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Three Papers on Risk and Personality

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An abstract of
A dissertation submitted to the Faculty of the
James T. Laney School of Graduate Studies of Emory University
in partial fulfillment of the requirements for the degree of
Doctor of Philosophy
in Economics
2013

Abstract

Three Papers on Risk and Personality

By Bing Jiang

Experimental studies of choice under risk show that there exists a large amount of heterogeneity in how people perceive risk. Despite of this, little effort has been made to identify the source of such heterogeneity. This study explores the possibility that the distinguishing personality profile of the decision-maker is linked to heterogeneity in risk preference. Using data from incentivized choice experiments combined with validated psychological questionnaires, I establish three interesting results. First, people can be clustered into distinct personality types and different types may have different risk preferences: the motivated view gambling more attractive, whereas the impulsive are the most capable of discriminating non-extreme probabilities. Second, individuals who score higher on future goal-orientation & fun-seeking trait are less risk seeking and more patient, while reward-driven individuals are less patient. Third, there also exists a correlation between personality and entrepreneurship: entrepreneurs are shown to be significantly more motivated than non-entrepreneurs. In addition, the trait of motivation is positively associated with one's probability of becoming an entrepreneur, whereas the trait of reward-driven is negatively related to such probability. These results suggest that the observed heterogeneity in risk preference may be explained by personality profiles, which can be elicited though standard psychological questionnaires. I believe these findings have important implications for understanding decision-making under risk, as well as informing economic theories and government policies.

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Can Personality Type Explain 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 though standard psychological questionnaires.

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

Can Personality Type Explain Probability Distortions?

1.1 Introduction

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, 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 below (see Latimore, Baker, and Witte 1992; Tversky and Kahneman 1992; Camerer and Ho 1994; Abdellaoui 2000; Starmer 2000). The 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 and Pinto 2000; Bruhin, Fehr-Duda, and Epper 2010; Fehr-Duda and Epper 2012; Gonzalez and Wu 1999; Wu and Gonzalez 1999; Wu and 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 1.1), 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 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-shaped 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 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 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., 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 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 and Tversky 1983). Secondly, personality reflects generally stable patterns in behavior, motivation, and cognition (Borghans et al. 2009; Zillig, Hemenover, and Dienstbier 2002). Borghans, Golsteyn, Heckman, and Meijers (2009) conducted an experiment on a sample of 347 Dutch high school students; they showed the differences in cognitive and non-cognitive 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, 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 questionnaires[1] 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 and 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,

[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).

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 and 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 different 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, and von Winterfeld 1994).

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.

1.2 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/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 participant’s choices on previous trials using an iterative staircase algorithm (PEST) that is outlined in detail in the next section. Figure 1.2 depicts an example of the lottery choices in two different trials.

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

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 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 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.

1.2.1 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 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 (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 fast for many pairs of different lotteries[3]. 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 and 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

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[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.

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,

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

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 1.3 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.

1.2.2 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, 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/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.

1.3 Results

Table 1.1 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 analysis[4] to identify participants based on their responses to the four psychological questionnaires[5]. We used hierarchical clustering analysis (Complete Linkage method[6]) to classify 47 subjects[7] 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

[4] The 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.

[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 to more extraversion in an impulsive one.

[6] We also tried out 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 didn't complete all the personality questionnaires, so this observation was excluded.

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 1.2 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 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 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 (9 subjects) were relatively more "Motivated". PersType2 (21 subjects) were more "Impulsive". Finally PersType3, which had 16 subjects, were more "Affective" (see Charts B and C for further details).

Behavioral differences among Types

Table 1.3 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 MANOVA[8]. We found noticeable overall differences among the three characteristic types (test statistics based on distances to centroids, $F(2, 43) = 3.092$, $p=0.056$). In particular, PersType1 (Motivated) differed significantly from PersType3 (Affective) with regard to the three estimated risk parameters (test statistics based on distances to centroids, $t(23) = 2.521$, permutation p-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

[8] Non-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.

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) (Mann-Whitney test or 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, PerstType1 (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.

1.4 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 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 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-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 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 it 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 and Rutström 2000; Andersen, Harrison, Lau, and Rutström 2008), yet, may differ when elicited through valuation mechanisms (e.g., auction vs. lottery choice – see Eckel and Grossman 2002; Berg, Dickhaut, and McCabe 2005; Isaac and 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 BDM and first-price auction institutions. Furthermore, the ranking across subjects of the numerical values of risk was 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')" (p. 4213). 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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Table 1.1

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 1.1 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 1.2

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 Chart B in the Appendix.

Table 1.3

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

Figure 1.1

Typical One-parameter Probability Weighting Functions $w(p) = \dfrac{\delta p^{\gamma}}{\delta p^{\gamma} + (1-p)^{\gamma}}$

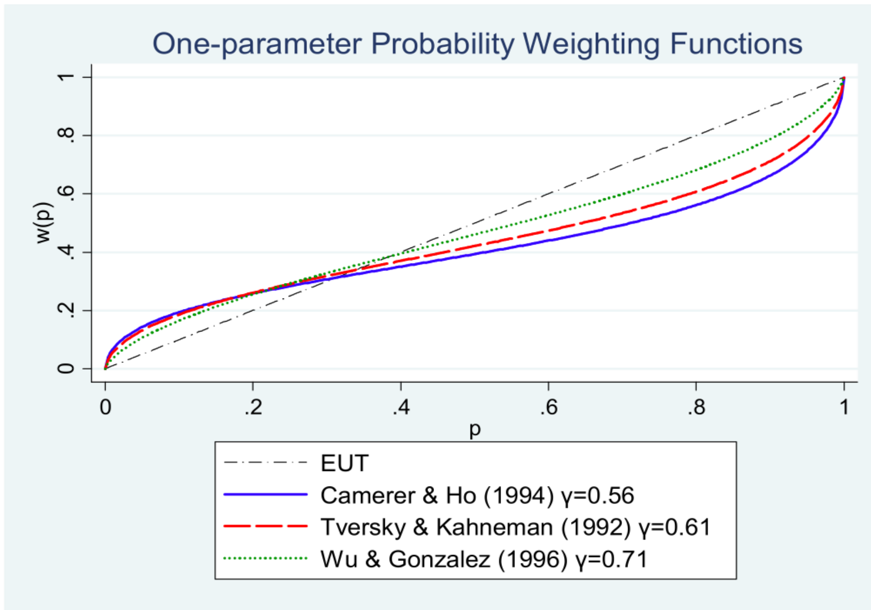
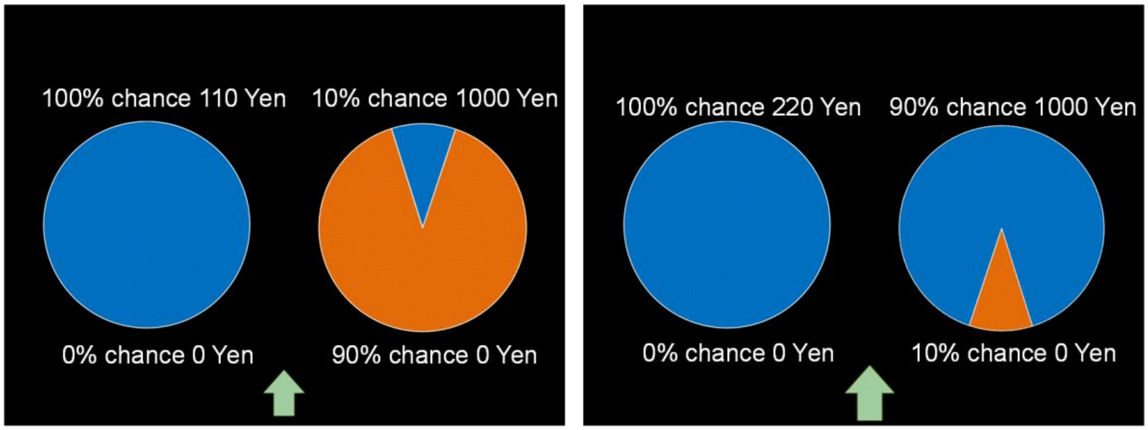


Figure 1.1. Subjective probability weights [w (p)] representing how individuals perceive objective probabilities throughout the [0, 1] interval. Under the Expected Utility Theory (EUT), there is no probability distortion, as presented by the 45-degree straight line. However, several studies suggest that people overweigh small probabilities of a gain, and underweigh medium and large probabilities; the "typical" probability weighting function has an inverse S-shape (see Latimore, Baker, and Witte 1992; Tversky and Kahneman 1992; Camerer and 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 and Pinto 2000; Bruhin, Fehr-Duda, and Epper 2010; Fehr-Duda and Epper 2012; Gonzalez and Wu 1999; Wu and Gonzalez 1996).

Figure 1.2

Examples of Lottery Choices



Trial (a) Trial (b)

Figure 1.2. 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 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.

Figure 1.3

Examples of Subjects with Different Curvature (Top) and Elevation (Bottom)

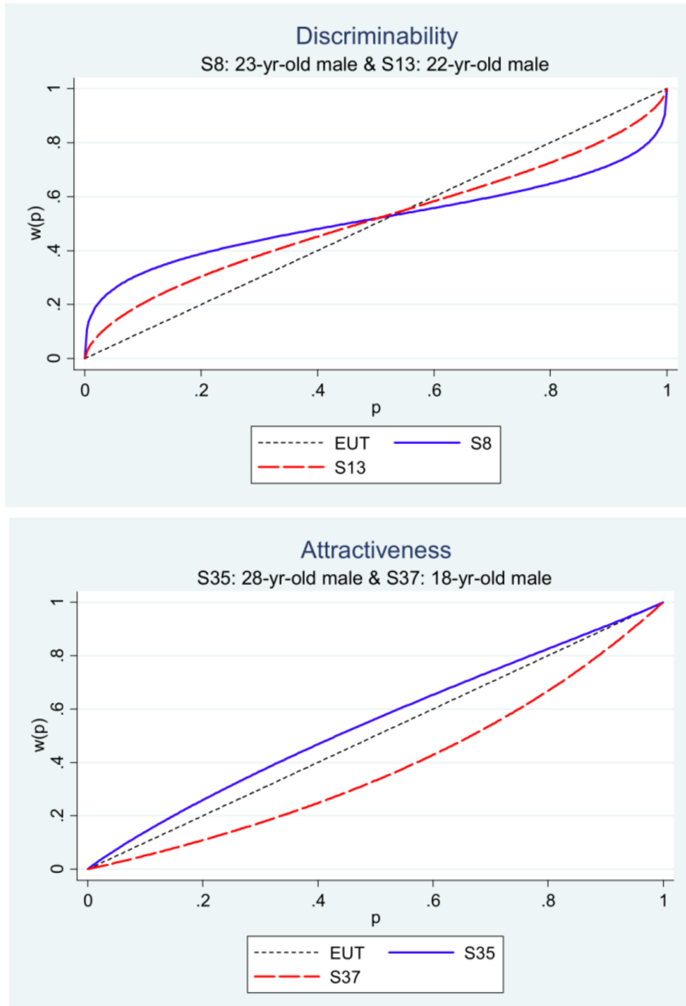


Figure 1.3. Shapes of the probability weighting for a few of our subjects.

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).

Appendix

Charts

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
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

Chart 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)
	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-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)
	Factor4	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)
	Gender	Gender of the student subjects. Dummy: 0 Male, 1 Female	0.64 (0.49)	1.00	1.00	(0.50, 0.78)
Demographics	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)
	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)
Estimated Parameters	Delta	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	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)

Chart C: Summary Statistics by Personality Type (47 Subjects)

Variables	Personality Type	Mean (Std)	Median	Maximum	Minimum	[95% Conf. Interval]
	1	-0.93 (0.47)	-1.00	-0.30	-1.59	(-1.29, -0.57)
Factor1	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)
	1	-1.06 (0.69)	-1.35	0.21	-1.98	(-1.59, -0.53)
Factor2	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)
	1	0.22 (0.83)	.19	1.55	-1.13	(-0.42, 0.87)
Factor3	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)
	1	-0.07 (0.45)	-.15	0.60	-0.69	(-0.42, 0.28)
Factor4	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)
	1	0.91 (0.69)	.48	2.04	0.09	(0.39, 1.44)
Gamma	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)
	1	1.67 (1.43)	1.03	5.00	0.57	(0.57, 2.77)
Delta	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)

Chart C

Variables	Personality Type	Mean (Std)	Median	Maximum	Minimum	[95% Conf. Interval]
	1	0.40 (0.13)	.45	0.53	0. 20	(0.30, 0.50)
Sigma	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)
	1	0.89 (0.33)	1.00	1.00	0.00	(0.63, 1.15)
Gender	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)
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)
	1	60.60 (5.24)	60.50	66.00	48.00	(56.57, 64.63)
Payment	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)

Chapter 2

Are Entrepreneurs A Different Breed?

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Keywords: Entrepreneurs; Risk Preferences; Time Preferences; Personality; Experiment

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Abstract

Entrepreneurs are often thought to be risk-taking and patient individuals who, unlike non-entrepreneurs, are willing to forgo their existing resources for a chance of a future larger reward. Entrepreneurs are also thought to more motivated, optimistic, and overconfident about their relative skills. How reliable are these assumptions? Do entrepreneurs really have different risk attitudes, time preferences and other relevant characteristics than non-entrepreneurs? To test and scientifically establish a correlation between individual characteristics and entrepreneurship, we developed a simple online experiment that consisted of three risk decision tasks, one time decision task, and a set of validated psychological questionnaires. We elicited individual risk attitudes and time preferences, and found that our sampled entrepreneurs and non-entrepreneurs did not exhibit different risk and time preferences. In analyzing subjects' risk decision tasks responses, we showed that higher scores on future goal-orientation & fun-seeking trait were correlated with less risk seeking. In analyzing subjects' time decision task responses, we found reward-driven individuals tended to be less patient, while future goal-oriented & fun-seeking individuals were more patient.

Keywords: Entrepreneurs; Risk Preferences; Time Preferences; Personality; Experiment

Are Entrepreneurs A Different Breed?

2.1 Introduction

A common assumption about entrepreneurs is that they tend to be risk-taking and patient individuals who, unlike non-entrepreneurs, are willing to forgo their existing resources for a chance of a future larger reward (Liles 1974). Entrepreneurs are also thought to be more motivated, optimistic, and confident about their relative skills (see Baron 1998; Kahneman and Lovallo 1994; Hatten 1997). Are these assumptions true?

The primary goal of this study is to provide direct evidence from an incentivized environment that entrepreneurs have different risk attitudes, time preferences, and other relevant characteristics than non-entrepreneurs. From a managerial point of view, characterizing entrepreneurs is important, because it could eventually help identify characteristics most closely predictive of entrepreneurial success. From a policy perspective, understanding differences in risk tolerance and time patience could help design policies to better serve this important segment of the population. For example, if entrepreneurs are generally responsive to losses, more flexible bankruptcy laws may be needed to incentivize entrepreneurship. Finally, from a theoretical point of view, theories of entrepreneurship assume different risk preferences between "firm owners" and "workers". If entrepreneurs are indeed more risk seeking than non-entrepreneurs, then we would have an appealing empirical substantiation for the Knightian theory of entrepreneurship (Kihlstrom and Laffont 1979).

There have been many attempts to characterize entrepreneurs. However, most of the previous work has relied on face-to-face interviews and hypothetical questionnaires (Brockhaus 1980; Cramer et al. 2002). Consequently, existing knowledge about the traits and characteristics of entrepreneurs has been both qualitative and inconclusive[1] (Gartner 1988; Hatten 1997; Carland et al. 1984; Forlani and Mullins 2000). In this study, we contribute to the current discussion in the following ways. First, we provide more reliable measures of entrepreneurs' key characteristics by incorporating incentivized choices in our surveys. In designing these surveys, we also introduced a novel experimental design that can be quickly replicated and implemented online to non-traditional participant pools, like ours, and with salient financial rewards. Finally by incorporating personality variables into the data analyses, we provide experimental evidence highlighting the importance of individual personality profile in the decision process.

Our sample of entrepreneurs and non-entrepreneurs included people enrolled in executive business and entrepreneurship courses. The experiment was conducted online, and it consisted of the following parts. First, subjects were asked to answer a pre-task questionnaire on basic demographics, risky behaviors such as smoking and alcohol consumption, and to provide information about their businesses. At the end of this part, participants were directed to the main contents of the survey, which included making choices in a set of paid decision tasks, and completing a series of tests and psychological questionnaires. The four paid tasks were designed to elicit individual-level risk attitudes and time preferences. Two quiz-based tests were used to assess individual cognitive abilities. Finally, four well-known psychological surveys provided validated measures of personality traits, such as motivation, optimism, confidence, and future goal-orientation & fun-seeking trait.

[1] Possibly due to this ambiguity in research findings, the business-influential blogosphere portrays entrepreneurs as being very risk averse (see Steven Berglas: http://www.berglas.com/), while also portraying them as very risk seeking (see Trip Hawkins: http://blog.digitalchocolate.com/).

We found sampled entrepreneurs and non-entrepreneurs did not exhibit different risk and time preferences. Interestingly, the median value of the power utility curvature parameter did not coincide with estimated values in previous studies (Tanaka et al. 2010; Liu and Huang 2013; Croson and Gneezy 2009), and our participants were shown to be more risk seeking. Our subject responses to the time decision task were bimodally distributed, unlike customarily encountered normal distribution (Andersen et al. 2008; Harrison, Lau, and Williams 2002). In analyzing subjects' risk decision tasks responses, we found that individuals who scored higher on future goal-orientation & fun-seeking trait switched to Plan B later and were less risk seeking in the risk decision Task 1. In analyzing subjects' time decision task responses, after incorporating the personality factors into the time decision model, the *gender* effect disappeared, while the traits of reward-driven and goal-orientation & fun-seeking became significantly important: a more reward-dependent or reward-driven individual tended to be less patient, while a more future goal-oriented & fun-seeking individual seemed to be more patient.

The remainder of the paper is structured as follows. In the next section, we describe the experimental design and procedures. In Section 2.3 we report the experimental data and empirical findings. Finally, in the last section, Section 2.4, we discuss the implications of our study.

2.2 Design and Procedures

Description of the Study

We recruited a total of 80 subjects (50 males, 50 self-identified entrepreneurs); 62 of them were executive business administration students at Emory Goizueta Business School, 15 of them were students enrolled in the entrepreneurship program at Santa Ana

College, and the rest were actual entrepreneurs who attended entrepreneurship training conferences and forums[2]. Our participants aged from 26 to 61, and the average age was 38.60 with a standard deviation of 9.03 years. In addition, our sampled entrepreneurs were significantly older on average (41 years old vs. 34.6 years old) than the non-entrepreneurs. 49% of entrepreneurs had parents who were born outside the U.S, as compared to 27% of non-entrepreneurs whose parents were not born in the U.S.

The experiment was conducted online via SurveyMonkey. All responses were anonymous and were kept secure after submission. The survey took about 20-30 minutes to complete, and expected earnings ranged between $4 and $970, with a pre-participation average payment of $45[3]. The survey consisted of the following parts. First, subjects gave online consent to participate in this study. Recruited subjects answered a pre-task questionnaire and provided information on their demographics (e.g., age, gender, ethnicity, education, and income), risky behaviors (e.g., smoking, alcohol consumption, and their height and weight with which we calculated their body mass index), and business information (e.g., length of one's business in operation, and expected growth rate of the business in the next three years)[4]. To study whether confidence played a role in entrepreneurship, self-reported current entrepreneurs were asked to rate the odds of

[2] In a related study, Cooper and Saral (2010) recruited a diverse subject population with a high proportion of active entrepreneurs and examined entrepreneurs' preferences towards joining teams versus working alone. Like in our experiment, their subjects included students at Florida State University's College of Business.

[3] These incentives were salient. During the recruiting process, and in post-survey focus groups, our participants told us that compensation was attractive to them, which was the main reason why they were compelled to participate.

[4] The information we requested was specific enough to ensure that the target participants, not surrogates answered the survey. In addition, answers to these questions provided us with a way to double-check the veracity of entrepreneurial self-declaration. Although we are relying on self-identification, there are no incentives for the subjects to lie about their businesses. In addition, their entrepreneurial identity was common knowledge as the subjects also participated in business training and information sessions that were unrelated to this experiment, but it was common knowledge.

their own business/business ideas succeeding, and the odds of any business like theirs succeeding. At the end of the pre-task questionnaire, all subjects were directed to the main contents of the survey, which included making choices for 4 decision tasks and completing a series of quizzes and psychological questionnaires. The four paid tasks were designed to elicit individual risk preferences (Task 1, Task 2 and Task 3, or the risk decision tasks; see Table A.2.1, A.2.2, and A.2.3 in the Appendix) and time preferences (Task 4, or the time decision task; see Table A.2.5 in the Appendix). A Numeracy test (Peters et al., 2006) and Mensa Quizzes were given after the risk decision tasks as a way to measure participants' cognitive capabilities including those for processing numbers and understanding probabilities, and to serve as fillers[5] for the decision tasks. As self-assessment tools for measuring self-confidence subjects were asked to rate how well, relative to other participants, they believed they did in each quiz. After the time decision task, subjects answered four sets of psychological questionnaires, including the Situational Motivation Scale (SIMS), the Life Orientation Test-Revised (LOTR), the Behavioral Activation System and Behavioral Inhibition System Scales (BAS/BIS), and the Life and Job Satisfaction Questionnaire. These questionnaires provided validated measures of individual-level motivation, optimism/ pessimism, behavioral activation and inhibition, and satisfaction, respectively (see Section 2.2.3).

Payment

All subjects were paid $25 for completing the survey. In addition, they all had a 4 in 5 chance of receiving extra money, or losing up to $21 from decisions in one of the

[5] Filler items were not used in scoring.

four equally weighted tasks[6]. On December 5, 2009, we constructed a random number device that determined 200 sets of five numbers. These sets of numbers were ordered from 1 to 200 to match the order of complete surveys submitted online. For example, if an individual was the 50th subject who submitted a completed survey, the set of numbers that determined his/her payoffs was the 50th set of five numbers drawn on December 5th of 2009. The former President of the World Chamber of Commerce, Solange Warner, underwrote this process. We have a written record of these numbers on a signed document that is available upon request.

The final payoff for a specific subject was determined jointly by his/her decisions in the tasks and a matched set of five random numbers[7]. Once we received a complete survey via SurveyMonkey, an electronic W-9 form and a confirmation email were sent to the subject, informing his/her set of five random numbers, and the amount of payment in the study. For taxation purposes, all subjects were required to return their signed W-9 forms either by fax or email to our research administers at Department of Economics,

[6] Although the random incentive mechanism (RIM) has been widely used in experimental research, as early as in the 90s, Holt (1986) argued that it was incentive compatible only for the preferences that satisfied the independence axiom. In Prospect Theory, Kahneman and Tversky (1979) assumed subjects isolated each task and evaluated one task independently of the other tasks. More recently, Cox et al. (2012) experimentally tested the isolation hypothesis from Prospect Theory and incentive compatibility of RIM. They showed isolation hypothesis was violated; the RIM did not elicit true preferences and choice behavior in RIM depended significantly on the other tasks involved. Their study challenges the widespread incentive compatibility of RIM on induced preferences. It is still unclear, however, whether the biases introduced by RIM are behaviorally relevant. But a recent working paper by Harrison and Swarthout (2012) suggests that the preference estimates obtained under RIM were statistically different from those obtained in a one-task design.

[7] The first random number (between 1 and 5) determined the Task Number for which the subject got paid. If the number randomly generated was 1, 2, 3 or 4, then Task 1, Task 2, Task 3 or Task 4 was counted respectively towards his/her payment. However, if this number was 5, then NONE of the tasks counted. The second random number (between 1 and 10) and the third random number (between 1 and 5) determined which of the 10 questions of Task 1 or Task 2 counted, and which of the 5 questions of Task 3 counted, respectively. The fourth random number (between 1 and 10) determined the Ball Number, and exactly how much the subject was paid for the chosen decision in Task 1, Task 2, or Task 3. Finally, the fifth random number (between 1 and 20) determined which of the 20 options in Task 4 was paid.

Emory University. After receiving the signed W-9 forms, subjects' final payments were processed and checks with their earnings were sent out immediately.

2.2.1 Eliciting Risk Preferences

In expected utility theory (EUT), risk preference is characterized solely by the concavity of a utility function. In contrast, Cumulative Prospect Theory (CPT) allows for nonlinear probability weighting, as well as loss aversion. Most of the previous experiments conducted in the field or that target non-traditional subject pools have tested simple models of risk characterized by one concavity parameter (Cardenas and Carpenter 2006). These simple models have often been rejected by experimental data, in favor of models with multiple components of risk preference (Frederick et al. 2002; Starmer 2000).

Building upon existing experimental findings, we used Tversky and Kahneman (1992)'s CPT [8] and the one-parameter Prelec (1998)'s probability weighting function to capture individuals' risk attitudes. Assuming p_k is the probability of monetary outcomes x_k from a lottery $L(p_1, p_2, \ldots p_k ;x_1, x_2, \ldots x_k)$, for the simplest binary lottery, the expected utility of the prospect can be written as:

$$EU_{lottery} = W(p_1) \times u(x_1) + [1- W(p_1)] \times u(x_2) \quad for \quad x_1 > x_2$$

where $W(p_1) = \dfrac{1}{\exp[\ln(1/p_1)]^{\alpha}}$

$u(x) = x^{\sigma}$ for gains $x \geq 0,$ and $u(x) = -\lambda(-x)^{\sigma}$ for losses; $x<0$.

[8] Reference point is crucial in CPT, because the theory postulates people exhibit different risk attitudes towards gains (i.e., monetary outcomes above the reference point), and losses (i.e., monetary outcomes below the reference point). In this study, participants were informed that they would receive $25 for sure if they completed the survey questionnaires. They could earn additional money up to $945; however, they also risked losing up to $21 in the choice tasks. Therefore in our study gains/losses are defined as monetary outcomes above/below the $25 participation fee (i.e., reference point).

Hence, the three key risk parameters to be measured are σ, the concavity of the CRRA utility function, α, the probability sensitivity parameter, and λ, the degree of loss aversion. Figure 2.1 plots the one-parameter Prelec (1998)'s probability weighting functions. As alpha approaches to one, subjective probabilities are getting closer to objective probabilities (i.e., as it is in EUT) throughout the (0, 1) interval, suggesting that individuals who have alpha values that are closer to one distort objective probabilities less. When alpha is less than one, the probability weighting function is inverse S-shaped (see Latimore et al. 1992; Camerer and Ho 1994; Abdellaoui 2000; Wu and Gonzalez 1996; Starmer 2000); when alpha is greater than one, the probability weighting function is S-shaped.

To elicit CPT parameters, previous experiments often involved a series of paired lotteries from which subjects were asked to choose preferred ones (e.g., Holt and Laury 2002; Andersen et al. 2008). In our study, we used a modified version of Tanaka et al. (2010)'s design (see Table A.2.1, A.2.2, and A.2.3 in the Appendix). Our version of paired lotteries had three series (i.e., two series of 10 lotteries over gains and one series of 5 lotteries over losses), and 25 rows, with each row that was a choice between two binary lotteries, Plan A or Plan B. Similar to Tanaka et al. (2010), we enforced monotonic switching by asking the subjects at which questions they would "switch" from Plan A to Plan B in each series. They could switch to Plan B starting with the first question and they did not have to switch to Plan B at all.

We properly modified Tanaka et al. (2010)'s paired lotteries design such that a particular set of choices in the three risk decision tasks determined a unique combination of risk parameters[9]. For example, suppose a subject switched from Plan A to Plan B at the fourth question in Task 1 and the seventh question in Task 2, a "reasonable" combination of (σ, α) that could realize these switches was (0.7, 0.7). Approximations of (σ, α) for all possible switches combinations are given in Table A.2.4.

The loss aversion parameter λ was determined by the switching point in Task 3. This task consisted of 5-paired lotteries. Depending on the curvature parameter of the utility function σ, the range of λ implied by each switching point is listed in Table A.2.4. The later one switches from Plan A to Plan B, the more loss-averse he/she is.

2.2.2 Eliciting Time Preferences

Laboratory experiments have been widely implemented to elicit individual discount rates (IDRs), the rates at which individuals are willing to trade an early payment for a larger amount of delayed payment. Previous experimental studies on IDRs often involved a multiple price list (MPL) where participants were asked to choose between receiving different payments at different times (Coller and Williams 1999; Dohmen et al. 2010; Tanaka et al. 2010; Andersen et al. 2008). Moving down the list, the early payment was fixed but the size of delayed payment increased in each row. The earlier one chooses

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[9] We constructed our risk decision tasks in the following way:
Assume payoffs in Plan A (\$40 and \$10 in Task 1, \$40 and \$30 in Task 2), smaller payoffs in Plan B (\$5), and winning probabilities remain fixed in each task series, only the larger amount of payoffs in Plan B vary, denoted as Ψ, with a subscript indicating the question number. When a subject switches from Plan A to B at the fourth question in Task 1, and seventh question in Task 2, the following inequalities should hold, assuming Prelec (1998)'s probability weighting:

$10^\sigma + W(0.3)\,(40^\sigma - 10^\sigma) > 5^\sigma + W(0.1)\,(\Psi_3{}^\sigma - 5^\sigma)$ at Question #3,

$10^\sigma + W(0.3)\,(40^\sigma - 10^\sigma) < 5^\sigma + W(0.1)\,(\Psi_4{}^\sigma - 5^\sigma)$ at Question #4;

$30^\sigma + W(0.9)\,(40^\sigma - 30^\sigma) > 5^\sigma + W(0.7)\,(\Psi_{16}{}^\sigma - 5^\sigma)$ at Question #16;

$30^\sigma + W(0.9)\,(40^\sigma - 30^\sigma) < 5^\sigma + W(0.7)\,(\Psi_{17}{}^\sigma - 5^\sigma)$ at Question #17.

After solving a series of inequalities as the above, the ranges of each Ψ values for questions numbered from 1 to 20 were obtained. Taking the lower bound of Ψ for each question, the larger payoffs in Plan B were constructed, as in Table A.2.1 and A.2.2.

the larger amount of delayed payment, more patient this individual is. Therefore, IDRs could be implicitly inferred from the decisions (or the switching points) in the MPL.

Similar to the discount rate experiment in Coller and Williams (1999), a MPL of 20-paired payment alternatives, Plan A or Plan B was presented to the subjects (see Table A.2.5). Plan A offered \$100 in 30 days and Plan B paid \$100+\$*x* in 90 days, where *x* is some positive amount. The subject was asked to select one of the rows from the MPL and the row number indicated he/she chose Plan A for question #1 through that row, and he/she preferred Plan B for the all other rows. All the subjects understood that, depending on their choices and chances, only one decision row would be selected at random to be paid out at the chosen date. They would receive checks with earnings in either 30 days or 90 days, if Task 4 was randomly chosen to count. To avoid arbitrage between the lab and the field that might cause errors in eliciting individual time preferences, Annual Interest Rates (ARs) and Annual Effective Interest Rates (AERs) were also provided[10], as well as the money market account annual rate in Georgia, which was no more than 2% at the time of the experiment. Since corresponding interest rates associated with each choices are given in the MPL, participants' responses (or their switching points) among the 20-paired payoff options revealed the intervals of each elicited IDRs. For instance, if the subject chose Plan A for question 1 through 5 and Plan B for all other questions, or he/she first switched from Plan A to Plan B at question 6, then his/her discount rate fell

[10] Annual rates (ARs) were simple interest rates and annual effective rates (AERs) were compounded daily. ARs and AERs were given because the purpose of this study was not to test whether the subjects were capable of calculating ARs and AERs in order to make comparisons between the paired payoff options, although they often tended to do so in both laboratory and field settings (Andersen et al. 2008).

into the interval of (17.34%, 22.12%). Therefore, an individual's response to the task implied his/her time preference, or level of patience[11].

It makes sense for a rational individual not to postpone payment in the experiment if the interest rate is lower than the external market rate (Andersen et al. 2008). However knowing that ARs and AERs provided in the experiment were higher than the market rate, an individual would be willing to delay payment because it seemed more worthwhile to wait than to invest smaller amount of earlier payment in the money market. Therefore, the presented MPL also included the first row with AR that was below 2%, in case a relatively patient individual chose to switch to Plan B at the first row.

Another important feature of our MPL is the implementation of front end delay (FED) of 30 days for both Plan A and Plan B. Subjects had the option of receiving \$100 in 30 days or \$100+\$*x* in 90 days, so the elicited annual discount rate is applicable to a time horizon of 60 days[12], or two months. This makes both payment options equally credible or "incredible" to the subject. Andersen et al. (2008) argued that the FED avoided a "passion for the present" and "the potential problem of the subject facing extra risk or transaction costs involved with the future income option" (including the possibility of default by the experimenter), as compared to the "instant" income option. However, existing experimental literature (e.g., Coller and Williams 1999; Coller, Harrison, and Rutström 2003) also showed that removing the FED increased elicited

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[11] Coller and Williams (1999) pointed out since rates revealed in the lab were influenced by subjects' field opportunities, their responses were censored by a lack of information on what rates they faced in the lab (either this information was unavailable or subjects were not able to calculate the rates correctly). Therefore they ran four information treatment sessions and found that providing information on the rates lowered both mean revealed discount rates and residual variance of subject responses in the MPL.

[12] The length of time horizon matters in the sense that the discount rate might vary over which time horizon it is elicited. For detailed discussions, see Andersen et al. (2008), Eckel et al. (2005), and Harrison, Lau, and Williams (2002).

IDRs dramatically by about 25 percentage points. Moreover, since estimates from the model rely heavily on parametric functional forms, experimental design has to be consistent with the theory in modeling time preferences. According to Andersen et al. (2008), the presence of FED led to the rejection of quasi-hyperbolic discounting specification. Although with FED, they found evidence of slight decline in elicited discount rates from exponential discounting, its magnitude was much smaller than if hyperbolic discounting specification was used. Hence, exponential discounting framework is most applicable to current experimental settings. Assuming an individual is risk neutral, he/she chooses to receive either M_t from Plan A in 30 days (i.e., at time t) or $M_{t+\tau}$ from Plan B in 90 days (i.e., at time $t+\tau$):

$$M_t = \frac{1}{(1+\delta)^{\tau}} M_{t+\tau}$$

where δ is the annual discount rate that makes the values of two monetary outcomes M_t and $M_{t+\tau}$ equal at time *t*. In the MPL (see Table A.2.5), M_t is simply \$100 in Plan A, and $M_{t+\tau}$ equals the exact amount paid by Plan B. Here is the example illustrated earlier: suppose an individual first switched from Plan A to Plan B at question 6, then his/her inferred annual discount rate lay within the range of (17.34%, 22.12%). This implies his/her annual discount factor $\frac{1}{(1+\delta)}$ ranges between (0.819, 0.852). Thus for this individual, \$1 today has equivalent value of \$0.819~\$0.852 on the same day of next year.

<u>Modeling Time Preferences</u>

Given that raw responses in the time decision task reflect unobserved individual time preferences or the IDRs, and values for the responses variable are integers ranged from 0 to 20[13], we consider the following ordered probit model:

$$y_i^* = \beta x_i + \varepsilon_i$$

Here, y_i^* is subject *i*'s individual discount rate and it is not directly observed,

x_i is a vector of explanatory variables including demographic and personality characteristics, and

ε_i is an error term, assuming it is distributed as a standard normal. Instead of observing y_i^*, we observe the responses variable y_i,

$$\begin{array}{l} y_i = 0 \quad \text{if } y_i^* \le \delta_0 \\ y_i = 1 \quad \text{if } \delta_0 < y_i^* \le \delta_1 \\ y_i = 2 \quad \text{if } \delta_1 < y_i^* \le \delta_2 \\ \vdots \quad \vdots \qquad \vdots \quad \vdots \quad \vdots \\ y_i = 20 \quad \text{if } y_i^* > \delta_{20} \end{array}$$

The δ_i are known threshold values of the Annual Effective Interest Rates (AERs), or the interval limits in the MPL: $\delta_0 = 2.01\%$, $\delta_1 = 5.12\%, \ldots$, and $\delta_{20} = 199.89\%$.

2.2.3 Personality Questionnaires

Existing psychological studies showed that entrepreneurs might have different personality characteristics (Littunen 2000; McClelland 1961, 1985; Gartner 1988; Carland et al. 1984), such as need for achievement/goal-orientation (Komives 1972;

[13] If the subject chose Plan A for question 1 through 1, 2 …or 20 from the MPL, his/her response was coded a 1, 2… 20, respectively. If he/she didn't want to select Plan A for any of the questions, he/she could respond "none" and it was coded as a 0.

McClelland 1961; McClelland and Winter 1969), need for independence and power, need for responsibility, internal locus of control, and life and job satisfaction (Brockhaus 1980; Brockhaus and Nord 1979; Hull et al. 1980; Liles 1974). More recently, Cooper and Saral (2010) conducted a team production experiment to study entrepreneurs' preferences towards joining teams versus working alone. They provided significant evidence suggesting that entrepreneurs who were motivated by desires for control and/or autonomy preferred to work alone rather than join teams.

To measure personality traits, we used well-established and validated psychological questionnaires/scales including the SIMS (Guay et al. 2000), the BAS/BIS (Caver and White 1994), the LOT-R (Scheier et al. 1994), and the Life & Job Satisfaction Questionnaire. The SIMS provides a situational measure of motivation in both field and laboratory settings. It assesses the constructs of intrinsic motivation, identified regulation, external regulation, and amotivation. Intrinsic motivation refers to performing an activity for itself, to experience pleasure and satisfaction inherent in the activity. External regulation occurs when behavior is regulated by rewards or in order to avoid negative consequences. In contrast, identified regulation occurs when an extrinsically motivated behavior is valued and perceived as being chosen by one-self. Last but not least, when amotivation occurs, individuals experience a lack of contingency between their behaviors and outcomes (i.e., they are neither intrinsically nor extrinsically motivated, or are irresponsive to incentives).

The BAS/BIS scales contained 24 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 Life Orientation Test-Revised (LOT-R) gives a brief measure of individual differences in generalized optimism versus pessimism. It contains 10 questions asking respondents to indicate at what extent they agree with each statement (i.e., strongly disagree, disagree, neutral, agree, or strongly agree). An overall optimism score is computed by summing up scores on 6 out of the 10 questions[14]. The optimism scores can range from 0 to 24, and a high score implies a greater level of optimism.

Finally, the Life and Job Satisfaction Questionnaire assesses individual levels of satisfaction. It contains two self-reported questions asking how satisfied individuals are with their current life and job. A higher score on this questionnaire indicates relatively higher level of life and job satisfaction.

2.3 Results

2.3.1 Description of the Data

<u>Risk Preferences</u>

In this section, we report subject responses in the risk decision tasks, as well as approximated risk parameters. Subjects' raw choices were coded as a 1, 2 … or 10 if they chose Plan A for questions 1 through 1, 2 … or 10. If one didn't want to select Plan A for any of the questions, he/she could respond "none" and it was coded as a 0.

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[14] Four of the items are filler items and are not used in scoring.

As Table 2.1.1 shows, median subject chose Plan A for questions 1 through 3 in Task 1 and Task 2, and Plan A only for question 1 in Task 3, and Plan B for all the others. Therefore, the median subject switched at question 4 in Task 1 and Task 2, and question 2 in Task 3. Table 2.1.2 displays a summary statistics of approximated risk parameters among the 80 subjects in our experiment. Eyeballing this table, median values of utility curvature parameter (i.e., σ) and loss-aversion parameter (i.e., *λ-average*, the average value of the elicited λ intervals) do not coincide with estimated values in studies using similar lotteries among student subjects (Croson and Gneezy 2009). In particular, our subjects seemed to be more risk seeking and less loss-averse than the traditional student population. Comparing approximated mean risk parameters in our experiment with Tanaka et al. (2010)'s, our participants seemed to be more risk seeking than their subjects who were members of households in rural Vietnamese villages[15]. Based on Table A.2.4 in the Appendix, a unique combination of risk parameters (σ, α, *λ-average*) that rationalizes median-subject's switches is (0.85, 0.85, 1.618).

Time Preferences

The MPL (see Table A.2.5) was presented to the subjects and their choices (or switching points) among the 20-paired payoff options revealed the intervals of each elicited IDRs. Subjects' raw choices were coded as a 1, 2 … or 20 if they chose Plan A for questions 1 through 1, 2 …or 20. If one didn't want to select Plan A for any of the questions, he/she could respond "none" and it was coded as a 0.

Table 2.2 describes subject responses in the time decision task. Interestingly, 50 percent of the sample either switched to Plan B at the first option (28.95 percent) or the

[15] Mean estimated value of utility curvature parameter σ is around 0.6 in Tanaka et al. (2010).

last option (21.05 percent). As shown in the left panel of Figure 2.2, distribution of all raw responses looked more like bimodal than the customarily encountered normal distribution in experimental studies using similar MPLs with field and student subjects (Andersen et al. 2008; Harrison, Lau, and Williams 2002). Not only raw responses of the sample as a whole formed a bimodal distribution, responses from each of the entrepreneurial and non-entrepreneurial groups were also bimodally distributed. Right panel of Figure 2.2 captures this feature in the sample. To summarize, median subject's response in the time decision task was 5.500, and the average was 8.118 with a standard deviation of 7.903.

Personality Characteristics

What kind of personality profile do these individuals have? To answer this question, first, we performed factor analysis to reduce the dimensionality of twelve trait items from the psychological questionnaires and cognitive quizzes to five personality factors[16]. The purpose of factor analysis was to remove possible double-counting or over-lapping in trait measures, so that the extracted factors were orthogonal and they each provided measurement for one unique characteristic only. Table 2.3 shows the rotated factor loadings and the uniqueness scores for each attribute. The five identified factors accounted for 71.35% of the variance. Then, we correlated relevant factors including Factor 1 (Motivation), Factor 3 (Proxy for IQ), and Factor 4 (Goal-orientation & Fun-seeking) with tasks responses. Table 2.4 shows the pair-wise correlation results and suggests the following interesting findings: the motivated and individuals who scored higher on IQ related tests tended to switch in the risk decision Task 3 significantly earlier;

[16] For a detailed descriptive statistics of all personality and demographic variables, see Table A.2.6 in the Appendix.

thus, they behaved as if they were less loss-averse in Task 3. In addition, participants who were more goal-oriented & fun-seeking seemed to switch in risk decision Task 1 significantly later and switch in the time decision task significantly earlier; therefore, they were less risk seeking in Task 1 and more patient in Task 4.

2.3.2 Differences between Entrepreneurs and Non-entrepreneurs

What makes for an entrepreneur? To answer this question, we performed a set of comparison tests and found entrepreneurs consisted of more males[17] (Mann-Whitney test or MWT, Z= 2.252, p=0.024), were significantly older (MWT, Z= -3.000, p=0.003), and more motivated (MWT, Z= -2.419, p=0.016) than non-entrepreneurs. In addition, 49% of entrepreneurs had parents who were born outside the U.S, as compared to 27% of non-entrepreneurs whose parents were not born in the U.S, and the difference was significant (MWT, Z=1.948, p=0.051). Table 2.5.1 summarizes demographic and personality differences between entrepreneurs and non-entrepreneurs.

We were particularly interested in examining what risk attitudes and time preferences entrepreneurs and non-entrepreneurs exhibited and whether they differed[18]. In what follows, we report relevant empirical findings.

<u>Risk Preferences</u>

Table 2.5.2 summarizes risk decision tasks responses for sampled entrepreneurs and non-entrepreneurs. We tested whether distributions of three risk decision tasks responses were significantly different. However, we did not observe significant

[17] We had 36 male entrepreneurs and 14 female entrepreneurs; 14 male non-entrepreneurs and 16 female non-entrepreneurs.

[18] Analysis of personality difference between entrepreneurs and non-entrepreneurs is reported in another manuscript.

differences between entrepreneurs and non-entrepreneurs (Task 1 Responses: Kolmogorov-Smirnov test statistic D= 0.196, corrected p-value=0.381; Task 2 Responses: Kolmogorov-Smirnov test statistic D= 0.176, corrected p-value=0.523; Task 3 Responses: Kolmogorov-Smirnov test statistic D= 0.083, corrected p-value= 0.999)[19]. Distributional plots of risk decision tasks responses between entrepreneurs and non-entrepreneurs are shown in Figure 2.3.

To explain individual risk attitudes, we analyzed a series of models using OLS, assuming subject responses in the risk decision tasks depended on a set of demographic and personality variables. The models and statistical results are described in Table A.2.7 and Table A.2.8 of the Appendix. A sampled entrepreneur switched to Plan B later in the risk Task 1 (at 10% significance level), while an individual who was future goal-oriented and fun-seeking also switched later in Task 1 (at 5% significance level). This means an entrepreneur and a more goal-oriented & fun-seeking individual seemed to be less risk seeking in Task 1. In the risk Task 2, marital status affected subject responses in the following way: a married individual tended to switch to Plan B earlier (at 10% significance level); hence, this individual was less risk averse in Task 2.

Time Preferences

We did not observe entrepreneurs and non-entrepreneurs differed in time preferences[20]. To provide robustness check of this finding and to examine the effects of

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[19] However sampled entrepreneurs and non-entrepreneurs might differ in their mean responses in Task 1 (MWT, Z= -1.819, p=0.069), and entrepreneurs tended to switch from Plan A to Plan B significantly later. This implies sampled entrepreneurs might behave as if they were more risk averse than non-entrepreneurs in Task 1.

[20] Entrepreneurs and non-entrepreneurs did not seem to differ in their mean responses in the time decision task (MWT, Z=-0.005, p=0.996); moreover, Kolmogorov-Smirnov test confirmed this: there wasn't significant difference in distributions of raw choices between entrepreneurs and non-entrepreneurs.

other demographic and personality variables on individual time preferences, we considered multiple models of subject responses to the time decision task, including the ordered probit model explained in Section 2.2.2 (see Table A.2.9 in the Appendix for a list of the models). We analyzed these models, and report findings and statistical results below.

Traditionally we assume an individual's choice depends largely on his/her observable characteristics such as age, gender, education, and marital status, etc. Hence, we model individual choice as a function of the observables, and make statistical inferences by looking at the marginal effects of these variables on the choice. The ordered probit (1) modeled individual time preference (i.e., the time task responses) exactly in this fashion, and only *gender* was shown to play an important role (at 10% significance level): females switched to Plan B later than males, and thus, females tended to be more impatient. However, the model is mis-specified: a joint test of the model that all coefficients are equal to zero cannot be rejected at 93.4% significance level. Therefore, obtained marginal effects of the observed demographics on the time preference are biased in the ordered probit (1).

To correctly specify the model, we incorporated five personality factors into the statistical analysis, and estimated the ordered probit (2) model[21]. For our particular time responses data, ordered probit performs better than OLS at generating consistent and efficient estimates; in addition, the ordered probit (2) is better than the ordered probit (1) because a joint test that all coefficients in the ordered probit (2) are indifferent from zero was rejected at 8% significance level. Given the sample size of current study, the ordered

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[21] Borghans et al. (2009) argued that personality characteristics were important in explaining performance in specific decision tasks, and thus, we incorporated the five personality factors into the model.

probit (2) model is fairly decent[22].

Table A.2.9 in the Appendix shows the effects of all explanatory variables on individual time task responses. Interestingly, after adding five personality factors in the ordered probit (2) model, *gender* was no longer significant; instead, the effects of Factor 4 (Goal-orientation & Fun-seeking Trait) and Factor 5 (Reward-driven Trait) became important at 5% significance level. Keeping all the other variables constant, if an individual was more future goal-oriented and fun-seeking, he/she tended to switch to Plan B earlier, and thus more patient; whereas, if one was more reward-dependent or reward-driven, he/she seemed to be less patient.

2.4 Discussion

Are entrepreneurs a different breed? Using qualitative methods such as face-to-face interviews, previous studies on this topic have identified risk bearing as a key characteristic of entrepreneurs (see Schumpeter 1934; Mill 1848; Carland et al. 1984; Forlani and Mullins 2000; Van Pragg et al. 2001). Moreover, entrepreneurs are also thought to be more patient, motivated, optimistic, and overconfident about their relative skills[23] (e.g., Baron 1998; Kahneman and Lovallo 1994; Hatten 1997). How reliable are these assumptions?

To test and scientifically establish a correlation between individual characteristics and entrepreneurship, we developed a simple online experiment that consisted of three

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[22] For a relatively large sample size (e.g., over 100 observations), if the significance level is 5% or lower for rejecting the joint test of all coefficients being zero, the model is okay.

[23] In this study, when current entrepreneurs were asked what the odds of their businesses succeeding were as compared to the odds of any businesses like theirs succeeding, they responded 6.56 out of 10, and 4.54 out of 10 on average, respectively. The odds differences are statistically significant (Wilcoxon Signed-rank Test, $Z=4.545$, $p<0.001$). This result indicated sampled entrepreneurs were pretty confident about their own businesses and relative skills.

risk decision tasks, one time decision task, and a set of validated psychological questionnaires. We elicited individual risk attitudes and time preferences, and found sampled entrepreneurs and non-entrepreneurs did not exhibit different risk and time preferences. However, our participants were shown to be more risk seeking than field and student subjects in previous studies using similar lotteries (Tanaka et al. 2010; Liu and Huang 2013; Croson and Gneezy 2009). Moreover, our subject responses to the time decision task were bimodally distributed, unlike customarily encountered normal distribution using similar MPLs with field and student subjects (Andersen et al. 2008; Harrison, Lau, and Williams 2002). In analyzing subjects' risk decision tasks responses, we showed that higher scores on future goal-orientation and fun-seeking trait were correlated with less risk seeking. In analyzing subjects' time decision task responses, after incorporating the personality factors into the time decision model, the only *gender* effect disappeared, while the traits of reward-driven and goal-orientation & fun-seeking became significantly important: a more reward-dependent or reward-driven individual tended to be less patient, while a more future goal-oriented & fun-seeking individual seemed to be more patient. Hence, we provided experimental evidence highlighting the importance of individual personality profile in the decision process.

There are two implications we have learnt from analyzing economic choices by incorporating personality characteristics. First, traditionally utilized demographic variables may not be sufficient in predicting economic preferences and outcomes. If exclusively relying on observable characteristics to explain individual choice and behavior, inferential predictions could be problematic. Second, personality has placed indispensable impacts on economic preferences such as risk and time preferences (Capra et al. 2013; Borghans et al. 2009), and decision-making processes (Cooper and Saral 2010; Dittrich et al. 2005). To better understand economic choices, one has to look into the personality profile of the decision-maker and find out what traits might be relevant. Apparently, if important personality variables are neglected, the decision models are mis-specified and results are biased.

Like many other experiments that were designed to obtain preference estimates, we were particularly interested in eliciting three risk parameters in CPT and intended to fit the model to observed choice data. In our experimental design, we used random incentive mechanism (RIM) and paid subjects at the end of the experiment. If using CPT to model choice under risk, isolation hypothesis needs to be satisfied to ensure the incentive compatibility of RIM. However, recent studies led by Cox et al. (2012) and Harrison and Swarthout (2012) showed that isolation hypothesis from prospect theory was violated and preference estimates obtained under RIM were different from those obtained in a one-task design. This implies CPT model should probably not have been used if the experiment was designed assuming EUT and incentive compatibility of RIM, like ours. If fitting the data to alternative models (e.g., EUT) of choice under risk, would the results be less biased than using CPT? One major difference among all existing theories of choice under risk lies in how each theory treats probability weighting. To properly elicit probability weighting parameter with less bias, what kind of lottery choice task needs to be constructed? We believe these are important questions to be addressed in the near future. Yet, with the current knowledge about these matters, our experiment represents the state of the art, but clearly there is substantial progress to be made.

Thus far, the core research question remains to be unanswered: if entrepreneurs and non-entrepreneurs do not differ in prevailing characteristics such as risk bearing and time preference as previous literature claimed, then what makes for an entrepreneur? Are entrepreneurs really a different breed from the rest of the population? In this study we found sampled entrepreneurs consisted of more males, were significantly older, and more motivated than non-entrepreneurs. In addition, 49% of entrepreneurs had parents who were born outside the U.S, as compared to 27% of non-entrepreneurs whose parents were not born in the U.S. This is consistent with a large number of studies conducted in the 1980s and 1990s which showed being a child of immigrants affected an individual's chance of becoming an entrepreneur (Bianchi 1993; Byers et al. 2000). Our findings about ethnicity differences in explaining entrepreneurship may be of particular interest, given the growing population of immigrant entrepreneurs in the United States over the past 20 years. Are immigrants more likely to become entrepreneurs because they are "forced" by their immigration status that makes it difficult for them to find other employment? Or, do immigrants willingly choose to become entrepreneurs? Questions like these are certainly interesting, but beyond the scope of our research, and we encourage interested audience to explore in future inquiry.

At this point, through our study, knowledge about entrepreneurial attributes can help inform small business investors and policy makers. For example, we learned that motivation is an important factor distinguishing entrepreneurs from non-entrepreneurs. This trait may be a crucial criterion for deciding whether to loan money to a start-up. Nevertheless, to better understand the attributes that truly explain and nourish entrepreneurship, we believe it is important to explore reasons and individual motives behind pursuing an entrepreneurial career (e.g., hope for success, fear of failure, and need for autonomy). Indeed, this could be a very interesting topic for future research.

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Table 2.1.1

Subject Responses in the Risk Decision Tasks

Statistics	Task 1 Choice	Task 2 Choice	Task 3 Choice
Mean	3.823	4.178	1.526
SE	0.370	0.459	0.209
Median	3.000	3.000	1.000
95% C.I.	(3.087, 4.558)	(3.264, 5.090)	(1.109, 1.943)
N	79	79	78

Note. Task 1, Task 2, and Task 3 Choices represent subject responses in the three risk decision tasks. Median subject chose Plan A for questions 1 through 3 in Task 1 and Task 2, and Plan A for question 1 in Task 3; for all the other questions, he/she chose Plan B. Therefore, the median subject switched at question 4 in Task 1 and Task 2, and question 2 in Task 3.

Table 2.1.2

Risk Parameters Approximations

Statistics	Prelec (1998) Probability Weighting	Utility Curvature	Utility Loss-aversion
	α	σ	*λ-average*
Mean	0.757	0.742	2.418
SE	0.037	0.044	0.160
Median	0.750	0.800	1.633
95% C.I.	(0.684, 0.830)	(0.655, 0.830)	(2.100, 2.736)

Note. Risk parameters approximations are based on the modified Tanaka et al. (2010) design. The loss-aversion statistics shown in the table represents the average value of the elicited λ intervals.

Table 2.2

Descriptive Statistics for Subject Responses in the Time Decision Task

Time Task	Elicited Interval (%)		Frequency	Percentage (%)	Cumulative (%)
Responses	AR	AER			
0	<1.99	<2.01	22	28.95	28.95
1	1.99-4.99	2.01-5.12	3	3.95	32.89
2	4.99-7.99	5.12-8.32	3	3.95	36.84
3	7.99-11.99	8.32-12.74	1	1.32	38.16
4	11.99-15.99	12.74-17.34	5	6.58	44.74
5	15.99-19.99	17.34-22.12	4	5.26	50.00
6	19.99-24.99	22.12-28.38	2	2.63	52.63
7	24.99-29.99	28.38-34.96	4	5.26	57.89
10	39.99-45.99	49.13-58.35	8	10.53	68.42
11	45.99-51.99	58.35-68.12	1	1.32	69.74
12	51.99-57.99	68.12-78.50	1	1.32	71.05
13	57.99-63.99	78.50-89.52	1	1.32	72.37
17	84.99-92.99	133.71-153.13	2	2.63	75.00
18	92.99-100.99	153.13-174.15	2	2.63	77.63
19	100.99-109.99	174.15-199.89	1	1.32	78.95
20	>109.99	>199.89	16	21.05	100.00
Total			76	100.00	

Note. The whole sample size was eighty, and four subjects didn't respond to the time decision task.

Table 2.3

Rotated Factor Loadings and Uniqueness Scores

Variable	Factor1	Factor2	Factor3	Factor4	Factor5	Uniqueness
Numeracy	0.1513	-0.0540	0.8166	-0.1077	0.0824	0.2889
MensaQuiz	-0.0421	-0.0587	0.8438	0.0580	-0.0373	0.2780
IntrinsicMot	0.8297	-0.0411	0.0130	0.1917	0.2169	0.2259
IdentifiedReg	0.8792	0.1177	0.1199	0.0807	-0.0376	0.1909
ExternalReg	0.5808	-0.2819	-0.3020	-0.2451	-0.3615	0.3012
Amotivation	0.2714	-0.2783	-0.3768	-0.5589	0.0976	0.3850
LOT-R	-0.0880	0.8285	-0.0660	0.2246	0.0850	0.2437
Satisfaction	0.0903	0.7780	-0.0093	-0.2752	-0.0259	0.2944
BAS-drive	0.1734	0.0797	-0.1624	0.6960	0.0098	0.4526
BAS-rewards	0.2387	0.1974	-0.0769	0.1368	0.8137	0.2173
BAS-funskg	0.3293	-0.1492	-0.0143	0.7057	0.1407	0.3512
BIS	-0.2783	-0.4599	0.1813	-0.1725	0.6630	0.2087

Note. IntrinsicMot, IdentifiedReg and ExternalReg are indicators of **Motivation Trait (Factor1)**, obtained from the SIMS questionnaire. LOT-R and Satisfaction assess individual level of **Optimism and Job & Life Satisfaction Trait (Factor2)**, given by the LOT-R and Satisfaction questionnaires. Numeracy and MensaQuiz are proxy for **IQ (Factor3)**, which comes from individual scores on the Numeracy test and Mensa Quiz. Amotivation, BAS-drive, and BAS-funsky belong to the SIMS and BAS/BIS questionnaires, measuring a lack of motivation and different subcategories of behavioral activation system underlie behavior and affect, respectively. They are indicators of **Goal-orientation & Fun-seeking Trait (Factor4)**. BAS-rewards and BIS are components of the BAS/BIS scales measuring individual sensitivity to the events that occurred or are expected. They positively relate to reward-dependence or **Reward-driven Trait (Factor5)**. For a more detailed description of trait variables, see Table A.2.6 in the Appendix.

Table 2.4

Pair-wise Correlations with Traits

	Risk Tasks (T1, T2, T3)			Time Task (T4)
VARIABLES	**Task 1 Choice**	**Task 2 Choice**	**Task 3 Choice**	**Task 4 Choice**
Factor1 (Motivation)			-0.226* (0.053)	
Factor3 (IQ)			-0.228** (0.050)	
Factor4 (Goal & Fun)	0.254** (0.029)			-0.220* (0.060)

Note. Pair-wise correlation coefficients. P-values in parentheses.

** Significant at the 5% level; * Significant at the 10% level.

Table 2.5.1

Characteristic Differences between Entrepreneurs and Non-entrepreneurs

Mean Statistics

Entrepreneurs Yes/ No	**Age**	**Sex**	**Parent2**	**Cigars**	**Business**	**Starter**	**Factor1 (Motivation)**
Yes (50 subjects)	41.000	0.280	0.510	0.000	0.520	0.500	0.242
No (30 subjects)	34.600	0.533	0.733	0.200	0.000	0.000	-0.376
All (80 subjects)	38.600	0.375	0.595	0.075	0.325	0.313	0.000

Table 2.5.2

Decision Tasks Responses for Entrepreneurs and Non-entrepreneurs

Entrepreneurs/ Non-entrepreneurs	**Task 1 Choice** Mean (se) Median	**Task 2 Choice** Mean (se) Median	**Task 3 Choice** Mean (se) Median	**Task 4 Choice** Mean (se) Median
Entrepreneurs	4.327 (0.476)	4.020 (0.543)	1.583 (0.279)	8.106 (1.129)
	4.000	4.000	1.000	6.000
Observations	49	49	48	47
Non-entrepreneurs	3.000 (0.563)	4.433 (0.830)	1.433 (0.317)	8.138 (1.541)
	3.000	2.500	0.500	5.000
Observations	30	30	30	29
All	3.823 (0.370)	4.177 (0.459)	1.526 (0.209)	8.118 (0.907)
	3.000	3.000	1.000	5.500

Note. Risk decision tasks: Task 1, Task 2, and Task 3; time decision task: Task 4.

Figure 2.1

One-parameter Prelec (1998)'s Probability Weighting Functions $W(p)=\frac{1}{\exp[\ln(1/p)]^{\alpha}}$

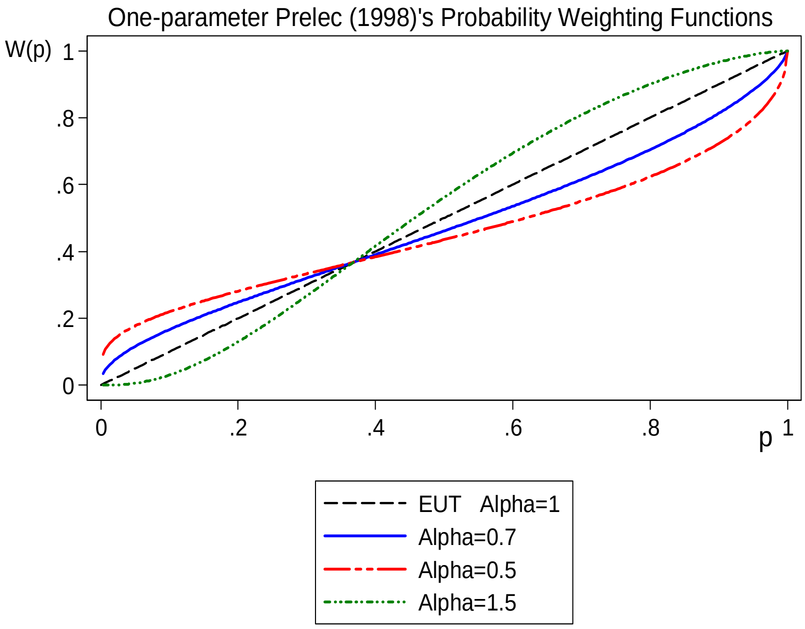


Figure 2.2

Distributions of Subject Time Task Responses

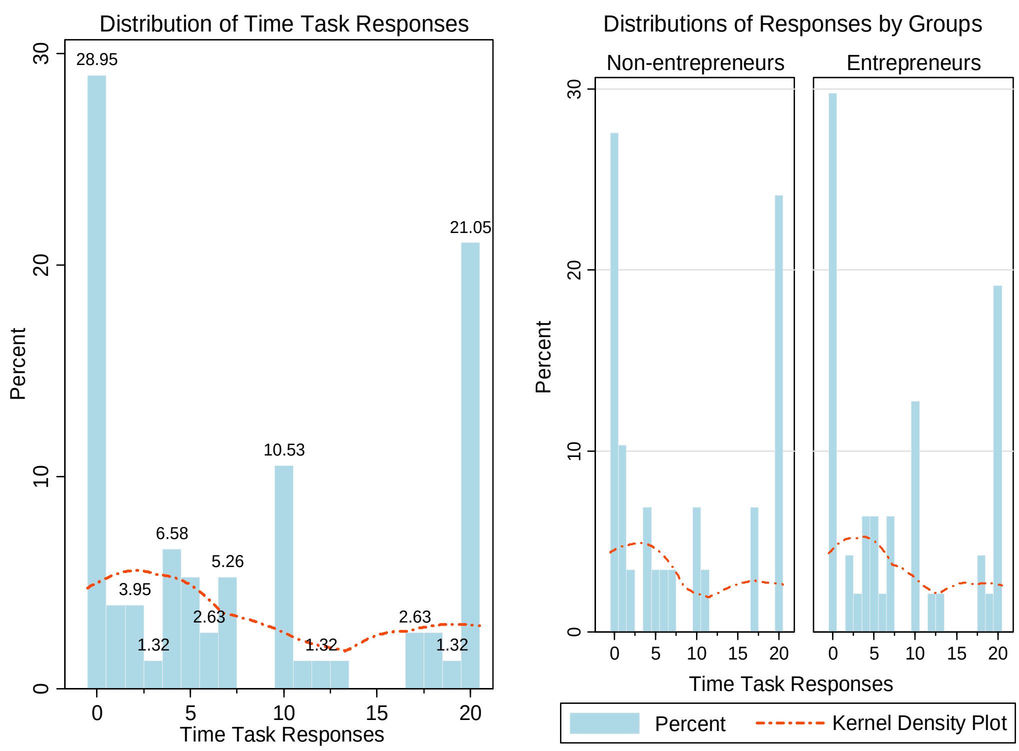
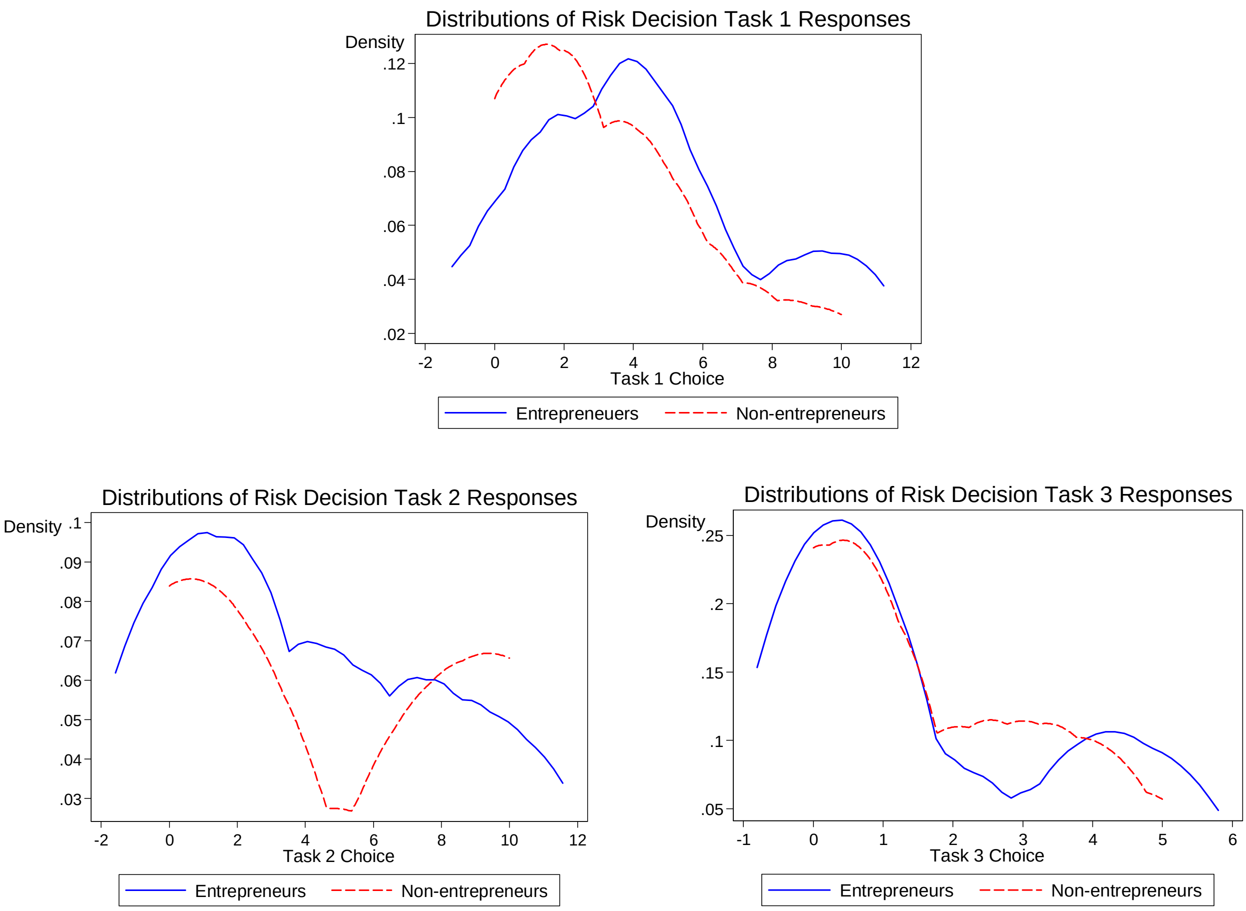


Figure 2.3

Distributions of Risk Tasks Responses for Entrepreneurs and Non-entrepreneurs



Note. Not significant differences between entrepreneurs and non-entrepreneurs in distributions of Task 1, Task 2, and Task 3 responses (Task 1 responses: Kolmogorov-Smirnov test statistic D=0.196, corrected p-value=0.381; Task 2 responses: Kolmogorov-Smirnov test statistic D=0.176, corrected p-value=0.523; Task 3 responses: Kolmogorov-Smirnov test statistic D=0.083, corrected p-value=0.999).

Appendix

Table A.2.1: Risk Decision Task Series 1

	Plan A	Plan B
1	\$40 if Balls No. 1-3 \$10 if Balls No. 4-10	\$75 if Ball No. 1 \$5 if Balls No. 2-10
2	\$40 if Balls No. 1-3 \$10 if Balls No. 4-10	\$93 if Ball No. 1 \$5 if Balls No. 2-10
3	\$40 if Balls No. 1-3 \$10 if Balls No. 4-10	\$125 if Ball No. 1 \$5 if Balls No. 2-10
4	\$40 if Balls No. 1-3 \$10 if Balls No. 4-10	\$145 if Ball No. 1 \$5 if Balls No. 2-10
5	\$40 if Balls No. 1-3 \$10 if Balls No. 4-10	\$170 if Ball No. 1 \$5 if Balls No. 2-10
6	\$40 if Balls No. 1-3 \$10 if Balls No. 4-10	\$210 if Ball No. 1 \$5 if Balls No. 2-10
7	\$40 if Balls No. 1-3 \$10 if Balls No. 4-10	\$280 if Ball No. 1 \$5 if Balls No. 2-10
8	\$40 if Balls No. 1-3 \$10 if Balls No. 4-10	\$400 if Ball No. 1 \$5 if Balls No. 2-10
9	\$40 if Balls No. 1-3 \$10 if Balls No. 4-10	\$595 if Ball No. 1 \$5 if Balls No. 2-10
10	\$40 if Balls No. 1-3 \$10 if Balls No. 4-10	\$945 if Ball No. 1 \$5 if Balls No. 2-10

Table A.2.2: Risk Decision Task Series 2

	Plan A	Plan B
11	\$40 if Balls No. 1-9 \$30 if Balls No. 10	\$54 if Ball No. 1-7 \$5 if Balls No. 8-10
12	\$40 if Balls No. 1-9 \$30 if Balls No. 10	\$56 if Ball No. 1-7 \$5 if Balls No. 8-10
13	\$40 if Balls No. 1-9 \$30 if Balls No. 10	\$58 if Ball No. 1-7 \$5 if Balls No. 8-10
14	\$40 if Balls No. 1-9 \$30 if Balls No. 10	\$60 if Ball No. 1-7 \$5 if Balls No. 8-10
15	\$40 if Balls No. 1-9 \$30 if Balls No. 10	\$62 if Ball No. 1-7 \$5 if Balls No. 8-10
16	\$40 if Balls No. 1-9 \$30 if Balls No. 10	\$65 if Ball No. 1-7 \$5 if Balls No. 8-10
17	\$40 if Balls No. 1-9 \$30 if Balls No. 10	\$68 if Ball No. 1-7 \$5 if Balls No. 8-10
18	\$40 if Balls No. 1-9 \$30 if Balls No. 10	\$72 if Ball No. 1-7 \$5 if Balls No. 8-10
19	\$40 if Balls No. 1-9 \$30 if Balls No. 10	\$83 if Ball No. 1-7 \$5 if Balls No. 8-10
20	\$40 if Balls No. 1-9 \$30 if Balls No. 10	\$100 if Ball No. 1-7 \$5 if Balls No. 8-10

Table A.2.3: Risk Decision Task Series 3

	Plan A	Plan B
21	Receive \$4 if Balls No. 1-5 Lose \$4 if Balls No. 6-10	Receive \$30 if Balls No. 1-5 Lose \$21 if Balls No. 6-10
22	Receive \$1 if Balls No. 1-5 Lose \$4 if Balls No. 6-10	Receive \$30 if Balls No. 1-5 Lose \$21 if Balls No. 6-10
23	Receive \$1 if Balls No. 1-5 Lose \$4 if Balls No. 6-10	Receive \$30 if Balls No. 1-5 Lose \$16 if Balls No. 6-10
24	Receive \$1 if Balls No. 1-5 Lose \$8 if Balls No. 6-10	Receive \$30 if Balls No. 1-5 Lose \$16 if Balls No. 6-10
25	Receive \$1 if Balls No. 1-5 Lose \$8 if Balls No. 6-10	Receive \$30 if Balls No. 1-5 Lose \$14 if Balls No. 6-10

Table A.2.4: Switching points in Task 1, 2, and 3, and approximations of σ (curvature parameter of the power utility function), α (probability sensitivity parameter in the weighting function) and λ (sensitivity parameter for loss aversion)

Approximation of σ:

σ	Switching point in Task 1 (Question 1-10)										
Task 2 (SP)	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Never**
1	1.40	1.25	1.10	1.00	0.95	0.90	0.85	0.80	0.75	0.65	0.50
2	1.30	1.15	1.00	0.95	0.90	0.85	0.80	0.75	0.70	0.60	0.50
3	1.20	1.10	0.95	0.90	0.85	0.80	0.75	0.70	0.65	0.55	0.45
4	1.15	1.00	0.90	0.85	0.80	0.75	0.70	0.65	0.60	0.50	0.40
5	1.05	0.95	0.85	0.80	0.75	0.70	0.65	0.60	0.55	0.50	0.35
6	1.00	0.90	0.80	0.75	0.70	0.65	0.60	0.55	0.50	0.45	0.35
7	0.95	0.85	0.75	0.70	0.65	0.60	0.55	0.50	0.45	0.40	0.30
8	0.90	0.80	0.70	0.65	0.60	0.55	0.50	0.45	0.40	0.35	0.25
9	0.80	0.70	0.60	0.55	0.50	0.45	0.40	0.35	0.30	0.25	0.20
10	0.65	0.55	0.50	0.45	0.40	0.35	0.30	0.25	0.20	0.20	0.10
Never	0.45	0.40	0.30	0.30	0.25	0.20	0.15	0.10	0.10	0.05	0.05

Approximation of α:

α	Switching point in Task 1 (Question 1-10)										
Task 2(SP)	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Never**
1	0.75	0.85	0.95	1.00	1.05	1.10	1.15	1.20	1.25	1.30	1.45
2	0.70	0.80	0.90	0.95	1.00	1.05	1.10	1.15	1.20	1.25	1.40
3	0.60	0.75	0.85	0.90	0.95	1.00	1.05	1.10	1.15	1.20	1.30
4	0.60	0.70	0.80	0.85	0.90	0.95	1.00	1.05	1.10	1.15	1.25
5	0.55	0.65	0.75	0.80	0.85	0.90	0.95	1.00	1.05	1.10	1.20
6	0.50	0.60	0.70	0.75	0.80	0.85	0.90	0.95	1.00	1.05	1.15
7	0.45	0.55	0.65	0.70	0.75	0.80	0.85	0.90	0.95	1.00	1.10
8	0.40	0.50	0.60	0.65	0.70	0.75	0.80	0.85	0.90	0.95	1.05
9	0.30	0.40	0.50	0.55	0.60	0.65	0.70	0.75	0.80	0.85	0.95
10	0.20	0.30	0.40	0.45	0.50	0.55	0.60	0.65	0.70	0.75	0.85
Never	0.05	0.15	0.25	0.30	0.35	0.40	0.45	0.45	0.55	0.55	0.60

Approximation of λ:

Switching Question	$\sigma = 0.2$	$\sigma = 0.6$	$\sigma = 1$
1	$0.14<\lambda<1.26$	$0.20<\lambda<1.38$	$0.29<\lambda<1.53$
2	$1.26<\lambda<1.88$	$1.38<\lambda<1.71$	$1.53<\lambda<1.71$
3	$1.88<\lambda<2.31$	$1.71<\lambda<2.25$	$1.71<\lambda<2.42$
4	$2.31<\lambda<4.32$	$2.25<\lambda<3.73$	$2.42<\lambda<3.63$
5	$4.32<\lambda<5.43$	$3.73<\lambda<4.82$	$3.63<\lambda<4.83$

Table A.2.5: Time Decision Task (Task 4)

	Plan A "Pays in **30 days**"	Plan B "Pays in **90 days**"	AR	AER
1	$ 100.00	$ 100.33	1.99%	2.01%
2	$ 100.00	$ 100.84	4.99%	5.12%
3	$ 100.00	$ 101.34	7.99%	8.32%
4	$ 100.00	$ 102.02	11.99%	12.74%
5	$ 100.00	$ 102.70	15.99%	17.34%
6	$ 100.00	$ 103.39	19.99%	22.12%
7	$ 100.00	$ 104.25	24.99%	28.38%
8	$ 100.00	$ 105.12	29.99%	34.96%
9	$ 100.00	$ 106.00	34.99%	41.87%
10	$ 100.00	$ 106.89	39.99%	49.13%
11	$ 100.00	$ 107.96	45.99%	58.35%
12	$ 100.00	$ 109.04	51.99%	68.12%
13	$ 100.00	$ 110.14	57.99%	78.50%
14	$ 100.00	$ 111.24	63.99%	89.52%
15	$ 100.00	$ 112.55	70.99%	103.24%
16	$ 100.00	$ 113.87	77.99%	117.94%
17	$ 100.00	$ 115.20	84.99%	133.71%
18	$ 100.00	$ 116.74	92.99%	153.13%
19	$ 100.00	$ 118.30	100.99%	174.15%
20	$ 100.00	$ 120.09	109.99%	199.89%

Table A.2.6: Description of Variables (80 subjects)

Category	Variable Name	Description / range of values	Mean (Std)	Median	Mode	95% C. I.
Personality Traits Questionnaire Items	IntrinsicMot	Intrinsic Motivation and it refers to performing an activity for itself, to experience pleasure and satisfaction inherent in the activity. Values range from 1 to 7.	5.101 (1.390)	5.250	6.000	(4.779, 5.423)
	IdentifiedReg	Identified Regulation and it occurs when an extrinsically motivated behavior is valued and perceived as being chosen by one-self. Values range from 1 to 7.	5.291 (1.422)	5.750	5.750 6.250 7.000	(4.961, 5.620)
	ExternalReg	External Regulation and it occurs when behavior is regulated by rewards or in order to avoid negative consequences. Values range from 1 to 7.	2.528 (1.548)	2.250	1.000	(2.169, 2.887)
	Amotivation	Amotivation and. it occurs when individuals experience a lack of Contingency between their behaviors and outcomes (they are neither intrinsically nor extrinsically motivated). Values range from 1 to 7.	1.882 (1.144)	1.500	1.000	(1.617, 2.147)
	BAS-drive	Behavioral activation sensitivity to driving motives. Values range from 8 to 16.	13.000 (2.047)	13.000	14.000	(12.529, 13.471)
	BAS-funskg	Behavioral activation sensitivity to fun-seeking motives. Values range from 7 to 16.	12.387 (2.211)	12.000	11.000 12.000	(11.878, 12.895)
	BAS-reward	Behavioral activation sensitivity towards rewards. Values range from 14 to 20.	18.160 (1.594)	18.000	19.000	(17.793,18.527)
	BIS	Behavioral inhibition sensitivity to unpleasantness. Values range from 8 to 27.	18.907 (4.363)	19.000	24.000	(17.903, 19.910)
	LOT-R	Scores on the Life Orientation Test-Revised (LOT-R), which measures individual differences in generalized optimism versus pessimism, and a high score implies a greater level of optimism. Values range from 7 to 24.	18.554 (4.181)	19.000	24.000	(17.585, 19.523)
	Satisfaction	Scores on the Life and Job Satisfaction Questionnaire, which contains two self-reported questions asking how satisfied individuals are with their current life and job. Values range from 1.5 to 10.	6.553 (2.066)	7.000	9.000	(6.078, 7.023)
	Numeracy	Scores on the Numeracy test, which assesses individuals' numerical ability. Values range from 2 to 11.	8.339 (2.100)	9.000	10.000	(7.861, 8.814)
	MensaQuiz	Scores on the Mensa quiz, which can reflects individuals' levels of intelligence. Values range from 0 to 5	2.566 (1.379)	3.000	2.000 3.000	(2.251, 2.881)
	Self-Est_N	Answers to the question "Please estimate how well you believe you did in this question (Numeracy Test) compared to other entrepreneurs". Answers are, 1 "Bottom 1-10%", 2 "Bottom 10-20%", 3 "Bottom 20-30%=3", 4 " Bottom 30-40%", 5 "In the middle", 6 "Top 30-40%", 7 "Top 20-30%", 8 "Top 10-20%", and 9 "Top 1-10%". Values range from 1 to 9.	5.740 (2.452)	5.000	5.000	(5.184, 6.297)
	Self-Est_M	Answers to the question "Please estimate how well you believe you did in this quiz (Mensa Quiz) compared to other entrepreneurs taking the quiz". Answers are, 1 "Bottom 1-10%", 2 "Bottom 10-20%", 3 "Bottom 20-30%=3", 4 " Bottom 30-40%", 5 "In the middle", 6 "Top 30-40%", 7 "Top 20-30%", 8 "Top 10-20%", and 9 "Top 1-10%". Values range from 1 to 9.	5.961 (2.375)	6.000	5.000	(5.418, 6.503)

Table A.2.6 (continued)

Five Factors	Factor1	Motivation, defined by Intrinsic Motivation, Identified Regulation, & External Regulation. Values range from -2.349 to 1.832.	-1.96E-9 (1.000)	0.135	——	(-0.232, 0.232)
	Factor2	Optimism & Satisfaction, defined by LOT-R & Satisfaction. Values range from -3.892 to 1.747	1.97E-09 (1.000)	0.090	——	(-0.232, 0.232)
	Factor3	Proxy for IQ, defined by Numeracy & Mensa Quiz. Values range from -2.731 to 1.985.	-8.94E-09 (1.000)	0.111	——	(-0.232, 0.232)
	Factor4	Goal & Fun, defined by BAS-drive, BAS-funskg & Amotivation. Values range from -2.338 to 2.632.	-5.91E-10 (1.000)	0.030	——	(-0.232, 0.232)
	Factor5	Defined by BIS & BAS-rewards. Values range from -2.489 to 1.749.	1.86E-09 (1.000)	0.090	——	(-0.232, 0.232)
Demographic Dummies	Sex	Gender of the subjects. Dummy: 1 Female, 0 Male	0.375 (0.487)	0.000	0.000	(0.267, 0.483)
	AgeDummy	Age group of the subjects. Dummy: 1 Older than average, 0 Younger than average.	0.463 (0.502)	0.000	0.000	(0.351, 0.574)
	Overweight	Weight of the subjects. Dummy: 1 BMI ≥25, 0 BMI <25.	0.658 (0.477)	1.000	1.000	(0.551, 0.765)
	HaveChildren	Dummy: 1 Yes, 0 No.	0.650 (0.480)	1.000	1.000	(0.543, 0.757)
	Married	Marital status of the subjects. Dummy: 1 Married, 0 Other.	0.550 (0.501)	1.000	1.000	(0.439, 0.661)
	White	Race of the subjects. Dummy: 1 White, 0 Other.	0.513 (0.503)	1.000	1.000	(0.401, 0.624)
	University	Education of the subjects. Dummy: 1 Have obtained BA/BS or higher, 0 Other.	0.813 (0.393)	1.000	1.000	(0.725, 0.900)
	Parent1	Birth country of the subjects' first parents. Dummy: 1 U.S, 0 Other.	0.575 (0.497)	1.000	1.000	(0.464, 0.686)
	Parent2	Birth country of the subjects' second parents. Dummy: 1 U.S, 0 Other	0.595 (0.494)	1.000	1.000	(0.484, 0.706)
	Country	Birth country of the subjects. Dummy: 1 U.S, 0 Other.	0.663 (0.476)	1.000	1.000	(0.557, 0.768)
	Smoke	Answers to the question "Have you ever smoked?" Answers are, 1 "Yes", 0 "No".	0.450 (0.501)	0.000	0.000	(0.339, 0.561)
	Entrepreneur	Answers to the question "Are you an entrepreneur?" Answers are, 1 "Yes", 0 "No".	0.625 (0.487)	1.000	1.000	(0.517, 0.733)
	Business	Answers to the question "Do you currently own a business?" Answers are, 1 "Yes", 0 "No".	0.325 (0.471)	0.000	0.000	(0.220, 0.430)
	Starter	Answers to the question "Did you start your business?" Answers are, 1 "Yes", 0 "No".	0.313 (0.466)	0.000	0.000	(0.209, 0.416)
Demographic Variables (non-dummies)	Age	Age of the subject. Values range from 20 to 61.	38.600 (9.034)	37.500	31.000 35, 36	(36.590, 40.610)
	BMI	The body mass index=(weight in pounds * 703) / (height in inches²) Values range from 20.015 to 38.967.	27.056 (4.338)	26.870	20.8, 23.0 23.7, 25.1 27.1, 27.9 29.2, 31.7	(26.085, 28.028)
	Race	1 "American Indian/Alaska Native", 2 "Asian", 3 "Black/African American", 4 "Hispanic/Latino", 5 "Native Hawaiian/Other Pacific Islander", 6 "White (non-Hispanic)". Min: 2; Max: 6.	4.575 (1.589)	6.000	6.000	(4.221, 4.929)
	Years	Answers to the question "How long have you been living in the US (in years)?". Min: 0; Max: 60.	30.253 (13.075)	33.000	31.000	(27.324, 33.182)
	Cigarettes	Answers to the question "How many cigarettes per day do you smoke on average?" Answers are, 0 "0", 2 "1~5", 3 "5~10", 4 "10~15", 5 "15~20", 6 "20~25", 7 "23~30", 8 "30~35". Min: 0; Max: 2.	0.075 (0.348)	0.000	0.000	(-0.002, 0.152)
	Alcohol	Answers to the question "How many alcoholic beverages do you Consume per week on average?" Answers are, 1 "0~1", 2 "2~7", 3 "8~13", 4 "14~21", 5 ">21". Min: 1; Max: 4.	1.513 (0.656)	1.000	1.000	(1.367, 1.658)
Approximation of Risk Parameters	Sigma	The curvature of the CRRA power utility function. It measures how risk seeking one is for potential gains, i.e. risk neutral if its value is 1. Min: 0.050; Max: 1.400.	0.742 (0.391)	0.800	1.400	(0.655, 0.830)
	Alpha (Prelec 1998)	The sensitivity parameter of the Prelec (1998)'s probability weighting function. If its value is 1, there is no probability distortion. Min: 0.050; Max: 1.450.	0.757 (0.325)	0.750	0.750	(0.684, 0.830)
	Lambda_avg	The degree of loss-aversion. It measures how one views potential losses. Lambda_avg is the average value of the elicited individual loss-aversion parameter intervals. Min: 1.226; Max: 5.888.	2.418 (1.410)	1.633	1.718	(2.100, 2.736)

Table A.2.7: Regression Models of the Effects on Risk Decision Tasks Responses

Variables	OLS (1) Task1Choice	OLS (2) Task1Choice	OLS (3) Task2Choice	OLS (4) Task2Choice	OLS (5) Task3Choice	OLS (6) Task3Choice
Age	-0.0114	-0.0842	0.0281	-0.00639	-0.0144	0.00412
	(0.0762)	(0.0868)	(0.0830)	(0.106)	(0.0392)	(0.0399)
Sex	0.889	1.476	1.156	1.391	-0.674	-0.468
	(0.902)	(0.999)	(1.154)	(1.342)	(0.453)	(0.529)
BMI	0.0335	0.0154	0.0621	0.0465	-0.0771	-0.0740
	(0.107)	(0.126)	(0.119)	(0.140)	(0.0575)	(0.0624)
HaveChildren	-0.0630	0.00749	0.0311	0.325	-0.0981	-0.00642
	(0.334)	(0.331)	(0.405)	(0.429)	(0.201)	(0.206)
Married	0.585	0.969	**-2.050***	**-2.156***	0.0516	0.110
	(0.960)	(1.134)	(1.091)	(1.243)	(0.472)	(0.455)
White	0.864	0.690	-0.997	-1.053	-0.818	-0.740
	(0.933)	(1.061)	(1.247)	(1.396)	(0.539)	(0.586)
University	0.265	0.302	1.461	1.074	0.814	1.101
	(1.332)	(1.564)	(1.528)	(1.779)	(0.637)	(0.720)
Country	-0.920	-1.645	0.567	-0.129	0.244	0.819
	(1.537)	(1.649)	(1.720)	(2.101)	(0.904)	(0.844)
Years	0.0160	0.0663	0.0344	0.0580	0.0268	-0.00226
	(0.0636)	(0.0758)	(0.0720)	(0.0951)	(0.0361)	(0.0410)
Cigarettes	-0.389	-0.515	-0.182	-0.208	-0.0763	-0.0795
	(1.074)	(1.063)	(1.754)	(2.093)	(0.396)	(0.461)
Alcohol	-0.230	-0.825	0.483	0.482	-0.220	-0.415
	(0.686)	(0.610)	(0.930)	(1.002)	(0.527)	(0.626)
Entrepreneur	**1.928****	**1.690***	-0.690	-0.735	0.257	0.271
	(0.924)	(0.979)	(1.187)	(1.254)	(0.589)	(0.604)
Factor1		-0.181		-0.695		-0.270
		(0.432)		(0.601)		(0.285)
Factor2		-0.317		-0.478		-0.298
		(0.401)		(0.459)		(0.230)
Factor3		0.0473		0.203		-0.336
		(0.408)		(0.578)		(0.283)
Factor4		**1.014****		0.0741		0.193
		(0.465)		(0.609)		(0.259)
Factor5		0.372		-0.0849		-0.00108
		(0.389)		(0.608)		(0.264)
Constant	1.422	4.062	-0.469	0.882	3.491*	2.974
	(3.958)	(4.399)	(4.821)	(5.404)	(2.031)	(2.075)
Observations	77	72	77	72	76	72
R-squared	0.098	0.229	0.119	0.146	0.122	0.237

Note. Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table A.2.8: Regression Models of the Effects on Approximated Risk Parameters

VARIABLES	OLS (1) Sigma	OLS (2) Sigma	OLS (3) Alpha	OLS (4) Alpha	OLS (5) Lambda_avg	OLS (6) Lambda_avg
Age	0.000705	0.00803	-0.00357	-0.00599	-0.00836	0.00736
	(0.00923)	(0.0105)	(0.00567)	(0.00743)	(0.0304)	(0.0349)
Sex	-0.147	-0.198	-0.0529	-0.0282	-0.455	-0.333
	(0.116)	(0.127)	(0.0830)	(0.0961)	(0.351)	(0.414)
BMI	-0.00753	-0.00628	-0.00588	-0.00364	-0.0405	-0.0458
	(0.0123)	(0.0138)	(0.00932)	(0.0115)	(0.0451)	(0.0498)
HaveChildren	-0.000335	-0.0311	-0.00107	-0.0203	-0.0252	0.0601
	(0.0432)	(0.0434)	(0.0263)	(0.0296)	(0.157)	(0.161)
Married	0.0638	0.0627	**0.153***	**0.182***	0.0397	0.117
	(0.112)	(0.123)	(0.0869)	(0.106)	(0.356)	(0.323)
White	0.0307	0.0371	0.101	0.115	-0.600	-0.523
	(0.114)	(0.127)	(0.106)	(0.119)	(0.382)	(0.426)
University	-0.0952	-0.0493	-0.0852	-0.0613	0.590	0.875
	(0.169)	(0.195)	(0.104)	(0.121)	(0.483)	(0.561)
Country	0.0486	0.170	-0.0761	-0.0917	0.257	0.726
	(0.170)	(0.180)	(0.150)	(0.186)	(0.698)	(0.699)
Years	-0.00540	-0.0106	-0.000633	0.00117	0.0123	-0.0114
	(0.00766)	(0.00936)	(0.00530)	(0.00699)	(0.0282)	(0.0343)
Cigarettes	-0.0160	-0.00544	-0.0184	-0.0209	-0.237	-0.233
	(0.105)	(0.147)	(0.175)	(0.185)	(0.234)	(0.334)
Alcohol	-0.0243	-0.00397	-0.0533	-0.0848	-0.0920	-0.283
	(0.0866)	(0.0799)	(0.0656)	(0.0801)	(0.398)	(0.437)
Entrepreneur	-0.0344	-0.0196	**0.180***	0.166	0.195	0.218
	(0.114)	(0.117)	(0.0972)	(0.102)	(0.437)	(0.452)
Factor1		0.0858		0.0332		-0.149
		(0.0594)		(0.0433)		(0.225)
Factor2		0.0586		0.0175		-0.239
		(0.0508)		(0.0296)		(0.186)
Factor3		-0.0242		-0.0191		-0.283
		(0.0545)		(0.0471)		(0.211)
Factor4		-0.0598		0.0700		0.0640
		(0.0544)		(0.0486)		(0.207)
Factor5		-0.00267		0.0126		0.0499
		(0.0525)		(0.0465)		(0.204)
Constant	1.202**	0.961*	1.059**	1.074**	3.332**	3.061*
	(0.466)	(0.494)	(0.404)	(0.458)	(1.610)	(1.690)
Observations	77	72	77	72	76	72
R-squared	0.067	0.164	0.153	0.195	0.100	0.214

Note. Lambda_avg is the average value of the elicited individual λ intervals.

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table A.2.9: Regression Models of the Effects on Time Preferences

Variables	**OLS (1)**	**OLS (2)**	**Ordered Probit (1)**	**Ordered Probit (2)**
Dependent variable: Time task responses ~ [0, 20]				
Age	0.0526	0.201	0.0101	0.0292
	(0.117)	(0.180)	(0.0146)	(0.0258)
Sex	**3.730***	1.861	**0.526***	0.336
	(2.211)	(2.351)	(0.295)	(0.329)
BMI	-0.0651	-0.256	-0.0131	-0.0426
	(0.212)	(0.255)	(0.0262)	(0.0354)
HaveChildren	-2.186	-3.471	-0.391	**-0.596***
	(2.502)	(2.604)	(0.327)	(0.344)
Married	0.576	1.048	0.142	0.193
	(2.379)	(2.217)	(0.317)	(0.328)
White	-1.310	-1.767	-0.109	-0.166
	(2.656)	(3.044)	(0.329)	(0.396)
University	0.439	1.218	-0.0202	0.128
	(2.240)	(2.926)	(0.313)	(0.433)
Country	0.345	3.690	0.174	0.553
	(3.423)	(4.331)	(0.438)	(0.609)
Years	0.0511	-0.111	0.00706	-0.0110
	(0.139)	(0.175)	(0.0196)	(0.0262)
Cigarettes	-2.644	-3.069	-0.330	-0.482
	(2.332)	(2.108)	(0.331)	(0.334)
Entrepreneur	0.138	1.557	0.0474	0.247
	(2.495)	(2.604)	(0.324)	(0.350)
Factor1		-0.363		-0.0379
		(1.172)		(0.177)
Factor2		**1.677***		**0.215***
		(0.945)		(0.131)
Factor3		-1.159		-0.175
		(1.205)		(0.190)
Factor4		**-2.213***		**-0.292****
		(1.107)		(0.144)
Factor5		**1.937****		**0.331****
		(0.955)		(0.138)
Constant	6.278	8.409		
	(7.524)	(9.386)		
Observations	74	72	74	72
R-squared	0.074	0.243		

Note. Ordered probit models generate consistent and efficient estimates.

In the order probit (1) model, Prob > $\chi^2 = 0.934$, whereas in the ordered probit (2) model, Prob > $\chi^2 = 0.084$. This means ordered probit (2) model is better, because the null that all the coefficients in the model are indifferent from zero is rejected at 8% significance level.

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Chapter 3

Understanding the Entrepreneurial Personality

Bing Jiang

Keywords: Entrepreneurs; Personality; Experiment

JEL Classification: D8, C91, C83

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Abstract

To better understand entrepreneurial personality, a simple online experiment was developed to elicit participants' risk attitudes and time preferences, and to measure a set of entrepreneurship-prone personality attributes. I found sampled entrepreneurs and non-entrepreneurs mainly differed in the trait of motivation, with entrepreneurs being significantly more motivated than non-entrepreneurs. In addition, the trait of motivation was positively associated with one's probability of becoming an entrepreneur, whereas the trait of reward-driven was negatively related to such probability. There existed significant correlations between personality traits and entrepreneurial process: the more intelligent and reward-driven an individual was, the longer his/her business could be in operation; a more self-confident individual would be more likely to start and operate his/her own business. These interesting findings on personality provide useful implications for individual career training, counseling, and occupational decision-making.

Keywords: Entrepreneurs; Personality; Experiment

Understanding the Entrepreneurial Personality

3.1 Introduction

The entrepreneur has long been perceived as a special person whose qualities and characteristics need to be investigated (Gartner 1988; Schumpeter 1934). Early empirical studies led by Brockhaus (1980), Brockhaus and Nord (1979), Sexton and Kent (1981), and many others carefully evaluated certain psychological traits but they could not differentiate entrepreneurs from the general population. After reviewing psychological entrepreneurship literature, Brockhuas and Horwitz (1986) had to conclude that there was no generic characteristic of the entrepreneur, or at least they did not have the psychological instruments to discover it at their time (Gartner 1988). It could be that "entrepreneurs come in every shape, size, color, and from all backgrounds" (Hatten 1997).

Doubts from early scholars on whether the entrepreneur could be characterized have not stopped researchers from attempting to do so. Many qualitative studies and narrative reviews suggest that entrepreneurs might have different personalities (Littunen 2000; McClelland 1961, 1985), and typical entrepreneurial characteristics may include: higher tolerance of risk, ambiguity and uncertainty; stronger motivation to excel (Timmons 1994); greater need for achievement/goal-orientation and independence and power (Komives 1972; McClelland 1965, 1961; McClelland and Winter 1969), stronger internal locus of control, and higher life and job satisfaction (Brockhaus 1980; Brockhaus and Nord 1979; Hull, Bosley, and Udell 1980; Liles 1974). A large number of studies conducted in the 1980s and 1990s also researched on the socio-economic backgrounds of successful entrepreneurs, and they found being a college graduate, being an immigrant or a child of immigrants, being the oldest child in the family, and being an offspring of self-employed parents affected an individual's chance of becoming an entrepreneur (Bianchi 1993; Byers et al. 2000).

Although there has been no unifying consensus around a set of general characteristics that might determine who is and who is not likely to become an entrepreneur (Brockhaus and Horwitz 1986; Gartner 1988), the personality approach to studying entrepreneurship gained momentum in the 1990s (Zhao et al. 2010; Brandstätter 2011) largely due to the wide acceptance of the five-factor personality model (Openness to Experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism, or the Big Five; Costa and McCrae 1992; Digman 1990). More recently, Zhao and Seibert (2006) examined the relationship between personality and entrepreneurial status using a meta-analysis. They found entrepreneurs scored higher than managers on Conscientiousness and Openness to Experience, and lower on Neuroticism and Agreeableness. In another related study, Zhao et al. (2010) showed four of the Big Five personality dimensions (except for Agreeableness) were associated with entrepreneurial intentions ("the expressed behavioral intention to become an entrepreneur"), and entrepreneurial performance, constructed by indicators of firm survival, growth, and profitability.

However, not all personality aspects can be captured by the Big Five model (Brandstätter 2011; Paunounen and Jackson 2000; Ashton et al. 2004). Some of the entrepreneurship-prone personality attributes outside of the Big Five need to be examined, such as risk-taking propensity (Zhao et al. 2010; Rauch and Frese 2007b;

Stewart and Roth 2004, 2001; Miner and Raju 2004), ability to tolerate delay/stress — perhaps reflecting a level of prudence or patience (Frese 2009; Rauch and Frese 2007b), overconfidence (Dittrich et al. 2005; Cooper et al. 1988), cognitive ability (Ray and Singh 1980), and achievement motivation (Stewart and Roth 2007; Collins et al. 2004). Considering entrepreneurs are a heterogeneous population, it is likely that some of them willingly choose to pursue an entrepreneurial career, while others are forced into this career due to inability to find other employment (Zhao et al. 2010). To better understand the characteristics that truly nourish entrepreneurship, it is important to explore the subcategories of the achievement motive such as hope for success vs. fear of failure or approach vs. avoidance goals (Brandstätter 2011), and need for autonomy (Ryan and Deci 2000).

Unfortunately, there have been controversy and heated debate over the valid psychological instruments to measure certain attributes relevant to entrepreneurship (Brandstätter 2011). For instance, most of the existing psychological studies (e.g., Nicholson et al. 2005; Miner and Raju 2004; Stewart and Roth 2001) assessed risk propensity by exclusively relying on hypothetical questionnaires (e.g., Risk-Taking Scale of the Jackson Personality Inventory, Kogan-Wallach Choice Dilemma Questionnaire, Miner Sentence Completion Scale-Form T or Risk Avoidance Subscale). Due to a lack of consistency in the risk measures, these studies might draw erroneous inferences based on the questionnaires used, which seemed to measure similar constructs (e.g., risk perception) rather than risk propensity (Stewart and Roth 2004; Mandrik 2005). On the other hand, Heckman (2007) questioned the validity of using behavioral proxies (e.g., smoking) for time preference, as they were "error-laden" and inconsistent across behavioral domains (Dely et al. 2008). Given that reliable cross-situational consistency in relevant measurements was lacking and that results on personality constructs were limited by these instruments, the personality approach to entrepreneurship has been criticized by the dominant position in entrepreneurship research (Rauch and Frese 2007a; Mischel 1968).

Within related stream of research, several experimental economists have utilized valid incentive-compatible instruments attempting to study individual characteristics and the role of personality traits in decision processes. Cooper and Saral (2010) designed a team production experiment to study entrepreneurs' preferences towards joining teams vs. working alone. They provided significant evidence suggesting that entrepreneurs who were motivated by desires for control and/or autonomy preferred to work alone rather than join teams. Using field experiments, Elston et al. (2005, 2006) showed full-time entrepreneurs were less risk averse and part-time entrepreneurs were more risk averse than non-entrepreneurs; moreover, entrepreneurs did not exhibit excess entry due to overconfidence. In contrast, Dittrich et al. (2005) investigated how overconfidence affected decision-making in an investment experiment. They found overconfidence drove actual investment decisions to deviate from optimal ones, and it was more pronounced in the more complex task involving risk. Interestingly, although they observed participants who believed their life was largely controlled by external factors were less likely to be overconfident, they did not understand when and why certain personality traits triggered overconfidence. Finally, Capra et al. (2013) explored the possibility that personality type was linked to individual heterogeneity in probability distortions. We found that the motivated viewed gambling more attractive, whereas the impulsive were the most capable of discriminating non-extreme probabilities. Hence, we provided experimental evidence highlighting the importance of individual personalities in decision processes.

Although experiments collect data on individual characteristics and economic preferences, determinants of who are likely to become entrepreneurs have not been established experimentally. A set of interesting yet important questions remain to be unexplored in the discipline: why do certain individuals choose to start their own business and pursue an entrepreneurial career, but others don’t? Is there a so-called “entrepreneurial personality”?

To answer these questions, this paper intends to draw on findings from a simple online experiment. It contributes to the existing literature in the following ways. First, utilizing validated incentive-compatible mechanism in experimental approach, this study provides proper instruments to scientifically measure individual risk attitude and time preference, and thus, it enriches the toolkit of psychological research. Second, this study provides experimental evidence emphasizing the important role of personality in determining entrepreneurship and explaining economic preferences and outcomes. Whereas in entrepreneurship research, experimental approach to studying entrepreneurship is widely missing, and in economic research, personality approach to explaining economic preferences and choices is often neglected.

This study recruited 80 participants (50 males, 50 self-identified entrepreneurs) who were either students from executive business and entrepreneurship programs or actual entrepreneurs attending entrepreneurship training conferences and forums. They aged from 26 to 61, and the average age was 38.60 with a standard deviation of 9.03 years. The experiment was conducted online, and it consisted of the following parts.

First, subjects were asked to answer a pre-task questionnaire on basic demographics, and to provide information about their businesses. At the end of this part, participants were directed to the main contents of the survey, which included making choices in a set of paid decision tasks, and completing a series of tests and psychological questionnaires. The four paid tasks were designed to elicit individual-level risk attitudes and time preferences. Two quiz-based tests were used to assess individual cognitive abilities. Finally, four well-known psychological surveys provided validated measures of personality traits, such as motivation, confidence, and goal-orientation & fun-seeking trait (see Section 3.2.2).

I found sampled entrepreneurs and non-entrepreneurs differed in the trait of motivation, with entrepreneurs being more significantly motivated than non-entrepreneurs. I also found the trait of motivation was positively associated with one's chance of becoming an entrepreneur, while the trait of reward-driven was negatively related to such probability. There existed significant correlations between personality traits and entrepreneurial process: the more intelligent and reward-driven an individual was, the longer his/her business could be in operation; a more self-confident individual would be more likely to start and operate his/her own business, confirming existing findings on the effect of confidence on entrepreneurship (Dittrich et al. 2005; Cooper et al. 1988).

The remainder of the paper is organized as follows. In the next section, I describe the experimental design and procedures. In Section 3.3, I report the experimental data and empirical findings. Finally, in the last section, Section 3.4, I discuss the implications of this study.

3.2 Design and Procedures

3.2.1 General Design

A total of 80 subjects (50 males, 50 self-identified entrepreneurs) were recruited; 62 of them were executive business administration students at Emory Goizueta Business School, 15 of them were students enrolled in the entrepreneurship program at Santa Ana College, and the rest were actual entrepreneurs who attended entrepreneurship training conferences and forums. The participants aged from 26 to 61, and the average age was 38.60 with a standard deviation of 9.03 years.

The experiment was conducted online via SurveyMonkey. All responses were anonymous and were kept secure after submission. The survey took about 20-30 minutes to complete, and expected earnings ranged between $4 and $970, with a pre-participation average payment of $45[1]. The survey consisted of the following parts. First, subjects gave online consent to participate in this study. Recruited subjects answered a pre-task questionnaire and provided information on their demographics (e.g., age, gender, education, and their height and weight with which their body mass index was calculated), and business information (e.g., length of one' business in operation, and expected growth rate of the business in the next three years)[2]. To study whether confidence played a role in entrepreneurship, self-reported current entrepreneurs[3] were asked to rate the odds of

[1] These incentives were salient. During the recruiting process, and in post-survey focus groups, participants responded that compensation was attractive to them, which was the main reason why they were compelled to participate.

[2] The information requested was specific enough to ensure that the target participants, not surrogates answered the survey. In addition, answers to these questions provided a way to double-check the veracity of entrepreneurial self-declaration.

3 Participants were aware that we also have access to their individual business and profile information from the EMBA program at Emory Goizueta Business School and the entrepreneurship program at Santa Ana

their own business/business ideas succeeding (e.g., YourOdds), and the odds of any business like theirs succeeding. At the end of the pre-task questionnaire, all subjects were directed to the main contents of the survey, which included making choices for 4 decision tasks and completing a series of quizzes and psychological questionnaires. The four paid tasks were designed to elicit individual risk preferences (Task1, Task2 and Task3, or the risk decision tasks) and time preferences (Task4, or the time decision task)[4]. A Numeracy test (Peters et al. 2006) and Mensa Quizzes were given after the risk decision tasks as a way to measure participants′ cognitive capabilities including those for processing numbers and understanding probabilities, and to serve as fillers[5] for the decision tasks. After the time decision task, subjects answered four sets of psychological questionnaires, including the Situational Motivation Scale (SIMS), the Life Orientation Test-Revised (LOTR), the Behavioral Activation System and Behavioral Inhibition System Scales (BAS/BIS), and the Life and Job Satisfaction Questionnaire. These questionnaires provided validated measures of individual-level motivation, optimism/ pessimism, behavioral activation and inhibition, and satisfaction, respectively (see Section 3.2.2).

Payment

All subjects were paid $25 for completing the survey. In addition, they all had a 4 in 5 chance of receiving extra money, or losing up to $21 from decisions in one of the four equally weighted tasks. On December 5, 2009, a random number device was constructed to determine 200 sets of five numbers. These sets of numbers were ordered

College. So there was no incentive for them to lie and we were confident about the self-reported truthfulness in the survey.

[4] The results of risk and time preferences are reported in another manuscript.

from 1 to 200 to match the order of complete surveys submitted online. For example, if an individual was the 50th subject who submitted a completed survey, the set of numbers that determined his/her payoffs was the 50th set of five numbers drawn on December 5th of 2009. The former President of the World Chamber of Commerce, Solange Warner, underwrote this process. A written record of these numbers on a signed document is available upon request.

The final payoff for a specific subject was determined jointly by his/her decisions in the tasks and a matched set of five random numbers[6]. Once a complete survey via SurveyMonkey was received, an electronic W-9 form and a confirmation email were sent to the subject, informing his/her set of five random numbers, and the amount of payment in the study. For taxation purposes, all subjects were required to return their signed W-9 forms either by fax or email to the research administers at Department of Economics, Emory University. After receiving the signed W-9 forms, subjects' final payments were processed and checks with their earnings were sent out immediately.

3.2.2 Personality Questionnaires

To properly measure certain entrepreneurship-prone attributes outside of the Big Five[7], a set of well-established and validated psychological questionnaires/scales were

[5] Filler items were not used in scoring.

[6] The first random number (between 1 and 5) determined the Task Number for which that subject got paid. If the number randomly generated was 1, 2, 3 or 4, then Task 1, Task 2, Task 3 or Task 4 was counted respectively towards his/her payment. However, if this number was 5, then NONE of the tasks counted. The second, third and fourth random numbers determined exactly how much the subject was paid for one of the chosen decisions in Task 1, Task 2, or Task 3 (the payment mechanism for the risk decision tasks are outlined in another manuscript). Finally, the fifth random number (between 1 and 20) determined which one of the 20 options in time decision task was paid.

[7] Brandstätter (2011), Paunounen and Jackson (2000), and Ashton et al. (2004) argued that not all entrepreneurially inclined personality constructs could be captured by the Big Five model.

used, including the SIMS (Guay et al. 2000), the BAS/BIS (Caver and White 1994), the LOT-R (Scheier et al. 1994), and the Life & Job Satisfaction Questionnaire. The SIMS provides a situational measure of motivation in both field and laboratory settings. It assesses the constructs of intrinsic motivation, identified regulation, external regulation, and amotivation. Intrinsic motivation refers to performing an activity for itself, to experience pleasure and satisfaction inherent in the activity. External regulation occurs when behavior is regulated by rewards or in order to avoid negative consequences. In contrast, identified regulation occurs when an extrinsically motivated behavior is valued and perceived as being chosen by one-self. Last but not least, when amotivation occurs, individuals experience a lack of contingency between their behaviors and outcomes (i.e., they are neither intrinsically nor extrinsically motivated, or are irresponsive to incentives).

The BAS/BIS scales contained 24 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 Life Orientation Test-Revised (LOT-R) gives a brief measure of individual differences in generalized optimism versus pessimism. It contains 10 questions asking respondents to indicate at what extent they agree with each statement (i.e., strongly disagree, disagree, neutral, agree, or strongly agree). An overall optimism score is computed by summing up scores on 6 out of the 10 questions[8]. The optimism scores can range from 0 to 24, and a high score implies a greater level of optimism.

Finally, the Life and Job Satisfaction Questionnaire assesses individual levels of satisfaction. It contains two self-reported questions asking how satisfied individuals are with their current life and job. A higher score on this questionnaire indicates relatively higher level of life and job satisfaction.

3.3 Results

3.3.1 Description of the Data

Personality

What makes for an entrepreneur? Demographic statistics of the sample indicate that median entrepreneur was significantly older than the median non-entrepreneur (40-year-old vs. 34.5-year-old; Mann-Whitney test or MWT, Z= -3.000, p=0.003). In addition, 49% of entrepreneurs had parents who were born outside the U.S, as compared to 27% of non-entrepreneurs whose parents were not born in the U.S., and the difference was significant (MWT, Z=1.948, p=0.051). Aside from age, gender and parent's immigration background, is there a so-called "entrepreneurial personality"? What typical characteristics does an entrepreneur possess?

To answer these questions, I constructed the personality profiles for each participants based on their responses to the psychological questionnaires. I found that sampled entrepreneurs and non-entrepreneurs differed in the following personality attributes: identified regulation (MWT, Z= -2.756, p=0.006), amotivation (MWT,

[8] Four of the items are filler items and are not used in scoring.

Z=1.907, p=0.057), BAS-funseeking (MWT, Z= -1.742, p=0.081), and BIS (MWT, Z=1.964, p=0.050). It's likely that surveyed attributes are highly correlated. To avoid double-counting or overlapping in attributes measures, I performed factor analysis to reduce the dimensionality of twelve trait items from the psychological questionnaires and cognitive quizzes to five personality factors. As a result, extracted factors were orthogonal and they each provided measurement for one unique characteristic only. Table 3.1 shows the rotated factor loadings and the uniqueness scores for each attribute (see Table A.3.1 in the Appendix for detailed description of the factors). The five identified factors accounted for 71.35% of the variance. Then I obtained factor scores for each individual and tested whether entrepreneurs and non-entrepreneurs differed in the five personality factors. Indeed, I found that entrepreneurs and non-entrepreneurs were significantly different in Factor 1 (Motivation) (MWT, Z= -2.419, p=0.016; median test, $\chi^2(1) = 4.593$, p=0.032), with entrepreneurs being more motivated than non-entrepreneurs.

3.3.2 Statistical Analysis

3.3.2.1 Entrepreneurship and Personality

At the individual level, I observed a large variability in participants' personality characteristics (see Table A.3.1 in the Appendix). To determine how personality profiles differed with respect to one's chances of becoming an entrepreneur, I used clustering analysis[9] to identify participants based on their responses to the four psychological

[9] The criterion for classifying subjects into clustered personality groups 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.

questionnaires and two cognitive quizzes[10]. I used hierarchical clustering analysis (Complete Linkage method) to classify 74 subjects[11] into different clusters. Based on the dengrogram of individual traits dissimilarities in Figure 3.1, I identified three distinct personality groups. Personality Group 1 (henceforth PersGroup1) had a total of 22 subjects (11 males), most of who had obtained BS/BA degrees or higher and the entrepreneur/non-entrepreneur ratio was the lowest. PersGroup2 was comprised of 10 subjects (8 males) who, on average, were the youngest. Finally, PersGroup3 had 42 subjects (27 males) who were the oldest and the entrepreneur/non-entrepreneur ratio was the highest.

What kind of personality profiles do these clustered groups have? Do groups differ in personalities also differ in the proportions of entrepreneurs in each group? To solve these questions, I compared and contrasted proportions of entrepreneurs in three clustered groups and found that PersGroup3 had 30.52% more entrepreneurs (MWT, $Z= -2.358$, $p=0.018$) than PersGroup1. With regard to personalities, PersGroup3 were the most motivated (highest average score on Factor1; MWT, $Z= -4.382$, $p<0.001$) yet the least reward-driven (lowest average score on Factor5; MWT, $Z=2.785$, $p=0.005$) among all groups. In contrast, PersGroup1 were the least motivated yet the most reward-driven. This implies motivation and reward-driven traits might play critical parts in explaining entrepreneurship.

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[10] Although correlating personality factors to Pr (Entrepreneur) without clustering the data may seem reasonable, this method hides the fact that the effect of a specific trait (e.g. extraversion) on Pr (Entrepreneur) is conditional on the general personality profile of the individual. For example, more motivated in a high IQ person has a contradictory effect compared to more reward-driven in a low-IQ one.

[11] The whole sample size was eighty, but four subjects didn’t respond to the time decision task, and two out of the remaining seventy-six subjects did not complete all the personality questionnaires, so six observations were excluded.

To determine how personality characteristics such as motivation and reward-driven traits may play roles in entrepreneurship, I estimated different models including linear probability model, probit and logit models, assuming the probability of becoming an entrepreneur, or Pr (Entrepreneur) depends on the variables listed in Table A.3.2 of the Appendix. Table 3.2 shows the marginal effects on the dependent variable. Without considering personality factors, only age and education seemed to be significant: being one year older increased one's chance of becoming an entrepreneur by 2.96% in probit (1) model and by 3.05% in logit (1) model, whereas having obtain BS/BA degree or higher reduced one's probability of becoming an entrepreneur by 30.7% in probit (1) model and by 29.7% in logit (1) model. These findings are consistent with existing literature on the effects of age and education on entrepreneurship (e.g., Bianchi, 1993; Byers et al., 2000). If personality factors are incorporated into the analyses, then one-point increase in Factor 1 (Motivation) contributes to a 13.2% rise in Pr (Entrepreneur) in probit (2) model, and one-point increase in Factor 5 (Reward-driven) decreases Pr (Entrepreneur) by 13.9% in both probit (2) and logit (2) models. Plots of predicted Pr (Entrepreneur) and its 95% confidence intervals depending on age, education, Factor 1 (Motivation), and Factor 5 (Reward-driven) are shown in Figure 3.2.

3.3.2.2 Entrepreneurial Process and Personality

How may personality affect the ways in which one operates his/her own business? To provide an answer to the question, I correlated personality variables (e.g., the five personality factors, and YourOdds, the self-reported odds of participants' business/business ideas succeeding — as a measure of self-confidence[12]) with business characteristics including Starter (whether an individual started his/her own business), Business (whether an individual currently owned a business), BusLength (length of an individual's business in operation), and ExpGrowth (an individual's expected growth rate of his/her business in the next three years). Table 3.3 presents pair-wise correlations between personality variables and business characteristics. If someone was more motivated, he/she expected his/her business to grow more in the next three years. Being more optimistic and satisfied towards job and life was more likely to help someone start his own business. The more intelligent and reward-driven an individual was, the longer his/her business could be in operation. Finally, significantly positive correlations between self-confidence and the likelihoods of starting and operating a business confirm existing findings on the important part that confidence plays in entrepreneurship (Dittrich et al. 2005; Cooper et al. 1988).

3.4 Discussion

Experimental approach to studying entrepreneurship is widely missing in entrepreneurship research, while personality approach to explaining economic preferences and choices is rarely focused in economic research. This study attempts to bridge personality psychology, entrepreneurship, and economics research by drawing on the methodologies and existing findings in each discipline. To better understand entrepreneurial personality, a simple online experiment was developed to elicit participants' risk attitudes and time preferences, and to measure a set of entrepreneurship-

[12] YourOdds collects participants' responses to the question "What are the odds of YOUR business /

prone personality attributes. I found sampled entrepreneurs and non-entrepreneurs differed in the trait of motivation, with entrepreneurs being significantly more motivated than non-entrepreneurs. In addition, the trait of motivation was positively associated with one′s probability of becoming an entrepreneur, whereas the trait of reward-driven was negatively related to such probability. There existed significant correlations between personality traits and entrepreneurial process: the more intelligent and reward-driven an individual was, the longer his/her business could be in operation; a more self-confident individual would be more likely to start and operate his/her own business.

Personality approach may be a very useful tool not only in explaining but also improving entrepreneurship and economic decision-making. Thus far, findings on personality from this study may be used in career training, counseling, and occupational decision-making. Although personality originates within the individual and remains fairly consistent throughout life (Borghans et al. 2009), the behaviors associated with certain attributes can be learnt from entrepreneurship training. For individuals who were not born with an entrepreneurship-prone personality, acquiring proper support and business consulting becomes necessary. On the other hand, an entrepreneurial career may not be the suitable path for everyone. To avoid employment mismatch and waste of resources, individuals low on achievement motivation and future goal-orientation traits should probably not pursue an entrepreneurial career.

Lately, ecological approach to studying entrepreneurship proposes to concentrate on the situational and environmental influences, and it has been quite effective (Rauch and Frese 2007a). In a specially designed experiment, Dimov et al. (2007) showed

business idea succeeding?" A higher score out of 10 indicates a relatively higher level of self-confidence.

individual and situational learning contingencies enabled an individual to act on his/her entrepreneurial insights and drive the opportunity process forward. Their finding highlighted the positive interaction between the individual and environment in promoting entrepreneurship. More recently, Obschonka et al. (2013) investigated the geographical distributions of entrepreneurship-prone personality profile in the U.S, Germany, and United Kingdom. They found an entrepreneurially inclined personality profile was clustered regionally, and its distribution coincided with the actual geographical distribution of entrepreneurial activity in each country. This study emphasized the influence of socio-ecological influences and the complex interplay with personality in driving entrepreneurial process. For future research, in quest of answers to how personality may interact with various decision situations, social-economic circumstances and cross-cultures, and how entrepreneurship-prone personality can be triggered by proximal situational and environmental variables could be promising.

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Table 3.1

Rotated Factor Loadings and Uniqueness Scores

Variable	Factor1	Factor2	Factor3	Factor4	Factor5	Uniqueness
Numeracy	0.1513	-0.0540	0.8166	-0.1077	0.0824	0.2889
MensaQuiz	-0.0421	-0.0587	0.8438	0.0580	-0.0373	0.2780
IntrinsicMot	0.8297	-0.0411	0.0130	0.1917	0.2169	0.2259
IdentifiedReg	0.8792	0.1177	0.1199	0.0807	-0.0376	0.1909
ExternalReg	0.5808	-0.2819	-0.3020	-0.2451	-0.3615	0.3012
Amotivation	0.2714	-0.2783	-0.3768	-0.5589	0.0976	0.3850
LOT-R	-0.0880	0.8285	-0.0660	0.2246	0.0850	0.2437
Satisfaction	0.0903	0.7780	-0.0093	-0.2752	-0.0259	0.2944
BAS-drive	0.1734	0.0797	-0.1624	0.6960	0.0098	0.4526
BAS-rewards	0.2387	0.1974	-0.0769	0.1368	0.8137	0.2173
BAS-funskg	0.3293	-0.1492	-0.0143	0.7057	0.1407	0.3512
BIS	-0.2783	-0.4599	0.1813	-0.1725	0.6630	0.2087

Note. IntrinsicMot, IdentifiedReg and ExternalReg are indicators of **Motivation Trait (Factor1)**, obtained from the SIMS questionnaire. LOT-R and Satisfaction assess individual level of **Optimism and Job & Life Satisfaction Trait (Factor2)**, given by the LOT-R and Satisfaction questionnaires. Numeracy and MensaQuiz are proxy for **IQ (Factor3)**, which comes from individual scores on the Numeracy test and Mensa Quiz. Amotivation, BAS-drive, and BAS-funsky belong to the SIMS and BAS/BIS questionnaires, measuring a lack of motivation and different subcategories of behavioral activation system underlie behavior and affect, respectively. They are indicators of **Goal-orientation & Fun-seeking Trait (Factor4)**. BAS-rewards and BIS are components of the BAS/BIS scales measuring individual sensitivity to the events that occurred or are expected. They positively relate to reward-dependence or **Reward-driven Trait (Factor5)**. For a more detailed description of trait variables, see Table A.3.1 in the Appendix.

Table 3.2

Marginal Effects on Pr (Entrepreneur)

Variables	Probit (1) dy/dx	Probit (2) dy/dx	Logit (1) dy/dx	Logit (2) dy/dx
Dependent variable: Pr (Entrepreneur)				
Age	**0.0296***	**0.0356****	**0.0305***	**0.0353***
	(0.0134)	(0.0136)	(0.0147)	(0.0144)
Sex (d)	-0.209	-0.0760	-0.207	-0.0901
	(0.127)	(0.163)	(0.132)	(0.201)
Married (d)	-0.145	-0.112	-0.133	-0.123
	(0.120)	(0.141)	(0.123)	(0.159)
White (d)	-0.223	-0.130	-0.217	-0.161
	(0.147)	(0.176)	(0.146)	(0.206)
University	**-0.307****	**-0.353****	**-0.297****	**-0.329***
	(0.100)	(0.128)	(0.0997)	(0.151)
Parent1	0.166	0.315	0.154	0.315
	(0.231)	(0.266)	(0.224)	(0.284)
Parent2	-0.210	-0.271	-0.184	-0.253
	(0.246)	(0.272)	(0.256)	(0.301)
Country (d)	-0.0526	-0.104	-0.0455	-0.0922
	(0.239)	(0.286)	(0.255)	(0.294)
Years	0.00422	-0.00317	0.00355	-0.00263
	(0.00992)	(0.0114)	(0.0105)	(0.0114)
Factor1		**0.132***		0.139
		(0.0664)		(0.0769)
Factor2		0.0234		0.0250
		(0.0621)		(0.0646)
Factor3		-0.0385		-0.0242
		(0.0815)		(0.0938)
Factor4		0.0678		0.0663
		(0.0795)		(0.0909)
Factor5		**-0.139***		**-0.139***
		(0.0610)		(0.0665)
Time Task		0.00541		0.00576
		(0.00831)		(0.00890)
N	78	72	78	72

Note. Marginal effects. Standard errors in parentheses

* p<0.05, ** p<0.01, *** p<0.001

y = predicted Pr (Entrepreneur) after probit or logistic regression models

(d) for discrete change of dummy variable from 0 to 1

Table 3.3

Correlations between Entrepreneurial Process and Personality

VARIABLES	Starter	Business	BusLength	ExpGrowth
Factor1				0.463**
(Motivation)				(0.030)
Factor2	0.205*			
(Optimism & Satisfaction)	(0.081)			
Factor3			0.369*	
(IQ)			(0.091)	
Factor5			0.439**	
(Reward-driven)			(0.041)	
YourOdds	0.337**	0.355***		
(self-confidence)	(0.018)	(0.012)		

Note. Pair-wise correlation coefficients. P-values in parentheses.

*** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level.

Figure 3.1

Dendrogram for Cluster Analysis

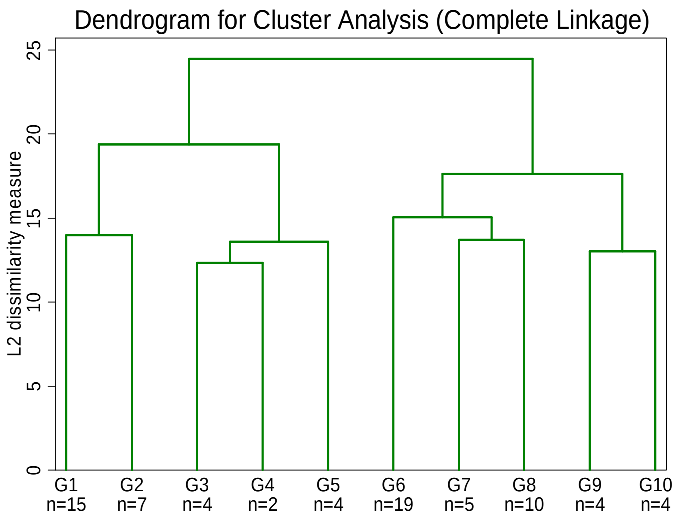
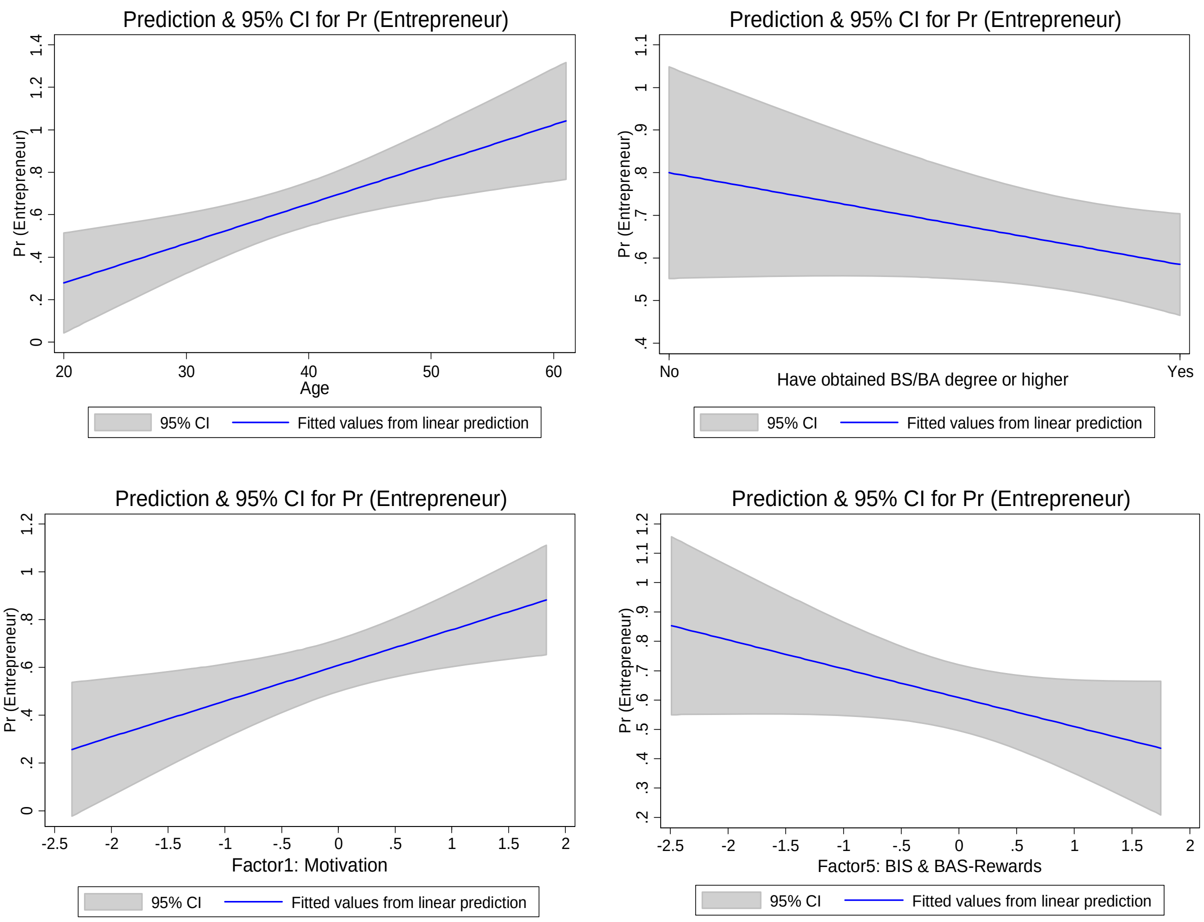


Figure 3.2

Determinants of Pr (Entrepreneur)



Appendix

Table A.3.1: Description of Variables (80 Subjects)

Category	Variables	Description / range of values	Mean (Std)	Median	Mode	95% C. I.
Personality Traits or Questionnaire Items	IntrinsicMot	Intrinsic Motivation and it refers to performing an activity for itself, to experience pleasure and satisfaction inherent in the activity. Values range from 1 to 7.	5.101 (1.390)	5.250	6.000	(4.779, 5.423)
	IdentifiedReg	Identified Regulation and it occurs when an extrinsically motivated behavior is valued and perceived as being chosen by one-self. Values range from 1 to 7.	5.291 (1.422)	5.750	5.750 6.250 7.000	(4.961, 5.620)
	ExternalReg	External Regulation and it occurs when behavior is regulated by rewards or in order to avoid negative consequences. Values range from 1 to 7.	2.528 (1.548)	2.250	1.000	(2.169, 2.887)
	Amotivation	Amotivation and. it occurs when individuals experience a lack of Contingency between their behaviors and outcomes (they are neither intrinsically nor extrinsically motivated). Values range from 1 to 7.	1.882 (1.144)	1.500	1.000	(1.617, 2.147)
	BAS-drive	Behavioral activation sensitivity to driving motives. Values range from 8 to 16.	13.000 (2.047)	13.000	14.000	(12.529, 13.471)
	BAS-funskg	Behavioral activation sensitivity to fun-seeking motives. Values range from 7 to 16.	12.387 (2.211)	12.000	11.000 12.000	(11.878, 12.895)
	BAS-reward	Behavioral activation sensitivity towards rewards. Values range from 14 to 20.	18.160 (1.594)	18.000	19.000	(17.793,18.527)
	BIS	Behavioral inhibition sensitivity to unpleasantness. Values range from 8 to 27.	18.907 (4.363)	19.000	24.000	(17.903, 19.910)
	LOT-R	Scores on the Life Orientation Test-Revised (LOT-R), which measures individual differences in generalized optimism versus pessimism, and a high score implies a greater level of optimism. Values range from 7 to 24.	18.554 (4.181)	19.000	24.000	(17.585, 19.523)
	Satisfaction	Scores on the Life and Job Satisfaction Questionnaire, which contains two self-reported questions asking how satisfied individuals are with their current life and job. Values range from 1.5 to 10.	6.553 (2.066)	7.000	9.000	(6.078, 7.023)
	Numeracy	Scores on the Numeracy test, which assesses individuals' numerical ability. Values range from 2 to 11.	8.339 (2.100)	9.000	10.000	(7.861, 8.814)
	MensaQuiz	Scores on the Mensa quiz, which can reflects individuals' levels of intelligence. Values range from 0 to 5	2.566 (1.379)	3.000	2.000 3.000	(2.251, 2.881)
	Self-Est_N	Answers to the question "Please estimate how well you believe you did in this question (Numeracy Test) compared to other entrepreneurs". Answers are, 1 "Bottom 1-10%", 2 "Bottom 10-20%", 3 "Bottom 20- 30%=3", 4 " Bottom 30-40%", 5 "In the middle", 6 "Top 30-40%", 7 "Top 20-30%", 8 "Top 10-20%", and 9 "Top 1-10%". Values range from 1 to 9.	5.740 (2.452)	5.000	5.000	(5.184, 6.297)
	Self-Est_M	Answers to the question "Please estimate how well you believe you did in this quiz (Mensa Quiz) compared to other entrepreneurs taking the quiz". Answers are, 1 "Bottom 1-10%", 2 "Bottom 10-20%", 3 "Bottom 20-30%=3", 4 " Bottom 30-40%", 5 "In the middle", 6 "Top 30-40%", 7 "Top 20-30%", 8 "Top 10-20%", and 9 "Top 1-10%". Values range from 1 to 9.	5.961 (2.375)	6.000	5.000	(5.418, 6.503)

Five Factors	Factor1	Motivation, defined by Intrinsic Motivation, Identified Regulation, & External Regulation. Values range from -2.349 to 1.832.	-1.96E-9 (1.000)	0.135	——	(-0.232, 0.232)
	Factor2	Optimism & Satisfaction, defined by LOT-R & Satisfaction. Values range from -3.892 to 1.747	1.97E-09 (1.000)	0.090	——	(-0.232, 0.232)
	Factor3	Proxy for IQ, defined by Numeracy & Mensa Quiz. Values range from -2.731 to 1.985.	-8.94E-09 (1.000)	0.111	——	(-0.232, 0.232)
	Factor4	Goal & Fun, defined by BAS-drive, BAS-funskg & Amotivation. Values range from -2.338 to 2.632.	-5.91E-10 (1.000)	0.030	——	(-0.232, 0.232)
	Factor5	Defined by BIS & BAS-rewards. Values range from -2.489 to 1.749.	1.86E-09 (1.000)	0.090	——	(-0.232, 0.232)
Demographic Dummies	Sex	Gender of the subjects. Dummy: 1 Female, 0 Male	0.375 (0.487)	0.000	0.000	(0.267, 0.483)
	AgeDummy	Age group of the subjects. Dummy: 1 Older than average, 0 Younger than average.	0.463 (0.502)	0.000	0.000	(0.351, 0.574)
	Overweight	Weight of the subjects. Dummy: 1 BMI ⩾25, 0 BMI <25.	0.658 (0.477)	1.000	1.000	(0.551, 0.765)
	HaveChildren	Dummy: 1 Yes, 0 No.	0.650 (0.480)	1.000	1.000	(0.543, 0.757)
	Married	Marital status of the subjects. Dummy: 1 Married, 0 Other.	0.550 (0.501)	1.000	1.000	(0.439, 0.661)
	White	Race of the subjects. Dummy: 1 White, 0 Other.	0.513 (0.503)	1.000	1.000	(0.401, 0.624)
	University	Education of the subjects. Dummy: 1 Have obtained BA/BS or higher, 0 Other.	0.813 (0.393)	1.000	1.000	(0.725, 0.900)
	Parent1	Birth country of the subjects' first parents. Dummy: 1 U.S, 0 Other.	0.575 (0.497)	1.000	1.000	(0.464, 0.686)
	Parent2	Birth country of the subjects' second parents. Dummy: 1 U.S, 0 Other	0.595 (0.494)	1.000	1.000	(0.484, 0.706)
	Country	Birth country of the subjects. Dummy: 1 U.S, 0 Other.	0.663 (0.476)	1.000	1.000	(0.557, 0.768)
	Smoke	Answers to the question "Have you ever smoked?" Answers are, 1 "Yes", 0 "No".	0.450 (0.501)	0.000	0.000	(0.339, 0.561)
	Entrepreneur	Answers to the question "Are you an entrepreneur?" Answers are, 1 "Yes", 0 "No".	0.625 (0.487)	1.000	1.000	(0.517, 0.733)
	Business	Answers to the question "Do you currently own a business?" Answers are, 1 "Yes", 0 "No".	0.325 (0.471)	0.000	0.000	(0.220, 0.430)
	Starter	Answers to the question "Did you start your business?" Answers are, 1 "Yes", 0 "No".	0.313 (0.466)	0.000	0.000	(0.209, 0.416)
Demographic Variables (non-dummies)	Age	Age of the subject. Values range from 20 to 61.	38.600 (9.034)	37.500	31.000 35, 36	(36.590, 40.610)
	BMI	The body mass index=(weight in pounds * 703) / (height in inches^2) Values range from 20.015 to 38.967.	27.056 (4.338)	26.870	20.8, 23.0 23.7, 25.1 27.1, 27.9 29.2, 31.7	(26.085, 28.028)
	Race	1 "American Indian/Alaska Native", 2 "Asian", 3 "Black/ African American", 4 "Hispanic/Latino", 5 "Native Hawaiian/ Other Pacific Islander", 6 "White (non-Hispanic)". Min: 2; Max: 6.	4.575 (1.589)	6.000	6.000	(4.221, 4.929)
	Years	Answers to the question "How long have you been living in the US (in years)?" Min: 0; Max: 60.	30.253 (13.075)	33.000	31.000	(27.324, 33.182)
	Cigarettes	Answers to the question "How many cigarettes per day do you smoke on average?" Answers are, 0 "0", 2 "1~5", 3 "5~10", 4 "10~15", 5 "15~20", 6 "20~25", 7 "23~30", 8 "30~35". Min: 0; Max: 2.	0.075 (0.348)	0.000	0.000	(-0.002, 0.152)
	Alcohol	Answers to the question "How many alcoholic beverages do you Consume per week on average?" Answers are, 1 "0~1", 2 "2~7", 3 "8~13", 4 "14~21", 5 ">21". Min: 1; Max: 4.	1.513 (0.656)	1.000	1.000	(1.367, 1.658)
Business Information	YourOdds	Answers to the question "What are the odds of YOUR business / business idea succeeding?" Answers are, 1 "1 out of 10", 2 "2 out of 10=2", etc. Min: 1; Max: 10.	6.560 (2.786)	7.000	7.000	(5.768, 7.352)
	BusLength	Answers to the question "How long has your business been in operation (in months)?" Min: 1; Max: 163.	57.538 (45.961)	48.000	60.000	(38.974, 76.103)
	ExpGrowth	Answers to the question "By how many percentage points do you expect your business to grow in the next three years? Min: 0; Max: 100.	38.269 (35.822)	25.000	100.000	(23.800, 52.738)

Table A.3.2: Regression Models of the Effects on Pr (Entrepreneur)

Variables	LPM (1)	LPM (2)	Probit (1)	Probit (2)	Logit (1)	Logit (2)
Dependent variable: Pr (Entrepreneur)						
Age	**0.0157*** **	**0.0159***	**0.0866****	**0.102****	**0.150***	**0.170****
	(0.00527)	(0.00860)	(0.0410)	(0.0403)	(0.0776)	(0.0711)
Sex	**-0.192***	-0.0818	**-0.595***	-0.216	-0.978	-0.425
	(0.111)	(0.123)	(0.355)	(0.455)	(0.609)	(0.928)
Married	-0.102	-0.0659	-0.432	-0.326	-0.665	-0.607
	(0.104)	(0.115)	(0.363)	(0.424)	(0.618)	(0.830)
White	-0.185	-0.138	-0.666	-0.376	-1.091	-0.789
	(0.149)	(0.164)	(0.456)	(0.519)	(0.758)	(1.048)
University	**-0.219****	-0.177	**-1.191****	**-1.409***	**-2.019****	-2.253
	(0.107)	(0.145)	(0.574)	(0.787)	(1.006)	(1.488)
Parent1	0.0886	0.205	0.480	0.895	0.741	1.489
	(0.210)	(0.265)	(0.667)	(0.776)	(1.071)	(1.364)
Parent2	-0.184	-0.256	-0.644	-0.830	-0.946	-1.306
	(0.213)	(0.263)	(0.786)	(0.892)	(1.359)	(1.647)
Country	-0.0537	-0.0576	-0.156	-0.308	-0.227	-0.458
	(0.150)	(0.250)	(0.724)	(0.879)	(1.298)	(1.524)
Years	0.00661	0.00210	0.0123	-0.00910	0.0175	-0.0127
	(0.00559)	(0.00917)	(0.0289)	(0.0327)	(0.0512)	(0.0549)
Factor1		**0.116***		**0.379****		**0.669***
		(0.0625)		(0.193)		(0.388)
Factor2		0.000409		0.0672		0.120
		(0.0514)		(0.179)		(0.311)
Factor3		-0.0127		-0.111		-0.117
		(0.0666)		(0.234)		(0.449)
Factor4		0.0428		0.195		0.319
		(0.0689)		(0.231)		(0.446)
Factor5		**-0.0994***		**-0.400****		**-0.671****
		(0.0542)		(0.171)		(0.312)
Time Task		0.00417		0.0155		0.0277
		(0.00738)		(0.0239)		(0.0430)
Constant	0.317	0.259	-1.177	-1.462	-2.181	-2.524
	(0.232)	(0.294)	(1.080)	(1.043)	(2.001)	(1.795)
Observations	78	72	78	72	78	72
R-squared	0.272	0.351				

Note. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1