0.64 (0.49)	1.00	1.00	[0.50, 0.78]
	Age	Age of the subjects. Age ranges from 18 to 45 years.	23.47 (5.40)	22.00	21.00	[21.88, 25.05]
	Payment	Subject's earnings from the experiment. Maximum is $76.00, minimum is $44.50.	60.18 (8.46)	60.00	60.00	[57.70, 62.67]
Estimated parameters	Gamma	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]
	Delta	The elevation of the probability weighting function. It measures how attractive one views gambling. Maximum is 5.00, minimum is 0.25.	1.03 (0.33)	0.83	1.00	[0.79, 1.27]
	Sigma	The curvature of the constant relative risk aversion utility function. Maximum is 1.53, minimum is 0.20.	0.57 (0.33)	0.47	—	[0.41, 0.74]

(*Appendix continues*)

Chart C: Summary statistics by personality type (47 subjects)

Factor	Personality type	Mean (*SD*)	*Mdn*	Maximum	Minimum	95% CI
1	1	−0.93 (0.47)	−1.00	−0.30	−1.59	[−1.29, −0.57]
	2	0.56 (0.74)	0.59	1.60	−1.18	[0.22, 0.89]
	3	−0.40 (0.68)	−0.49	0.79	−1.71	[−0.76, −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]
2	1	−1.06 (0.69)	−1.35	0.21	−1.98	[−1.59, −0.53]
	2	−0.30 (0.71)	−0.31	0.81	−2.01	[−0.62, 0.03]
	3	0.91 (0.58)	0.91	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]
3	1	0.22 (0.83)	0.19	1.55	−1.13	[−0.42, 0.87]
	2	−0.48 (0.79)	−0.45	0.55	−2.33	[−0.83, −0.12]
	3	0.42 (1.11)	0.31	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]
4	1	−0.07 (0.45)	−0.15	0.60	−0.69	[−0.42, 0.28]
	2	−0.14 (1.06)	−0.22	1.64	−2.21	[−0.62, 0.34]
	3	0.26 (1.16)	0.368	1.83	−2.37	[−0.36, 0.88]
	4	−0.59 (0.00)	−0.59	—	—	—
	Total	1.80E−08 (1.00)	−0.06	1.83	−2.37	[−0.29, 0.29]
Gamma	1	0.91 (0.69)	0.48	2.04	0.09	[0.39, 1.44]
	2	1.06 (0.87)	0.87	3.91	0.30	[0.67, 1.46]
	3	0.67 (0.51)	0.50	1.99	0.10	[0.40, 0.94]
	4	0.50 (0.00)	0.50	—	—	—
	Total	0.89 (0.82)	0.74	3.91	0.09	[0.67, 1.10]
Delta	1	1.67 (1.43)	1.03	5.00	0.57	[0.57, 2.77]
	2	0.90 (0.50)	0.73	2.31	0.46	[0.67, 1.13]
	3	0.87 (0.56)	0.78	2.50	0.25	[0.57, 1.17]
	4	0.42 (0.00)	0.42	—	—	—
	Total	1.03 (0.33)	0.83	5.00	0.25	[0.79, 1.27]
Sigma	1	0.40 (0.13)	0.45	0.53	0.20	[0.30, 0.50]
	2	0.65 (0.39)	0.52	1.53	0.20	[0.47, 0.82]
	3	0.58 (0.31)	0.44	1.35	0.28	[0.41, 0.74]
	4	0.32 (0.00)	0.32	—	—	—
	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	0.00 (0.00)	0.00	0.00	—	—
	Total	0.64 (0.49)	1.00	1.00	0.00	[0.50, 0.78]
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	20.00 (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	70.00 (0.00)	70.00	60.00	—	—
	Total	60.18 (8.46)	60.00	76.00	44.50	[57.70, 62.67]

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