WORKING PAPER

Are Economists' Preferences Psychologists' Personality Traits?

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Abstract

This paper establishes an empirical mapping between economic preferences and psychological personality traits. I use the Random Preference Model to estimate distributions of risk and time preferences complete with their individual-level stability and people's propensity to make mistakes from unique experimental data. Using factor analysis to extract information on individuals' ability and personality, I show that their link with preferences is much stronger than previously documented. I explain up to 50% of the variation in both average preferences and in individuals' capacity to make consistent rational choices using four factors related to cognitive ability and three of the Big Five personality traits. Furthermore, the five structural parameters of my model largely dominate a wide range of demographic and socioeconomic variables when it comes to explaining observed individual choices between risky lotteries and time-separated payments.

1 Introduction

There is extensive evidence that preferences, ability, and personality predict a wide range of economic outcomes (see for example Heckman et al., 2006; Chabris et al., 2008; Conti et al, 2010; Becker et al., 2012; Beauchamp et al. 2017). However, the question of whether they work through one another or side by side had not been conclusively answered. It is important to do so in order to be able to correctly specify reduced form and structural economic models and to accurately interpret their results. I add to this effort by estimating a full structural model of decision making under delay and uncertainty using data from a unique field experiment in which each participant made over 100 choices on incentivized tasks designed to elicit risk and time preferences. I use the extensive associated survey data to map both economic preferences and the stochastic components of decision-making onto cognitive ability and three of the *Big Five* personality traits expressed as factors. My approach makes three main contributions, both technical and substantive, to the literature concerned with measuring preferences and explaining their heterogeneity.

My main contribution is to explain up to 50% of the heterogeneity in both the true (or average) preferences, in their individual-level stability, and in people's propensity to make mistakes using cognitive ability and three of the *Big Five* personality traits: extraversion, conscientiousness, and internal locus of control[1]. Defined as stable, person-specific determinants of behavior, they are the natural counterparts of economic preferences in the psychology literature. Indeed, they have been shown to predict many of the same real-world outcomes (Barrick and Mount, 1991; Heckman et al., 2006; Vazsonyi et al., 2001). However, despite this "intuitive mapping of preferences to traits, the empirical evidence supporting such mappings is weak. The few studies investigating empirical links typically report only simple regressions or correlations without discussing any underlying model." (Almlund et al., 2011)[2] This paper is the first attempt to establish such a mapping in a full structural framework of decision-making under uncertainty and delay. The amount of explained cross-sectional variation is large compared to previous research (see for example Becker et al, 2012). For comparison purposes, when I try to explain heterogeneity in preferences using a standard set of demographic and socioeconomic variables, I can account for at most 5% of their observed variation (this is in line with previous findings, see for example Dohmen and Falk, 2010 and Von Gaudecker et al., 2011). My results suggest that preferences and personality do not simply function side by side as claimed by Becker et al. (2012) but that they are strongly related. I believe that one of the reasons that I am able to find a stronger relationship between preferences and personality than previous studies is that I estimate each trait from multiple noisy indicators using a factor model. This should address attenuation bias resulting from measurement error (see for example Carneiro et al., 2003; Cunha and Heckman, 2009; and Cunha et al., 2010)). Because preferences and traits have both been shown to predict outcomes

[1] Roberts (2009) characterizes personality traits as "the relatively enduring patterns of thoughts, feelings, and behaviors that reflect the tendency to respond in certain ways under certain circumstances." The Big Five personality traits were constructed by psychologists as five orthogonal overarching factors which succinctly describe human personality. The extraversion trait is associated with excitement-seeking and active, sociable behavior. Conscientiousness is associated with ambition, self-discipline, and the ability to delay gratification. Internal locus of control is associated with high self-esteem, low rates of depression, and the belief that one's own actions, rather than luck or fate determine his outcomes. While it is not directly part of the *Big Five*, it has been connected to it in the literature. Notably, a perceived internal locus of control should be highly negatively correlated with the *Big Five* neuroticism trait (see Almlund et al. (2011).

[2] The question is as valid now as it was seven years ago. In a 2018 Journal of Economic Perspectives symposium on "Risk in Economics and Psychology", Mata et al., 2018 mention the need "to make conceptual progress by addressing the psychological primitives or traits underlying individual differences in the appetite for risk."

and as they may be highly heritable[3], this finding has ramifications for explaining inequality and the inter-generational transmission of socio-economic status.

If preferences influence outcomes also through one another, this has implications for specifying reduced form and structural economic models and for accurately interpreting their results. On the one hand, I corroborate Von Gaudecker et al.'s (2011) claim that preferences contain much more useful information than that which could be captured by socio-demographics alone and that they should therefore be used to complement the standard set of controls used in empirical research aimed at explaining heterogeneity in economic outcomes. Indeed, I find that preferences dominate demographic and socio-economic variables when it comes to explaining the variation in observed choices under risk and delay. On the other hand, I show that when this is not possible, omitted variable bias could potentially still be alleviated by adding controls for ability and personality as those are heavily correlated with preferences. Indeed, using only the coefficients from my structural model, information on observed heterogeneity, and my estimates of the prevalences of unobserved types, I am able to simulate as rich a distribution of preferences and of the random components of decision-making as as can be obtained from estimates based on the full set of observed individual choices.[4] Nevertheless, I find that a large part of the cross-sectional variation is attributable to unobserved heterogeneity embodied by unobserved types. I thus conclude that economists' preferences and psychologists' personality traits are related but distinct concepts.

My second contribution is to estimate distributions of risk and time preferences using the Random Preference Model (RPM). Previous efforts to estimate preferences structurally mainly relied on the workhorse Random Utility Model (RUM) (Andersen et al., 2008; Andreoni and Sprenger, 2012; and Belzil and Sidibe, 2016). However, recent work by Apesteguia and Ballester (2018) demonstrates that choice probabilities derived using the RUM exhibit important non-monotonicities which are at odds with a basic theoretical definition of risk-aversion, calling into question its continued use in preference estimation. I am the first to jointly estimate full population distributions of risk and time preference parameters and of their associated stochastic components using the RPM framework unburdened by these shortcomings. Even though my estimates are based on a population which is largely homogeneous in terms of educational level and age, I find significant dispersion in risk and time preferences, in their individual-level precision, and in the agents' propensity to make random mistakes. This suggests that it may not be sufficient to use a simple population average of risk and time preferences in the calibration of structural models as has often been done before. Because preferences factor non-linearly into a wide range of microeconomic and macroeconomic models, such a simplification is likely to have ramifications for predicting agents' responses to changes in economic conditions and for calculating the welfare implications of new policy.

Third, I provide a comprehensive treatment of random errors associated with both the stability of preferences and with the propensity to make random mistakes. I call these the **rationality parameters** as opposed to **preference parameters** - the coefficient of risk aversion and the discount rate - which characterize a person's true (or average) preference towards risk and time respectively. While the addition of various types of stochastic components to models of decision-

[3]Heritability estimates are about 50% for cognitive skills and personality (see for example Bouchard and Loehlin, 2001 and Bergen et al., 2007). Evidence is more mixed regarding the heritability of preferences although recent research has shown that they may be as heritable as cognitive and non-cognitive traits, see for example Beauchamp et al. (2017). My results documenting the strong link between preferences and traits combined with extensive psychological research on the heritability of personality support this hypothesis.

[4]For comparison purposes, using only observed and unobserved heterogeneity, von Gaudecker et al. (2011) can cover only about one third of the distribution of risk preferences which they obtain using information on individual choices on incentivized tasks designed to elicit risk preferences.

making is not new, my approach is unique in that I introduce a total of three distinct rationality parameters and that I let each of them be a function of both observed and unobserved heterogeneity.

I build on a rich literature concerned with separating out true preferences from stochastic components affecting decision-making. Andersson et al. (2016) find that random errors, if not accounted for, may bias preference estimates. Insofar as these errors depend on observed and unobserved heterogeneity, they can also lead to the detection of spurious correlations between estimated preferences and explanatory variables (in their example, between risk aversion and cognitive ability). Beauchamp et al. (2017) find that simply accounting for measurement error improves the test-retest predictability of risk preferences in repeated samples and provides tighter estimates of their relationship with personality traits. Von Gaudecker et al. (2011) come perhaps the closest to my treatment of random errors. They include both a parameter representing the stability of individuals' choices under risk and a "trembling hand" parameter which embodies completely random decision-making some percentage of the time. However, while they admit that it would be useful to let both error types be individual-specific, they say that "in practice it appears to be difficult to estimate heterogeneity in [them] separately (although both are identified, in theory)". I can do so, as I have a large number of incentivized choice tasks per individual, some designed to elicit risk preferences and others time preferences. On the one hand, the **stability parameters** – the standard deviation of the coefficient of risk aversion and the standard deviation of the discount rate – are identified from small inconsistencies in choices centered around an individual's true or average preference for either risk or time. On the other hand, the **trembling hand parameter** related to an individual's propensity to make mistakes is identified from situations in which he chooses either strictly dominated options or makes choices far from his average preferences.

The importance of distinguishing between these two types of random errors is reflected in their association with different dominant personality traits. I show that the rationality parameters associated with the *stability of individuals' choices* are best explained by the conscientiousness trait while the *propensity to make mistakes* is related to cognitive ability. Specifically, more conscientious individuals have more stable risk and time preferences and higher ability individuals make errors in decisions less frequently. Having estimates of the standard deviation of the coefficient of risk aversion and of the discount rate lets me obtain distributions of preferences complete with information on their individual-level precision. I take the view that they represent actual instability in an individual's risk and time preferences and thus that their presence does not necessarily point to irrational behavior. In the model, an individual would still be choosing his preferred alternative according to expected utility maximization given the "instantaneous" draw of risk preference from his distribution of the coefficient of risk aversion. Preferences could be unstable due to imperfect self-knowledge (for example, an individual may be uncertain whether he requires a 8.1% or 8.2% rate of return when trading off between payments across time) or they could vary due to external factors such as rising temperature in the room. Alternatively, these stability parameters can be viewed as measurement error describing the degree of precision to which I can measure a person's true (or average) preference. While the economic interpretation of my results may be different depending on whether one or the other hypothesis is true, both reflect the fact that individuals exhibit various degrees of choice inconsistency even on simple tasks performed in controlled laboratory environments which cannot be explained by the variation alone in the task parameters. The *trembling hand* rationality parameter allows for individuals to make mistakes and actually *pick their less preferred alternative* some percentage of the time. This can be due to inattention or as a result of lack of sufficient cognitive ability to correctly process the parameters of the choice task at hand. The latter hypothesis is supported by my finding that heterogeneity in the trembling hand parameter is best explained through variation in cognitive ability.

The existence of heterogeneity in rationality parameters which characterize the stochastic components of decision-making may have a large impact on economic outcomes. It implies that there is a distribution of preferences not only across people but also for any given individual. Choi et al. (2014) show that the quality of decision-making measured as consistency of choices with the general axiom of revealed preference (GARP) has a casual impact on the variation in accumulated lifetime wealth. While making mistakes can clearly be costly in many situations, the point is slightly more subtle when it comes to preference instability. Individuals with less stable preferences may be penalized in environments like the stock market which tend to reward stable, long-term decisions. One could construct an index of decision-making consistency which would reflect an individual's position on the joint distribution of the three rationality parameters (akin to Choi et al.'s, 2014 index based on the GARP). If cognitive ability and personality traits are assumed to function also as primitives of economic models alongside preferences, their combined impact on outcomes such as accumulated wealth may be further magnified: for example take a situation in which conscientiousness makes an individual do well financially both through its direct impact on his career success and indirectly through a lower associated discount rate which will induce him to make better savings and investment decisions.

My structural model has two main parts: a factor model used to derive the latent cognitive ability and personality traits from multiple observed indicators; and a model of decision-making under uncertainty and delay based on the assumption that decisions are driven by utility maximizing behavior which itself depends on an individual's risk and time preferences and is subject to random errors following the RPM framework. I assume that measures of individual traits as well as all preference and rationality parameters depend on observed heterogeneity and on unobserved factors of ability and personality. In addition, I allow the structural parameters of the model to depend on "true" unobserved heterogeneity (unrelated to any observed characteristics or measures) in the form of unobserved types.

I estimate the model empirically through simulated maximum likelihood (SML) using data from "The Millenium Foundation Field Experiment on Education Financing" based on a representative sample of 1,248 Canadian high school seniors. An individual's likelihood contribution is the probability of jointly observing his choices on A) 55 incentivized tasks designed to elicit risk preferences, B) 48 incentivized tasks designed to elicit time preferences, and C) his answers to 38 questions designed to measure cognitive ability and personality traits, all given his observed characteristics, the four unobserved latent factors[5], and five unobserved types. The joint estimation of all three components of the structural model allows for an optimal use of the information in the dataset. Furthermore, failure to estimate risk and time preferences jointly has been shown to lead to unrealistically high estimates of the discount rate (see Andersen et al., 2008 and 2014; Cohen et al., 2016).

I am thus able to answer the following questions:

- Do psychometric measures of cognitive and non-cognitive traits explain individual choices through the intermediary of economic preference and rationality parameters?
- If they do, does the explanatory power of personality traits reside in structural preference

[5]The factors of interest are: an individual's cognitive skills and his non-cognitive personality traits. The latter consist of internal locus of control, extraversion, and conscientiousness: stable personality traits identified by the psychologists as particularly important predictors of behavior and part of the *Big Five* personality traits. These factors have been chosen to capture both "soft" and "hard" skills.

parameters or more in the parameters governing the stability of preferences and choices?

- After accounting for the individual factors, how much of the variation in individual preference and rationality parameters is explained by true heterogeneity (orthogonal to psychometric factors)?
- Overall, are individual choices better explained by preference or rationality parameters?

My results show that heterogeneity in preferences explains a majority of the variation in observed choices between risky lotteries and when trading off payments across time. Indeed, the five estimated structural preference and rationality parameters alone have explanatory power which is an order of magnitude larger than that of nearly two dozen demographic and socio-economic variables. While preference parameters account for a vast majority (80-100%) of the explained variation in the overall number of risky or intertemporal choices, rationality parameters also have a non-negligible influence and predict inconsistencies in individual behavior. Both the true (or average) preferences and their associated stochastic components map robustly onto cognitive ability and personality traits. Overall, the conscientiousness trait exhibits the strongest links. It explains 45% of the cross-sectional variation in discount rates, 10% of the variation in risk aversion, and 20% of the variation in their individual-level stability. Furthermore, extraversion is strongly related to risk aversion and high cognitive ability reduces the trembling hand parameter. The latter confirms Andersson et al.'s (2016) suspicion that the failure to properly account for the presence of random errors and of their link to observables in previous research likely resulted in biased estimates of both risk aversion and of its relationship with observed heterogeneity such as cognitive ability.

The rest of the paper is organized as follows: Section 2 describes the data, Section 3 presents the theoretical underpinnings of the structural model, Section 4 details the empirical methodology, Section 5 presents the empirical results, Section 6 provides a general discussion of the broader implications of the findings presented in this article, and Section 7 concludes.

2 Data

The data comes from "The Millenium Foundation Field Experiment on Education Financing" conducted on a representative sample of 1,248 Canadian full time students in their last year of high school. Of those 1,224 are Canadian citizens (the remaining 24 individuals are excluded from my analysis). These are the basic descriptive statistics of the sample:

Observations:	1224
Male	46%
Female	54%
English	68%
Other Language	32%
Age 15-16	12%
Age 17	67%
Age 18	15%
Age 19+	6%

The experiment contains 103 choice tasks designed to elicit risk and time preferences. The students knew they would get paid for a random subset of these tasks. The full experimental setup is included in Section 11 of the Online Appendix.

2.a Holt & Laury's (H&L) Multiple Price List Design

Of the 55 tasks designed to measure risk aversion, the first 30 are of the Holt and Laury (H&L) type invented by Miller et al. (1969) and used in Holt and Laury (2002). Choice payments and probabilities are presented using an inuitive pie chart representation popularized by Hey and Orme (1994). There are 3 groups of 10 questions. In each group of questions, subjects are presented with an ordered array of binary lottery choices. In each choice task they choose between lottery A (safer) and lottery B (riskier). In each subsequent row, the probability of the higher payoff in both lotteries increases in increments of 0.1. While the expected value of both lotteries increases, the riskier option becomes relatively *more* attractive. As in the first row of each set of questions the expected value of the safer lottery A is greater than that of the riskier lottery B, all but risk-seeking individuals should choose the safer option. Midway through the 10 questions, the expected value of the riskier lottery B becomes greater than that of the safer lottery A. At this point, risk neutral subjects should switch from the safer to the riskier option. In the remaining rows the relative attractiveness of lottery B steadily increases until it becomes the dominant choice in the last row.[6] By the last row of each set of H&L questions, all individuals are expected to have switched to the riskier option. Each person's "switching point" should be indicative of his risk aversion. By design, in the absence of a shock to either his preferences or utility, each individual should switch at exactly the same point of the 3 sets of H&L questions. The fact that this is not the case in reality highlights the need to use a model which allows for some randomness in decision-making.

2.b Binswanger's Ordered Lottery Selection (OLS) design

The remaining 25 tasks designed to measure risk aversion used in this study are of the ordered lottery selection (OLS) design developed by Binswanger (1980) and used by Eckel and Grossman (2002 and 2008). They consist of 5 groups of 5 questions. Once again, in each group of questions, subjects are presented with an ordered array of binary lottery choices. In each choice task they choose between lottery A (safer) and lottery B (riskier). This time, lottery A offers a certain amount in the first row and all other alternatives increase in expected payoff but also in its variance. In each subsequent row the riskier option becomes relatively *less* attractive. Individuals are thus expected to switch from the risky to the safe option at some point (assuming that they initially picked the risky option). Once more, the "switching point" should be indicative of each individual's risk preferences. By design, the switching point for a given individual should vary among the 5 sets of OLS type questions, unlike in the H&L type ones. In the absence of stochastic shocks to utilities of preferences, the H&L tasks should allow for the identification of an interval for an individual's risk aversion while the OLS tasks should permit the refinement of this interval. Furthermore, while the H&L tasks focus on the most common range of risk preferences (up to a coefficient of risk aversion of 1.37), MPL tasks let us identify highly risk-averse individuals.

Harisson and Rutstrom (2008) find a risk-aversion of 0.75 using H&L type tasks and of 0.66 using OLS type tasks for the same sample of individuals. However, the estimate is less precise using OLS type questions. They thus conclude that "[t]he results indicate consistency in the elicitation of risk attitudes, at least at the level of the inferred sample distribution". Both types of lottery choice tasks are thus treated the same in the structural model.

[6] In the last row of all three sets of H&L type questions designed to measure risk aversion, both lotteries offer the higher payment with certainty. Therefore lottery B dominates lottery A.

2.c Temporal Choice Tasks

All 48 questions designed to elicit time preferences are of the type used in Coller and Williams (1999). They consist of 8 groups of 6 questions. In each group of questions, subjects are presented with an ordered array of binary choices. In each choice task they choose between an immediate payment[7] and a future payment. In each subsequent row the magnitude of the future payment increases. Most individuals are thus expected to switch from the immediate to the future payment at some point. The "switching point" should be indicative of each individual's time preferences. By design and in the absence of stochastic shocks, each individual should have one switching point in the first 4 sets of temporal choice tasks and another one in the 2nd set. If information on his risk aversion is available, the two sets of tasks designed to elicit time preference should thus yield two (overlapping) intervals for his discount rate.

2.d Observed Individual Choices

Figure 1 plots the distributions of individuals' choices on tasks designed to elicit their preferences. It shows that that there is significant heterogeneity in choices and that extremes of both distributions (all risky or all safe and all immediate or all distant payments) have non-zero mass. While on the lottery choice tasks the distribution roughly resembles normality this is not the case on temporal choice tasks. The latter distribution is very wide and has high mass points at the extremes. Around 10% of the overall population choose either all immediate payments or all distant payments. Particularly striking is the large share of seemingly very impatient people. However, as mentioned before, one needs to have estimates of individuals' risk aversion in order to be able to draw clear conclusions about their discount rates.

Figure 1: Distribution of Individual Choices on Lottery and Temporal Tasks

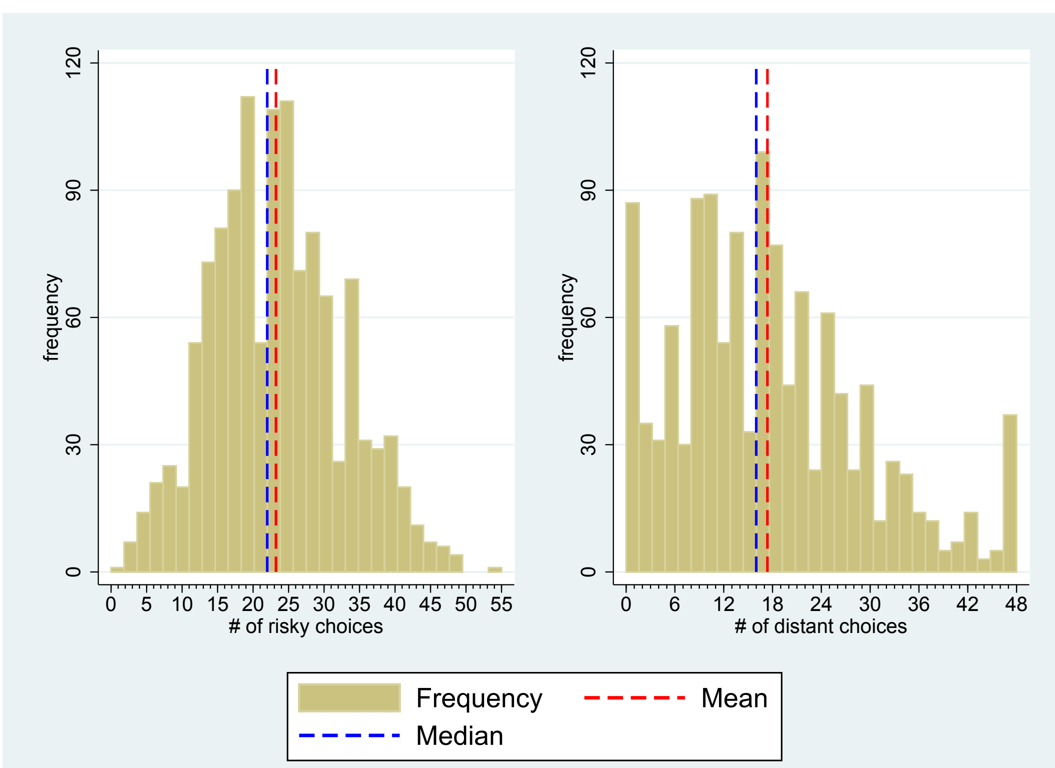


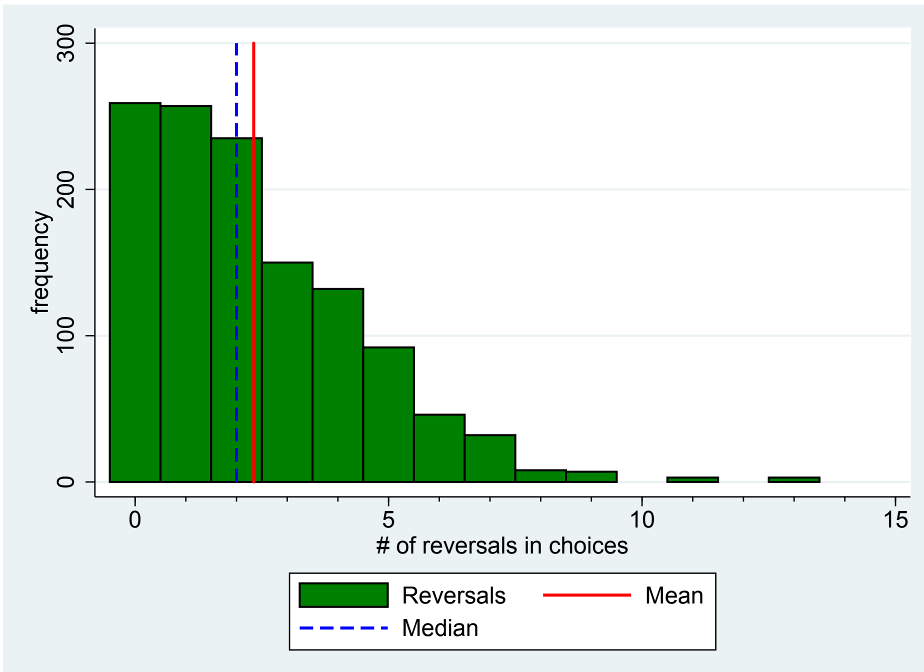
Figure 2 shows that contrary to standard predictions, some individuals exhibit reversals in their choices within a set of choice tasks.[8] This shows the utility of collecting data on the full set of tasks as opposed to assuming that each individual will maintain his choice after his "switching

[7] I refer to the earlier of two payments as "immediate" even though it is not always paid out right away.

[8] A reversal is defined as follows. Take for example one set of 10 H&L lottery choice tasks. If an individual starts

point" (as is often done in the literature, see for example Dohmen et al., 2010). Observed reversals in choices within a set of questions allow for a cleaner identification of the rationality parameters. They are mainly explained by mistakes embodied by the trembling hand parameter (as opposed to differences in an individual's switching points in different sets of choice tasks which are attributable to preference instability embodied by the standard deviations of risk aversion and of the discount rates).

Figure 2: Observed Reversals per individual on Lottery and Temporal Choice Tasks



2.e Background Information

The experiment also solicits a large amount of background information both from students and from their parents. The collected information includes grades, a measure of intelligence, measures of non-verbal ability, personality, finances, school and job aspirations, etc. See Section 9.a of the Appendix for a list of measures selected to approximate cognitive ability and 3 of the *Big Five* personality traits and of the loadings associated with each measure of these factors. The magnitudes of the loadings vary widely. This shows that some indicators are better measures of the underlying ability and personality traits than others. It confirms the usefulness of using a factor model to address measurement errors inherent in measures of ability and personality (see for example Cunha and Heckman, 2009).For more information on the experiment, see Belzil et al. (2016) or Johnson and Montmarquette (2015).

3 Model

Before providing technical details, let us expose the general set-up of the model. As described in the previous section, every individual i performs a large number of choice tasks. Each choice task consists of a binary choice. In some cases, the choice is made between lotteries with different expected payoffs and variances and therefore provides information about an individual's specific risk aversion parameter. In other cases, the choice is between an early (immediate) payment

out by picking the safer option and then at some point switches to the riskier one as the riskier option becomes more attractive, this is considered standard behavior. If however he then reverts back to the safer option on the same set of tasks, this is considered a reversal. The definition is analogous for OLS type lottery tasks and for temporal choice tasks.

and a later payment. In conjunction with the risk aversion estimate, it can be used to identify an individual's discount rate. The lottery choice tasks are indexed by l and the temporal choice tasks are indexed by t. Because individuals perform a large number of tasks, and in line with the Random Preference Model (RPM), I introduce two stochastic shocks (one for each preference parameter) and assume that each preference parameter is hit by one of the possible realizations of these shocks every time a task is performed. These shocks are independent across tasks and across individuals. Formally, this entails assuming that both risk aversion and the discount rate are random variables from whose distributions a particular realization is drawn every time a choice task is performed. This could be due to actual preference instability, imperfect self-knowledge, or measurement error.

Because I have access to a large number of psychometric measurements for the individuals who performed these choice tasks, I can investigate the existence of a mapping from individual-specific preference parameters onto psychological traits using a factor model. Unlike what has been previously done in the literature, I extend the notion of preference heterogeneity to also incorporate heterogeneity in the stability of individual preferences and in seemingly irrational choices. This approach allows one to differentiate between heterogeneity in the curvature of the utility function (or in discount rates) and heterogeneity in parameters capturing stochastic behavior.

Ability and the psychological traits (which I shall refer to as factors) are themselves unobserved. They are, however, noisily measured by observed indicators proper to each individual. This data structure makes it amenable to study using factor analysis. I estimate risk-aversion and time-preference parameters jointly with the factor distributions for maximum efficiency. I then relate all components of the model in a structural framework where preference and rationality parameters are a function of observed characteristics, underlying factors, and pure unobserved heterogeneity. The following sections describe in turn each of the building blocks of the model.

3.a Preferences

In the RPM framework, an individual's preference parameter is hit by a random shock in each choice task he faces. His "instantaneous" preference is thus composed of an average deterministic part and of a random shock $\epsilon_{i,t}$ which hits individual i in each task t. This essentially makes the preference parameter a random variable centered around its expected value for each individual.

Utility is assumed to be constant relative risk aversion (CRRA). To simplify, I assume 0 background consumption ω and $U(\omega) = 0$ as in Apesteguia and Ballester (2018).[9]

3.a.i Risk Aversion

Risk aversion, in its most basic sense, can be defined such that if an individual is faced with two choices one of which is riskier, his probability of picking the riskier option decreases as his risk aversion rises. A convincing model of choice under risk should therefore predict a monotonically

[9] Using the same experimental dataset, Belzil and Sidibé (2016) compared an "alternative" model with a similar assumption to one where background consumption was either constant at five values between \$5 and \$100 or structurally estimated for each individual in the sample. They find that "the alternative model is capable of fitting the data as well as the standard model". Furthermore, they note only a small difference in estimated risk aversion parameters whether \$5 or \$100 is used for background consumption in their "standard" model (the difference is somewhat larger for the time preference parameter). When they estimate individual coefficients on the parameter, they discover that "a vast majority" of the subjects in the sample use a background consumption reference point that approaches 0.

decreasing relationship between the probability of choosing the riskier option and aversion to risk. Apesteguia and Ballester (2018) demonstrate that the Random Utility Model (RUM) used almost exclusively in previous literature to estimate risk preferences does not satisfy this condition. The RPM, on the other hand, does.

For a lottery with two choices, the first of which offers a payoff a_1 with probability p_{a_1} and payoff a_2 with probability $1 - p_{a_1}$, an individual's expected utility is:

If $\Theta_i \neq 1$

$$E(U_{i,1}) = p_{a_1} * \frac{a_1^{(1-\Theta_i)}}{1-\Theta_i} + (1 - p_{a_1}) * \frac{a_2^{(1-\Theta_i)}}{1-\Theta_i} \tag{1}$$

If $\Theta_i = 1$

$$E(U_{i,1}) = p_{a_1} * ln(a_1) + (1 - p_{a_1}) * ln(a_2) \tag{2}$$

where Θ_i is individual i's coefficient of risk aversion.

The expected utility of the second option $U_{i,2}$ is calculated in a similar fashion. Assume that lottery 1 is less risky than lottery 2 in all lottery choice tasks l=1,...,L that an individual faces. Following Apesteguia and Ballester (2018), one can then define a threshold level of risk aversion, $\Theta_{12,l}$, at which the expected utilities of the two lotteries will be equal for each individual. This threshold will vary depending on the parameters of the two lotteries in each lottery choice task. For each choice task l, agents with a lower level of risk aversion than the associated threshold of indifference will choose the riskier option while those with a higher one will choose the safer option.

Figures 1 and 2 of Section 9.b of the Appendix show the calculated indifference thresholds for each H&L type and OLS type lottery choice task respectively, along with the percentage of the individuals who picked the riskier option on each task.

The 3 sets of H&L design choice tasks share a common set of indifference thresholds $\Theta_{12,l}$. The thresholds are monotonically increasing from Q1 to Q10 in each set of such questions reflecting the increasing attractiveness of the riskier option. As predicted by the RPM model, the percentage of individuals choosing the riskier option is also monotonically increasing. However, while the proportion of the sample who choose the riskier option on questions with a common indifference threshold in each of the 3 sets is similar, it is by no means the same. This observation confirms the necessity of using stochastic shocks in a structural model of observed behavior.

The 5 sets of OLS design choice tasks do not exhibit the same congruence between the monotonic evolution of indifference thresholds and observed choices. While, $\Theta_{12,l}$ are monotonically decreasing from Q1 to Q5 in each set of OLS, the same cannot be said of the percentage of individuals choosing the riskier option. The latter initially increases in Sets 2, 4, and 5 of OLS before starting to fall as predicted. Moreover, in the last question of each OLS choice set the indifference threshold is equal to 0. This means that risk averse individuals should choose the safe option while risk seeking ones should choose the risky option. One wold thus expect a similar percentage of individuals choosing the risky option on each of these five questions. Yet, the actual percentages vary between 14% and 35%, suggesting a very high degree of inconsistency in individual choices. This is in line with observational evidence on choice reversals presented in Figure 2 in the previous section and provides further justification for estimating both preference and rationality parameters in the structural model.

Under the RPM framework the error term is assumed to hit the preference parameter directly.

More formally, assuming a normal distribution of the error terms, the riskier option is preferred in lottery choice task l if:

$$\Theta_i + \sigma_{\Theta,i} * \epsilon_{i,l} < \Theta_{12,l} \tag{3}$$

or, rearranging:

$$\epsilon_{i,l} < \frac{\Theta_{12,l} - \Theta_i}{\sigma_{\Theta,i}} \tag{4}$$

where $\epsilon_{i,l} \sim N(0,1)$ is the shock to individual i's risk preference as he considers lottery choice task l and $\sigma_{\Theta,i}$ is the standard deviation of his risk aversion. Standard deviation of an individual's risk aversion has Θ as subscript to distinguish it from the dispersion of the discount rate which will be discussed in the next section. The lower an individual's $\sigma_{\Theta,i}$, the more consistent are his risk preferences over a set of (similar) choices he has to make. Thus $\sigma_{\Theta,i}$ can be interpreted as a parameter governing the stability of an individual's risk aversion.

The resulting probability of preferring the riskier option has a closed form expression:

$$P(RP_{i,l} = 1) = \Phi(\frac{\Theta_{12,l} - \Theta_i}{\sigma_{\Theta,i}}) \tag{5}$$

where $RP_{i,l}$ is a binary variable which takes on the value of 1 if individual i derives higher expected utility from the riskier option in lottery choice task l than from the safer one.

The probability of preferring the safer option is simply:

$$P(RP_{i,l} = 0) = 1 - P(RP_{i,l} = 1) \tag{6}$$

Notice, that so far I have been talking about an individual *preferring* the riskier option to the safer one rather than actually *choosing* it. While the RPM model has the advantage compared to the RUM of preserving monotonicity in individuals' choices as the value of their preference parameter (here risk aversion) increases, it predicts that dominated choices are never chosen. Because in RPM the error term hits the preference parameter directly, there is 0 predicted probability of choosing an option which no value of risk aversion can make higher utility than its alternative.[10] Yet in reality some individuals do choose such dominated options and we observe this behavior in our experiment.

This is when the *trembling hand* concept comes in handy. Basically one can assume that each individual's hand will *tremble* some percentage of the time and he mistakenly picks his less preferred option when this occurs.[11] Let us call the tremble parameter K_i.

Both $\sigma_{\Theta,i}$ and K_i measure the consistency of an individual's choice. However, there is an important difference between the two. On the one hand, $\sigma_{\Theta,i}$ is related to the stability of preferences. While those can vary somewhat from question to question, given his instantaneous draw of risk aversion, an individual would still be making a calculated rational choice. On the other hand, K_i is more

[10]This is not the case in RUM models where an error term is simply added to the utility and thus any choice can be picked with a non-zero probability assuming it is hit with a sufficiently large draw of the error term.

[11]It is *a priori* unclear whether this occurs because of a simple attention problem, due incomprehension of a given choice task, or whether such behavior may be rational. In the latter case, one could speak of rational inattention. If an individual faces some cost in evaluating the choices before him and payoffs are sufficiently low, he may not wish to spend his mental energy and instead choose randomly.

a measure of an individual's rationality. As it leads him to choose his less preferred option some percentage of the time his choice cannot be logically justified unless he made a mistake or was not paying attention.

Incorporating the tremble parameter, I can finally get an expression for the probability that individual i *chooses* the riskier option in lottery choice task l. He will do so if he actually prefers the riskier option and does not make a mistake or when he prefers the safer option and does make a mistake:

$$P(RC_{i,l}=1)=P(RP_{i,l}=1)*(1-K_i)+[1-P(RP_{i,l}=1)]*K_i \tag{7}$$

where $RC_{i,l}$ is a binary variable which takes on the value of 1 if individual i *chooses* the riskier option in lottery choice task l.

An individual's contribution to the likelihood based on his choice on lottery choice task l thus becomes:

$$P(RC_{i,l}=rc_{i,l})=P(RC_{i,l}=1)^{RC_{i,l}}*P(RC_{i,l}=0)^{1-RC_{i,l}} \tag{8}$$

or, in full:

$$\begin{aligned}P(RC_{i,l}=rc_{i,l})=\{\Phi(\frac{\Theta_{12,l}-\Theta_i}{\sigma_{\Theta,i}})*(1-K_i)+\langle 1-\Phi(\frac{\Theta_{12,l}-\Theta_i}{\sigma_{\Theta,i}})\rangle*K_i\}^{RC_{i,l}}*\\ *\{\langle 1-\Phi(\frac{\Theta_{12,l}-\Theta_i}{\sigma_{\Theta,i}})\rangle*(1-K_i)+\Phi(\frac{\Theta_{12,l}-\Theta_i}{\sigma_{\Theta,i}})*K_i\}^{1-RC_{i,l}}\end{aligned} \tag{9}$$

where Θ_i, $\sigma_{\Theta,i}$, and K_i are assumed to be functions of observed characteristics and unobserved factors. Their exact formulas will be discussed in Section 3.b.

3.a.ii Time Preference

Time preference is treated analogously to risk aversion as in Apesteguia and Ballester (2018). Whether it is risk or delay that people are averse to, when presented with two choices which differ in one or the other dimension one can always identify their threshold value of indifference between the two options. However, in the case of discount rates this value is conditional on an individual's risk aversion.

Once again, an individual's time preference will be characterized not only by its average value but also by its stability across choice tasks. The latter will be embodied by the standard deviation of the discount rate. As before, both the average value of an individual's discount rate and its standard deviation are allowed to depend on observed and unobserved heterogeneity.

An individual will *prefer* the later of two options if the instantaneous draw from his discount rate distribution is less than his threshold level of indifference associated with the particular temporal choice task. He will *choose* the later option if he prefers it and does not make a mistake or if he prefers the immediate payment and does make a mistake. For the full formal exposition of the theoretical model governing choices under delay, please consult Section 10.b of the Online Appendix.

The likelihood contribution of individual i from all his observed choices is the probability of jointly observing his 55 lottery choices and 48 temporal choices:

$$L_i = \prod_{l=1}^{55} P(RC_{i,l} = rc_{i,l}) * \prod_{t=1}^{48} P(LC_{i,t} = LC_{i,t}) \tag{10}$$

where $RC_{i,l}$ is a binary variable which takes on the value of 1 if individual i chooses the riskier option in lottery choice task l and $LC_{i,t}$ is a binary variable which takes on the value of 1 if individual i chooses the later option in lottery choice task t.

3.b Observed Heterogeneity

A major contribution of this paper is to allow the coefficient of risk aversion and the discount rate, as well as their consistency and individuals' propensity to make mistakes, to be functions of observed and unobserved heterogeneity. The former consists of individual characteristics such as sex, age, and language spoken and of unobserved factors related to ability and personality noisily identified by observed measures. The latter is pure unobserved heterogeneity for which no proxies exist in the data. It is assumed to affect the intercept of the preference and rationality parameters. For the precise formulas of the preference and rationality parameters, please consult Section 10.c of the Online Appendix.

The unobserved factors are estimated from multiple observed measures (for seminal work on using factor analysis to estimate cognitive and non-cognitive skills see Cunha et al. (2010). Belzil et al. (2017) provide a more recent application using the present dataset). Each measure is assumed to be a noisy reflection of the underlying factor of interest and the noise to signal ratio of each measure is estimated. This approach allows for a more efficient extraction of information on ability and personality from their measures contained in our experimental data than an alternative approach of constructing a simple index from the observed indicators.

A measure's contribution to the overall likelihood depends on whether the measure is discrete or continuous. In the case of discrete measures, the existence of an underlying latent variable $M_{i,j,f}$ is assumed for each measure j of factor f for individual i:

$$M_{i,j,f} = \gamma_{0,j,f} + \gamma_{1,j,f} * F_{i,f} + \epsilon_{i,j,f} \tag{11}$$

where $\gamma_{0,j,f}$ is the measure population mean, $\gamma_{1,j,f}$ is the loading of factor f in measure j, $F_{i,f}$ is the value of factor f for individual i, and the exogenous error term $\epsilon_{i,j,f}$ represents measurement error and follows a Normal distribution with mean 0 and variance 1.

The factor itself is composed of a deterministic part which contains an individual's characteristics (sex, citizenship status, native language, and age) and of an orthogonal random part:

$$F_{i,f} = \alpha_0 + \alpha_f{}' X_i + \widetilde{F}_{i,f} \tag{12}$$

where $\alpha_f{}'$ is a set of coefficients on the individual's observed characteristics which enter into factor f. The exogenous error term $\widetilde{F}_{i,f}$ follows a Normal distribution with mean 0 and variance σ_f^2, specific to each factor. The assumption that a random effect, here the unobserved factor, is composed of a deterministic part related to individual characteristics and a residual, normally distributed, orthogonal error term was first made by Chamberlain (1980). It allows for a potential correlation between the various factors based on observed characteristics.

A binary measure's contribution to the likelihood function is:

$$P(M_{i,j,f} = m_{i,j,f}) = [1 - \Phi(-\gamma_{0,j,f} - \gamma_{1,j,f} * F_{i,f})]^{M_{i,j,f}} * \Phi(-\gamma_{0,j,f} - \gamma_{1,j,f} * F_{i,f})^{1-M_{i,j,f}} \tag{13}$$

The corresponding probabilities for multi-valued and continuous measures can be found in Section 10.d of the Online Appendix.

3.c Unobserved Heterogeneity

Unobserved heterogeneity is incorporated through 5 unobserved types who differ by the intercepts of their preference and rationality parameters. Each type is thus characterized by a vector of 5 intercepts, one for each parameter of interest. For each individual, the likelihood of observing his particular set of choices on the lottery and temporal choice tasks is calculated for all possible unobserved types. Since here we are talking about pure unobserved heterogeneity, types are assumed to be orthogonal to all other variables in the model and each person is thus equally likely to be any of the unobserved types. His resulting likelihood contribution will thus be a weighted average of the individual type likelihoods, where the weights correspond to each type's prevalence in the overall sample. These are parameters to be estimated.

4 Empirical Methodology

Estimation is done through maximum likelihood. The estimator maximizes the joint likelihood of observing the factor measures and individual choices in the lottery and temporal choice tasks given unobserved factors driving both the observed measures and the choices. As the factors are unobserved, the probabilities from the previous section cannot be calculated directly. The random effects model is used rather than a fixed effects model as we are interested in the effect of the factors on preferences, their stability, and individuals' propensity to make mistakes. Fixed effects would not allow us to distinguish between the impact of ability and personality on the parameters of interest as they are assumed constant for an individual across measures and choices.

As an illustration, take the example of a binary measure. Combining equations 11 and 12, the probability of observing value 1 on binary measure $M_{i,j,f}$ using factor $F_{i,f}$ as a random effect is:

$$\begin{aligned} P(M_{i,j,f} = 1 \Big| \widetilde{F}_{i,f}) &= P\Big(\epsilon_{i,j,f} < \gamma_{0,j,f} + \gamma_{1,j,f} * (\alpha_0 + \alpha_f{}' X_i) + \gamma_{1,j,f} * \widetilde{F}_{i,f} \Big| \widetilde{F}_{i,f}\Big) = \\ &= \Phi\Big(\gamma_{0,j,f} + \gamma_{1,j,f} * (\alpha_0 + \alpha_f{}' X_i) + \gamma_{1,j,f} * \widetilde{F}_{i,f} \Big| \widetilde{F}_{i,f}\Big) \end{aligned} \tag{14}$$

The unconditional probability of observing the binary measure is obtained by integrating out the unobserved factors:

$$P(M_{i,j,f} = 1) = \int_{-\infty}^{+\infty} \Phi\Big(\gamma_{0,j,f} + \gamma_{1,j,f} * (\alpha_0 + \alpha_f{}' X_i) + \gamma_{1,j,f} * \widetilde{F}_{i,f}\Big) * \frac{1}{\sigma_{F_f}} \phi\Big(\frac{\widetilde{F}_{i,f}}{\sigma_{F_f}}\Big) d\widetilde{F}_{i,f} \tag{15}$$

Empirically, the above integral is approximated using 200 independent draws of the orthogonal random part of the factor $\widetilde{F}_{i,f}$ per individual from a normal distribution with mean 0 and variance

$\sigma^2_{F_f}$ which is estimated. A similar logic holds for the approximation of the probability of observing each measure and individual choice. Their likelihood is calculated given each particular random draw of vector $\widetilde{F}_i$ of individual i's orthogonal components of his factor. The loading of the 1st measure of each factor is normalized to 1 to pin down the scale in the probit estimation of factor loadings.

The joint individual likelihood of observing all measures and choices given a particular draw of simulated factors and unobserved type of individual i is:

$$L_i\Big|(\widetilde{F}_i = \widetilde{F}_{i,1}, \widetilde{F}_{i,2}, ..., \widetilde{F}_{i,F}; UT_i = ut_i) = \prod_{f=1}^{F}\prod_{j=1}^{J} P(M_{i,j,f} = m_{i,j,f}\Big|\widetilde{F}_{i,f}) * \prod_{l=1}^{55} P(RC_{i,l} = rc_{i,l}\Big|\widetilde{F}_i, UT_i) * \\ * \prod_{t=1}^{48} P(LC_{i,t} = lc_{i,t}\Big|\widetilde{F}_i, UT_i) \quad (16)$$

where $L_i\Big|\widetilde{F}_i, UT_i$ is the individual likelihood of jointly observing j=1,...,J measures of each factor f=1,...,4, l=1,...,55 lottery choice task decisions, and t=1,...,48 temporal choice task decisions for individual i given a particular draw $\widetilde{F}_i$ of the orthogonal components of his factors f=1,...,F, and assuming a particular value of his unobserved type UT_i. The relevant probabilities for observing each of the aforementioned are given in equation 13 for binary measures, equations 34-36 for multi-valued measures, equation 37 for continuous measures, equation 9 for lottery choice tasks, and in equation 28 for temporal choice tasks[12]. Note that unobserved types only affect choice probabilities on lottery and time choice tasks as each unobserved type is a set of intercepts on the preference and rationality parameters and is assumed orthogonal to both unobserved factors and to the observed measures which proxy for the factors.

One now has a choice whether to first integrate out the unobserved factors or the unobserved types.[13]. I proceed by integrating out the former:

$$L_i\Big|(UT_i = ut_i) = \int_{\widetilde{F}_i} \cdots \int \prod_{f=1}^{F}\prod_{j=1}^{J} P(M_{i,j,f} = m_{i,j,f}\Big|\widetilde{F}_{i,f}) * \prod_{l=1}^{55} P(RC_{i,l} = rc_{i,l}\Big|\widetilde{F}_i, UT_i) * \\ * \prod_{t=1}^{48} P(LC_{i,t} = LC_{i,t}\Big|\widetilde{F}_i, UT_i) * f(F_1, ..., F_F) d\widetilde{F}_i \quad (17)$$

Where $f(F_1,...,F_F)$ is the joint probability of observing the full set of simulated factor values $\widetilde{F}_i$ for individual i. Because the factor draws are assumed independent, I can write:

$$L_i\Big|(UT_i = ut_i) = \int_{\widetilde{F}_i} \cdots \int \prod_{f=1}^{F}\prod_{j=1}^{J} P(M_{i,j,f} = m_{i,j,f}\Big|\widetilde{F}_{i,f}) * \prod_{l=1}^{55} P(RC_{i,l} = rc_{i,l}\Big|\widetilde{F}_i, UT_i) * \\ * \prod_{t=1}^{48} P(LC_{i,t} = LC_{i,t}\Big|\widetilde{F}_i, UT_i) * \frac{1}{\sigma_{F_1}}\phi\Big(\frac{\widetilde{F}_{i,1}}{\sigma_{F_1}}\Big) * ... * \frac{1}{\sigma_{F_F}}\phi\Big(\frac{\widetilde{F}_{i,F}}{\sigma_{F_F}}\Big) d\widetilde{F}_i \quad (18)$$

The above is implemented through simulation by averaging over the 200 factor draws for each

[12]The formulas for multi-valued and continuous measures as well as those for the temporal choice tasks are in Section 10.a of the Online Appendix.

[13]The latter will actually correspond to a finite sum as there is a finite number of discrete unobserved types

individual. The unconditional individual likelihood can then be expressed as:

$$L_i = \sum_{ut=1}^{UT} (L_i \Big| ut) * p_{ut} \tag{19}$$

where p_{ut} is the prevalence of unobserved type ut in the overall population. Since this is pure unobserved heterogeneity, each person is equally likely to be any of the unobserved types and thus p_{ut} is not indexed by i. His resulting likelihood contribution is a weighted average of the likelihoods calculated for each type where the weights correspond to the prevalence of each type in the overall population.

Finally, the log of the average individual likelihoods is summed up across all individuals to yield the objective function to be maximized. As the objective function is complicated and not necessarily smooth across all parameters, estimation is repeated with many random starting values and the result of the maximization with the highest value of the objective function is retained. Reassuringly, in simulations this leads to the recovery of the true underlying structural coefficients of the model.

5 Empirical Results

The empirical results presented below come from two distinct structural specifications of the model presented in the previous section. The first specification shall be referred to as the **fixed effects model**. It is estimated by maximizing the likelihood, described in equation 10, of observing each individual's choices on the lottery and temporal choice tasks. Estimation is performed individual by individual. This means that each of the 1,224 test subjects will have an estimated vector of five preference and rationality parameters. This specification does not use a factor structure nor does it parametrize preferences as a function of observable characteristics and personality traits.

The second specification shall be referred to as the **full model**. It is estimated by maximizing the likelihood of observing each individual's choices as well as his responses to questions designed to measure his personality (see equation 19). Results are obtained using simulated maximum likelihood. This specification includes observed and unobserved heterogeneity and allows me to map economists' preference parameters onto psychologists' personality traits.

The two specifications are complementary. The fixed effects model provides individual point estimates of the preference and rationality parameters. These can later be used in regression analysis to estimate their impact on various outcomes. The full model does not provide individual estimates of the parameters of interest. However, it enables me to link the parameters of interest to measures of observed and unobserved heterogeneity. Both specifications yield distributions of preference and rationality parameters. The first one through direct estimation and the second one through simulation based on estimated values of the structural parameters. These will be used as a point of comparison in the subsections below.

Results are broken down by those concerning deep economic preference parameters (risk aversion and discount rates) and rationality parameters (those governing the stability of preferences and the propensity to make mistakes).

5.a Preference Parameters

Results from the full model summarized in Figure 3 below reveal that an average individual[14] in the population has approximately logarithmic risk aversion and a 20% discount rate. Interestingly, the average woman is more risk averse and more patient than the average man.

Figure 3: Parameter Values for the Average Person

	Prevalence	Risk Aversion	Risk Aversion SD	Discount Rate	Discount Rate SD	% Hand Trembles
Average		1,14	0,59	0,20	0,25	0,05
Female Average		1,18	0,58	0,18	0,22	0,05
Male Average		1,08	0,61	0,23	0,28	0,04
Type 1 Average	0,08	5,00	1,00	0,01	0,00	0,08
Type 2 Average	0,32	1,05	0,64	0,01	0,01	0,04
Type 3 Average	0,13	-0,14	0,32	0,79	1,00	0,02
Type 4 Average	0,24	0,24	0,38	0,69	0,56	0,14
Type 5 Average	0,24	0,47	0,39	0,29	0,23	0,02

One of the advantages of the structural model is that it allows us to move beyond simple observed heterogeneity. Indeed, the impact of unobserved types turns out to be important. Approximately half of the population (types 4 and 5) have moderate rates of risk aversion and impatience. The most prevalent type (type 2) has logarithmic risk aversion and is very patient. There is also one risk seeking type (type 3) who is at the same time quite impatient. One could call them the daredevils. This type represents 13% of the population which falls within the range of approximately 10-20% of individuals who make choices consistent with risk-seeking preferences on the lottery choice tasks (see Section 9.b of the Appendix for more details). Finally, 8% of the population are fully risk averse and very patient (type 1).

These results suggest that the inclusion of unobserved types is warranted and necessary to explain heterogeneity in observed choices. However, one can move beyond examining simple population moments and look at the full distribution of preferences in the population. This is easily done using results from the fixed effects model. With the full model, the task is more challenging: we need to use its estimated structural parameters and construct a simulated dataset.[15]

Figure 4 superposes the distributions of preference parameters estimated using alternatively the fixed effects model and the full model. They are remarkably similar. Notably, the medians (marked by the dashed lines) of the two distributions for each parameter are very close. The median value of risk aversion is 0.67 using the fixed effects model and 0.56 using the full model while the median value of the discount rate is 0.21 using both. These results are coherent with previous estimates (Harrison and Rutstrom, 2008; Andersen et al., 2014; Belzil and Sidibe, 2016; Cohen et al, 2016). The distribution of the risk aversion parameter in the population resembles normality.[16] The discount rate distribution is skewed towards zero (patient individuals) but the full range up to 1 is covered and there is a spike at the upper end.[17] It reflects the fact that a non-negligible portion

[14]An average person is defined as being average on each of the attributes - 46% male, speaking 68% English,...

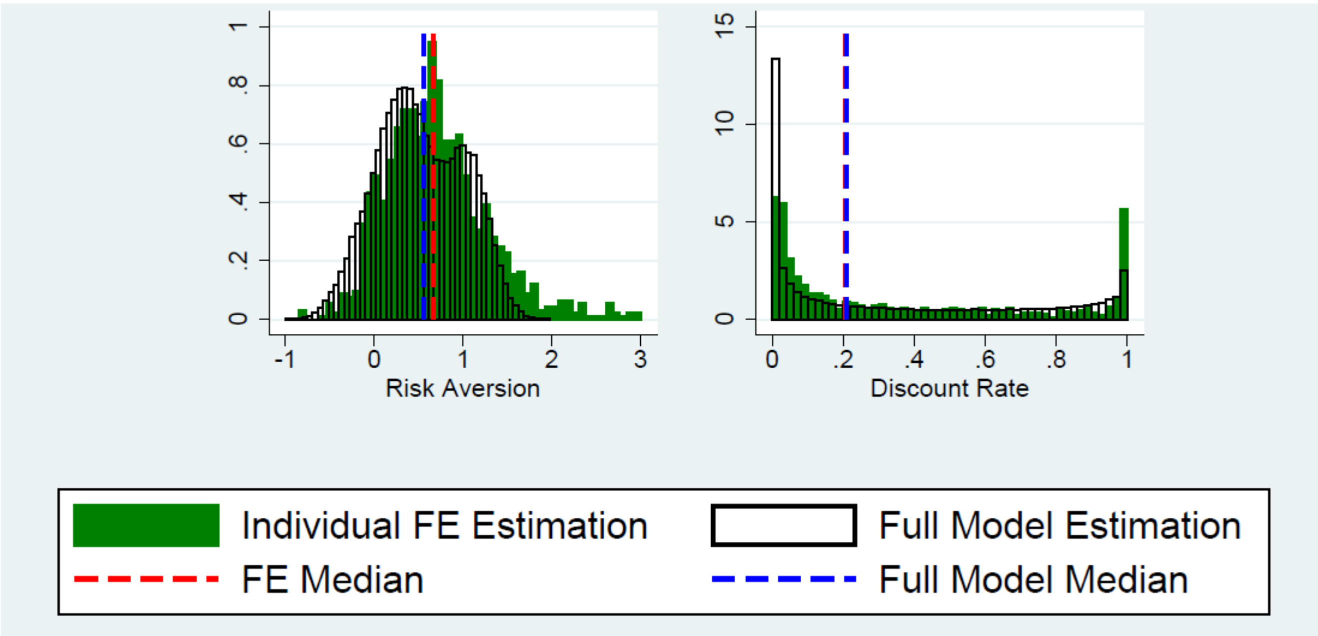
[15]The simulation is performed exactly according to the model presented in Section 3. It uses observed characteristics of individuals in the data with each individual being drawn 100 times. The unobserved types are assigned randomly using their respective estimated prevalences in the population summarized in Figure 3.

[16]In both the fixed effects estimation and the full model simulation, risk aversion is capped at -1 on the low end and at +5 at the high end. The displayed chart only goes through risk aversion of +3 as the overwhelming majority of observations fall within this range. There is a spike again at +5 as a result of the existence of individuals choosing all or almost all safe options. These are the "type 1".

[17]The spike at the upper bound does not disappear if the upper bound on discount rates is relaxed up to +3 in the fixed effects estimation. This is indicative of the existence of *fully impatient* individuals in the sample.

of the individuals choose either all immediate or all distant payments as described in the Data Section 2.

Figure 4: Sample Distributions of Risk and Time Preferences



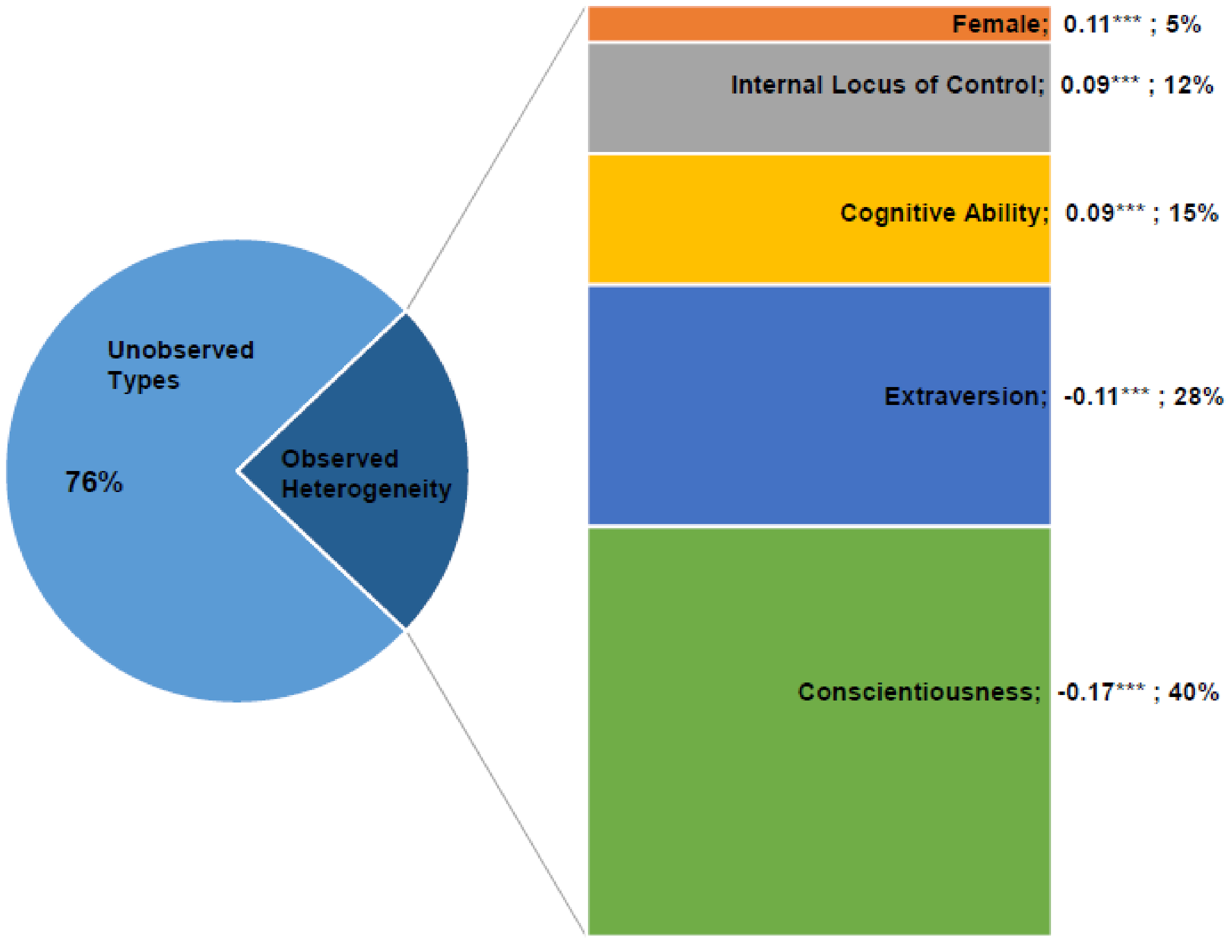
5.a.i Link with Personality Traits

Results from the structural model confirm and quantify the supposed relationship between preferences and personality traits. The few a priori expectations that one might have had on the signs of the coefficients are confirmed - extraversion (measured here in large part through the facet of self-reported risk seeking behavior) decreases risk aversion, conscientiousness (measured here in large part through the facet of being able to delay gratification) decreases discount rates, and cognitive ability reduces the propensity to make mistakes. Furthermore, these personality traits and ability explain a non-negligible part of the variation in preference and rationality parameters. While these findings may seem intuitive, they should not be taken for granted as existing empirical evidence is tenuous even for the most intuitive relationships between traits and preferences. [18]

Figure 5 illustrates the contribution of observed and unobserved heterogeneity to the overall cross-sectional variation in risk aversion. It includes both the estimated marginal effects of sex, ability, and personality traits; and the percentage of variation in risk aversion attributed to observed heterogeneity that each of them explains.

[18] For example, while Bibby and Ferguson (2011) find a significant effect of extraversion (which is related to reported risk-seeking tendencies) on their measure of risk aversion, Eckel and Grossman (2002) find no significant effect.

Figure 5: Heterogeneity in the Coefficient of Risk Aversion



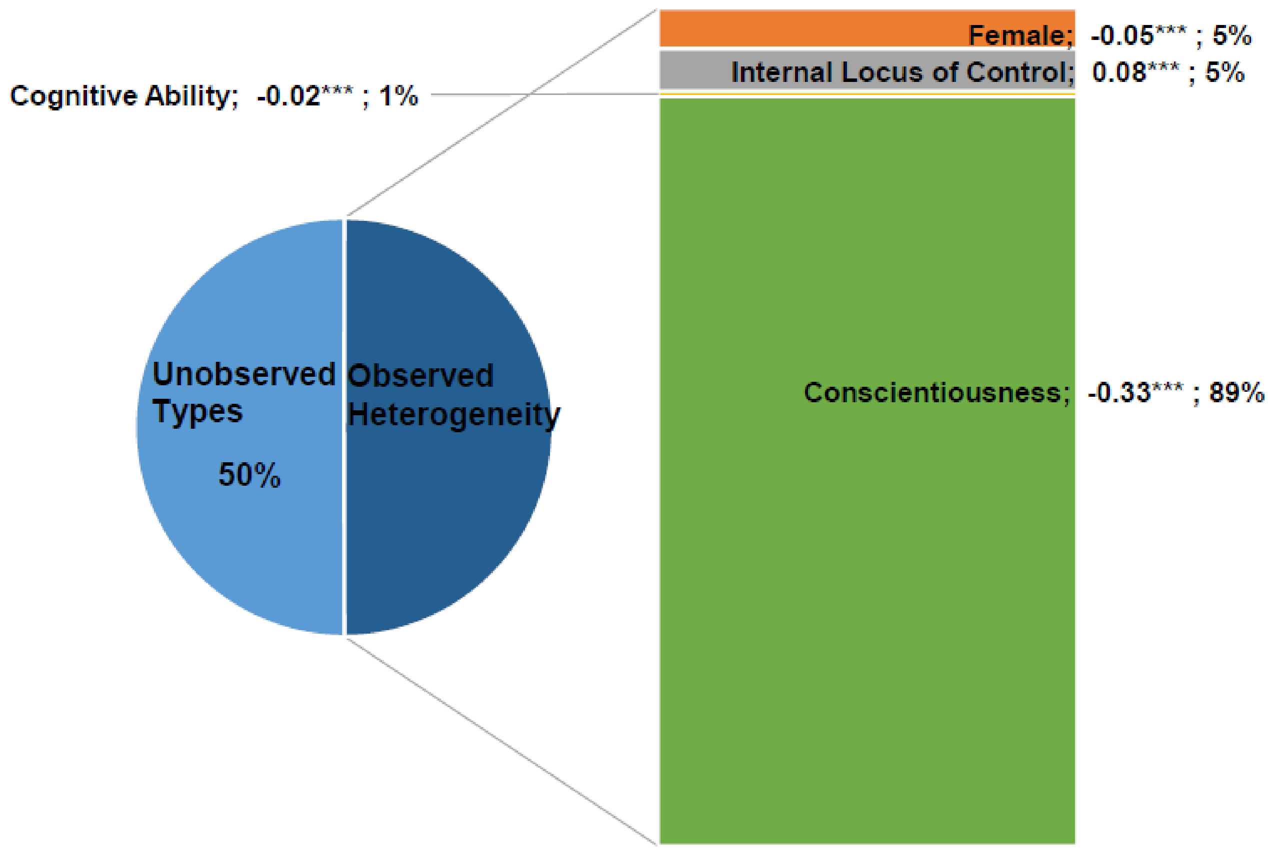
For observed heterogeneity, the first value corresponds to the marginal effect of changing each factor by 1 standard deviation (and sex from male to female) on risk aversion; the second value gives the percentage contribution of each heterogeneity component to the overall explanatory power of observed heterogeneity.

Observed heterogeneity explains one quarter of the population variation in risk aversion.[19] The conscientiousness and extraversion personality traits have the highest explanatory power. The coefficient on extraversion is negative. This seems reasonable as questions measuring this personality trait are in large part related to self-reported real-world risk- and thrill- seeking behavior. The marginal effect of changing extraversion by 1 standard deviation is a 0.11 decrease in the coefficient of risk aversion. This represents a 20% decrease from its estimated median value and a 12% decrease from the average value. The coefficient on conscientiousness is also negative and its marginal effect is even stronger than the one on extraversion. I can explain its sign through its estimated link with time preference (higher conscientiousness individuals tend to be more patient and thus also more willing to accept risk as they adopt a longer-term perspective). In contrast, higher cognitive ability, internal locus of control, and being female increase risk aversion.

Observed heterogeneity explains half of the cross-sectional variation in discount rates. This can be seen in Figure 6.

[19] As above, values of risk aversion above 3 are excluded from the analysis. These extreme values can be entirely attributed to unobserved type 1 which represents 8% of the population with limit values of risk aversion. It is a result of the fact, that some individuals choose all safe choices on the 55 lottery choice tasks in the experiment.

Figure 6: Heterogeneity in Discount Rates



For observed heterogeneity, the first value corresponds to the marginal effect of changing each factor by 1 standard deviation (and sex from male to female) on the discount rate; the second value gives the percentage contribution of each heterogeneity component to the overall explanatory power of observed heterogeneity.

Conscientiousness once more possesses the highest explanatory power. In fact, it explains 45% of the total cross-sectional variation in time preference. It also has a very high estimated marginal effect. Conscientious individuals have lower discount rates and are thus more patient. The sign of the relationship is as expected given that the conscientiousness trait is related to a self-professed capacity to delay gratification. The relative contributions of sex, ability, and of the remaining personality traits to people's time preference is much lower. Their estimated coefficients suggest that females and individuals with high cognitive ability tend to be more patient whereas those with a high internal locus of control tend to have higher discount rates. Finally, the extraversion trait does not map onto time preference.

Interestingly, on the one hand fully risk averse individuals who can be identified in the population by always choosing the safer option coincide perfectly with unobserved type 1. On the other hand, no single unobserved type fully explains extreme delay aversion. One can thus conclude that personality traits, cognitive ability, and gender partially explain extreme time preferences but not extreme risk preferences.

Figure 4 of the Appendix shows the estimated raw coefficients for equations 29-33 along with their associated standard errors.[20]

5.b Rationality Parameters

This section presents results on the rationality parameters. The first two parameters govern the stability of an individual's preferences. They represent the standard deviation of an individual's

[20]Standard errors are estimated through bootstrap with 200 redraws.

risk and time preference respectively. The last one is the trembling hand parameter. It represents the percentage of time that an individual makes a mistake i.e. when he in fact chooses his less preferred option.

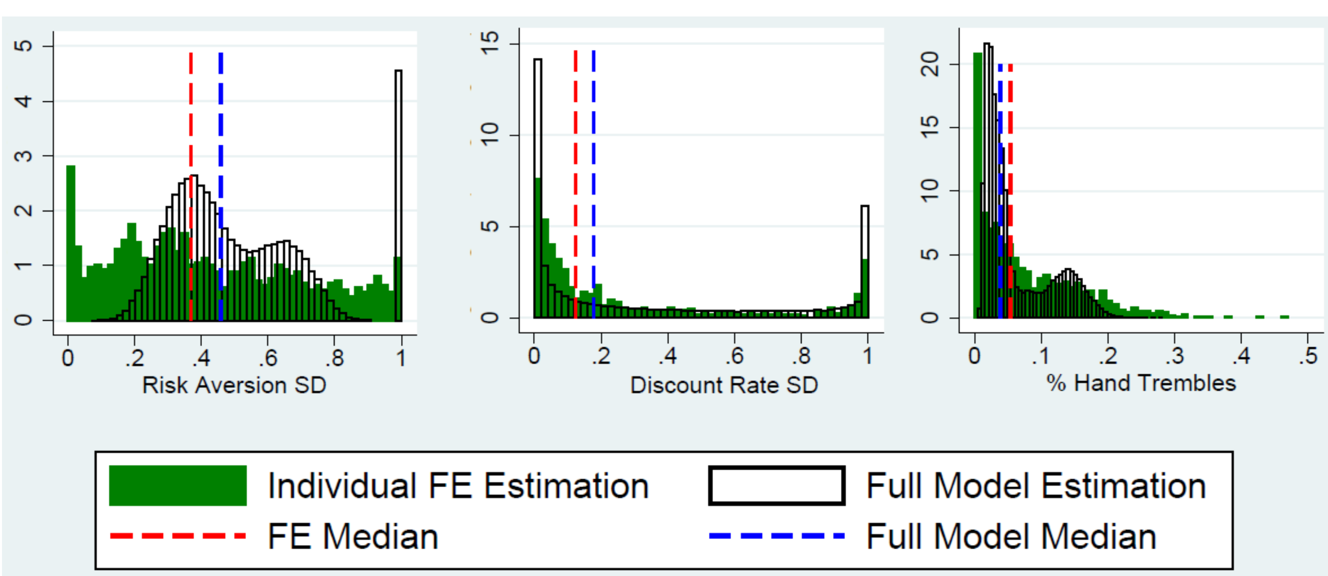
Overall, individuals' preferences seem to vary significantly between choice tasks. As can be seen in Figure 3, an average individual has a standard deviation of approximately 0.6 on his coefficient of risk aversion and of 0.25 on his discount rate.[21] While the stability of risk preferences is unaffected by gender, women's time preferences are a little more stable than men's on average.

Once more, the impact of unobserved heterogeneity is important. Approximately 60% of the population (types 3, 4, and 5) have a low level of instability in their risk preference with a standard deviation of around 0.3, 30% have a moderate level of instability, and the remaining 8% have a standard deviation of 1 (the maximum).[22] The dispersion is even wider with discount rates: 40% of the population have completely stable time preference, half have moderate levels of instability, and 13% have very unstable time preferences.

The trembling hand parameter varies a lot less in the population. An average person chooses his less preferred option 5% of the time and men make slightly fewer mistakes than women. About two thirds of the population behave rationally over 95% of the time while one quarter choose their less preferred option in over 10% of the choice tasks.

Figure 7 plots full population distributions of the rationality parameters. Once more, distributions estimated from the fixed effect model and from the full model are superposed for comparison purposes. The two models yield different distributions of the standard deviation of individuals' risk aversion. On the one hand, using the fixed effects model the estimated distribution looks almost uniform. On the other hand, its simulated counterpart is the union of multiple normal distributions centered around the unobserved types' intercepts. The distribution of the standard deviation of the discount rate resembles that of the discount rate itself. It is heavily skewed towards 0 but has a fat tail. Finally, the distribution of the kappas is also heavily skewed towards zero but has almost no mass beyond 0.2.

Figure 7: Sample Distributions of Rationality Parameters



It is not surprising that distributions obtained using the two models diverge more than in the

[21] As a reminder, the distribution of the errors is assumed normal for risk preference and lognormal for time preference.

[22] Since this last group is also the one which is fully risk averse, a large standard deviation on the coefficient of risk aversion (or the trembling hand) is necessary to explain them choosing the risky option at least some of the time.

case of preference parameters. Rationality parameters are identified from the *inconsistencies* in individual behavior. In the context of the present experiment, they manifest themselves either in choice reversals within a choice set or, more subtly, in inconsistent switching points between choice sets. While both exist (as documented in Section 2 describing the data), they are but deviations from the norm and most individuals exhibit relatively few such deviations. The fixed effect model which is estimated individual by individual, can thus be expected to be quite noisy in this case. Therefore estimated distributions of rationality parameters using individual fixed effects should be viewed with some caution.[23] This should be less of an issue in the full model which parametrizes the rationality parameters as a function of observed and unobserved heterogeneity and thus pools information from all individuals' choices.

5.b.i Link with Personality Traits

High conscientiousness makes risk and time preferences more consistent and explains 19% and 30% respectively of individual heterogeneity in their standard deviation[24]. The marginal effect of conscientiousness on the standard deviation of the discount rate is stronger than on the standard deviation of risk aversion. Sex and internal locus of control explain another 1-2% of the variation each, although their impact goes in opposite directions. Females have slightly more stable preferences whereas individuals with a high internal locus of control display less stability in their risk and time preferences. Cognitive ability is the only factor which pushes the stability of risk and time preferences in opposite directions. It increases the former and lowers the latter. While it explains 7% of the variation in the standard deviation of risk aversion, it has negligible explanatory power in the case of discount rates. Finally, individuals with high extraversion have slightly more stable risk preferences. These results are summarised in Figures 6 and 7 of the Online Appendix.

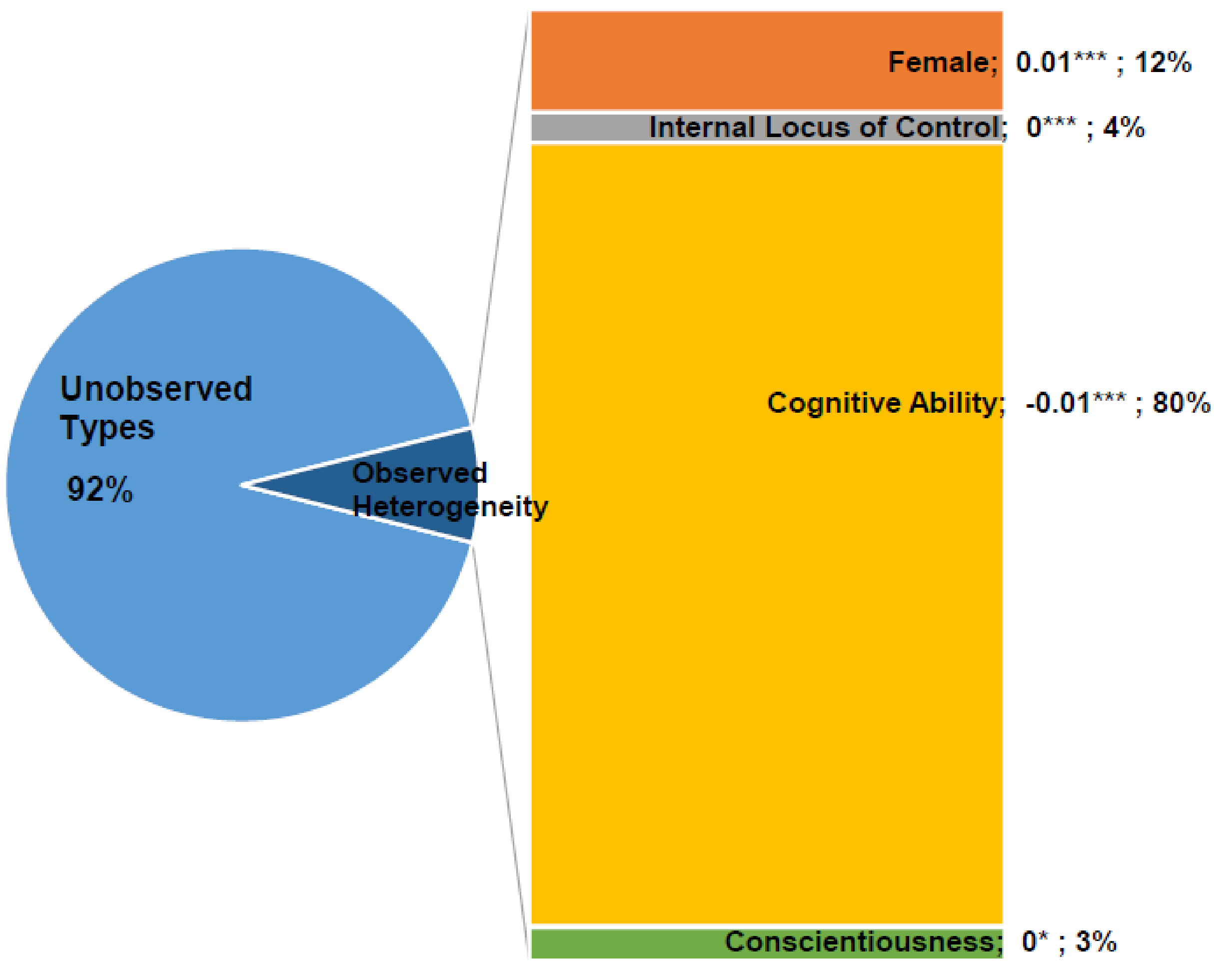
The trembling hand parameter is the only one amongst all the preference and rationality parameters for which the conscientiousness trait is not the factor with the highest explanatory power (see Figure 8 below). In fact, its impact is negligible. This time, cognitive ability comes in first place and is responsible for a majority of the explained variation in individuals' propensity to make mistakes in their choices. It accounts for 80% of the variation explained by observed heterogeneity and 6% of the total cross-sectional variation in the parameter. Unsurprisingly, individuals with higher cognitive ability behave more rationally. A one standard deviation increase in cognitive ability reduces the propensity to make mistakes by one percentage point which corresponds to a quarter of its estimated median value in the population. This suggests that some individuals face cognitive hurdles when evaluating the risk and temporal choice tasks in this experiment. In fact, combined with the insignificant coefficient on conscientiousness, one might conclude that individuals make wrong choices not simply due to inattention but because they do not well understand the task at hand. This supports Andersson et al.'s (2016) finding that cognitive ability ability may be related to "random decision making". Thanks to my use of a complete structural model, I am able to clarify and quantify this relationship. Furthermore, by explicitly modeling the role of mistakes in decision making I am able to address their concern that the correlational studies which previously reported a relationship between cognitive ability and risk aversion had both biased estimates of risk preferences and of their relationship to explanatory variables.

[23]For this reason, the fixed effect estimation was also performed using a fixed value of 0.4 for the standard deviation of risk aversion and of 0.3 for the standard deviation of the discount rate. Results on the distributions of risk aversion, discount rates, and kappa were qualitatively unchanged.

[24]As with the coefficient of risk aversion, the analysis of its standard deviation excludes observations attributed to unobserved type 1 which represents 8% of the population and exhibits limit values of risk aversion.

The remaining components of observed heterogeneity have only a marginal impact on the trembling hand parameter (of those, sex is the most influential, with women making slightly more mistakes than men).

Figure 8: Heterogeneity in Individuals' Propensity to Make Mistakes



For observed heterogeneity, the first value corresponds to the marginal effect of changing each factor by 1 standard deviation (and sex from male to female) on the trembling hand parameter; the second value gives the percentage contribution of each heterogeneity component to the overall explanatory power of observed heterogeneity.

5.c Preference vs. Rationality Parameters in Observed Choices

Having estimated the distributions of preference and rationality parameters and mapped them onto personality traits, one important question still remains. Which of the two - preference or rationality parameters - better explain observed individual choices and how does their explanatory power compare to a standard set of demographic and socioeconomic controls.

In order to answer this question, I take key moments of the distribution of individual choices and regress them on estimated preference and rationality parameters from the fixed effects model and on 18 demographic and socioeconomic variables. The R2 from these regressions represents the proportion of the variation in each choice moment explained by the parameters included in the regression. These are simple linear regressions and the model implies that the estimated parameters enter choices in a non-linear fashion. Nevertheless, they serve as a useful approximation.

Figure 9 presents first the R2 of regressions with the demographic and socioeconomic variables. Their explanatory power in terms of observed individual choices is marginal and an order of magnitude smaller than that of the model's structural preference and rationality parameters shown in the second row. This confirms the unique explanatory power of preferences when it comes to choices between risky or temporally separated payments. Subsequent rows break down the explained part of the variation in choices through the five estimated parameters into parts explained by preference and rationality parameters respectively. This lets us compare their relative explanatory power. It is included in the table below, expressed as a percentage. Finally, rationality parameters are broken down by "stability" parameters - the standard deviation of risk aversion and of the discount rate - and by the trembling hand parameter related to people's tendency to make mistakes.

Preference and rationality parameters estimated using the fixed effects model together explain over 50% of the overall variation in observed individual choices on both lottery and temporal choice tasks. Both the total (and therefore also average) number of "safe" and "immediate" picks[25] are overwhelmingly explained by preference parameters. In the case of the temporal choice tasks, both the coefficient of risk aversion and the discount rate play a role. The discount rate dominates, as expected - for a breakdown of the percentage contributions by individual parameters, see Figure 5 of the Appendix.

Rationality parameters also play a role in explaining choices. They account for approximately 15% of the explained variation of the total number of safe choices on lottery choice tasks compared with less than 5% of the explained variation in the total number of immediate payments on temporal choice tasks. In both cases, randomness in individual decisions impacts average choices mainly through preference instability. Furthermore, choice reversals (for example switching back to the safe option after having already picked the risky one on a given set of lottery choice tasks even though the risky option became even more attractive, evidence of a form of irrationality) presented in the last two columns of Figure 9 seem to be largely due to mistakes which people make. Indeed, over 90% of the explained variation in the population distribution of choice reversals is attributable to the trembling hand parameter.

Figure 9: Explanatory Power on Observed Choices of Preference and Rationality Parameters vs. Demographic and Socioeconomic Variables

		# Safe Choices	# Immediate Payments	# Risk Reversals	# Time Reversals
Demographic and Socioeconomic Variables	R2	0.04	0.06	0.02	0.02
All Parameters	R2	0.71	0.54	0.51	0.04
Preference Parameters		85.2%	97.6%	1.5%	8.7%
Rationality Parmeters		14.8%	2.4%	98.5%	91.3%
- Stability		90.0%	83.0%	0.1%	7.4%
- Mistakes		10.0%	17.0%	99.9%	92.6%

Notes: The rows labeled "R2" list the R2 of the regression of the moment listed in each column title alternatively on 18 demographic and socioeconomic variables and on the 5 estimated structural preference and rationality parameters. Demographic variables include the students' sex, age, language number of siblings living with him, his parents' age, as well as information on whether he was born in Canada and whether he is of aboriginal origin. Socioeconomic variables include parents' level of education and income.
The rows below represent the relative explanatory power of the relevant subgroups of parameters, expressed as a percentage.

5.d Factor Determinants

The estimated coefficients from the factor equations are displayed in Figure 10 below. R2 here never exceeds 5% indicating that the orthogonal component of the factors dominates the one re-

[25] As before, a "safe" choice is defined as picking the less risky of two lotteries in a given lottery choice task and an "immediate" choice is defined as picking the less distant of two options in a given temporal choice task.

lated to observable characteristics. This is consistent with the *Big Five* personality traits being initially constructed as to be a parsimonious representation of personality through five orthogonal components predictive of behavior (Goldberg, 1990). The internal locus of control and cognitive ability factors have estimated standard deviations of around 0.3 while the extraversion and conscientiousness factors have estimated standard deviations of around 0.9. Being female is associated with lower extraversion and with higher conscientiousness. Both these personality traits are higher for native English speakers and for older individuals (with peak extraversion at age 18). The remaining coefficients on observable characteristics are small.

Figure 10: Estimated Coefficients On Factor Components

	Female	English	Age==17 (15&16 omitted)	Age==18	Age>=19	R2	Standard Deviation	Implied Sample Average
Internal Locus of Control	-0,05	0,01	0,06	0,06	0,06	0,01	0,35	-0,11
Cognitive Ability	0,02	0,01	0,10	0,02	-0,01	0,02	0,30	1,62
Extraversion	-0,35	0,08	0,07	0,26	0,19	0,05	0,90	-0,11
Conscientiousness	0,26	0,17	0,16	0,14	0,15	0,05	0,83	0,15

Estimated factor loadings for each measure are positive, consistent with the assumption that each set of measures is associated with one underlying factor. As can be seen in Section 9.a of the Appendix, the magnitudes of the loadings vary widely. This suggests that some questions measure more closely the underlying ability and personality traits while others contain more noise. It confirms the usefulness of using a factor model to address measurement errors inherent in indicators for ability and personality (see for example Cunha and Heckman, 2009). A simple additive score based on the measures of each trait often used in previous literature would seem insufficient in this case.

6 Discussion

This paper provides strong empirical evidence on the hypothesized link between economic preferences and psychological personality traits. A rich unique dataset combined with the use of factor analysis and of the random preference model allows me to better account for measurement error and for the random components of decision-making. I am thus able to show that ability and personality explain a much larger share of the variation in preferences within and across individuals than previously supposed.

I use a factor model to address measurement error in indicators for ability and personality. This ensures a more efficient extraction of information on the underlying factors of interest contained in the numerous measures available in my dataset. One obvious advantage over simply using an additive score of the measures for each trait is that I can explicitly allow for the possibility that some indicators are closer measures of a particular personality trait than others. This turns out to be the case and is reflected in the estimated loadings on the measures of each of the factors. Furthermore, I allow the factors to depend on observable characteristics. While I find that the orthogonal random component explains most of the variation in personality traits, this feature allows for potential correlation between individual traits.

With information from 103 incentivized choice tasks per individual, I am able to estimate not only risk and time preferences but also their individual-level stability and people's propensity to make mistakes. This allows me to address the problem identified by Andersson et al. (2016) who show that random components of decision-making, if not controlled for, can lead to biased estimates of both risk aversion and of its relationship to observed heterogeneity. I document a relationship between preference instability and conscientiousness and between the making of mistakes and cognitive ability supporting the notion that these two types of randomness are fundamentally separate and related to individuals' biological characteristics. I also find that almost a quarter of the cross-sectional variation in risk aversion and half of the variation in discount rates can be explained by variation in individuals' conscientiousness and extraversion. I am thus able to establish a formal mapping between three of the *Big Five* personality traits and cognitive ability on the one hand and risk aversion, discount rates, and parameters governing their stability and individuals' propensity to make mistakes on the other hand. In so doing, I fill the gap in the literature identified by Almlund et al. (2011) and reiterated by Mata et al. (2018).

Using unobserved types in the structural model, I quantify the relative importance of observed and unobserved heterogeneity. The latter still explains a majority of the population variation in both preference and rationality parameters. This suggests that economists' preferences cannot be reduced to a mere extension of psychologists' personality traits. Both concepts are important, distinct while related, and merit further study.

The population distributions of the estimated parameters have relatively high mass concentrations at their extremes. This is in line with observed choices on both lottery and temporal choice tasks where a number of individuals make choices consistent with limit values of risk and time aversion. It highlights the importance of looking at more than just the population average of the preference and rationality parameters. Indeed, if only one population moment were to be chosen, the median seems preferable to the mean. However, an examination of the full distribution seems warranted and I recommend that it be used in future research aimed at predicting the impacts of economic policy and calculating their welfare implications.

I demonstrate that the estimated structural preference and rationality parameters explain a majority of the variation in individuals' observed choices under risk and delay. In contrast, a standard set of demographic and socio-economic variables has negligible explanatory power. This confirms that preferences contain useful information which is not captured by commonly used controls and should be included in reduced form econometric models when possible to reduce omitted variable bias.

With information on over 100 incentivized choices for each individual, I am able to provide population distributions of the parameters of interest obtained both through fixed effects estimation and through simulation using estimated coefficients for the full model with observed and unobserved heterogeneity. The fact that both methods produced similar results is reassuring. It also suggests, that with only information on individuals' ability, personality traits, and estimates of the distribution of unobserved types found in a population, one can obtain a reasonable prediction of that population's distribution of preferences towards risk and time. This is an important finding as controls for ability and traits are more easily obtainable than those on preferences which in general require a large and expensive set of incentivized choice tasks for each individual.

The estimates of distributions of risk and time preferences look reasonable given the actual distributions of observed choices and all three à priori expectations regarding the mapping of the structural parameters onto cognitive ability and personality traits (a negative link between risk aversion and extraversion, between the discount rate and conscientiousness, and between the propensity to make mistakes and cognitive ability) are confirmed by the estimates. These results demonstrate that the Random Preference Model can be used to obtain reasonable estimates of the distributions of preferences and of their relationship with explanatory variables. I thus provide a "proof of concept" for estimating and explaining the population heterogeneity in preferences and in individuals' capacity to make consistent rational choices using the RPM.

7 Conclusion

This paper is the first piece of structural research mapping economists' preference and rationality parameters onto ability and psychologists' personality traits incorporated as latent factors. It uses the Random Preference Model (RPM) and factor analysis to deal with measurement error and the random components of decision-making. I thus address the potential bias in previous risk aversion estimates and in their relationship to observed heterogeneity identified by Andersson et al. (2016). Using the RPM to structurally estimate population distributions of risk aversion and discount rates as well as of parameters governing their stability and individuals' propensity to make mistakes is in itself a contribution to the existing literature. The median coefficient of risk aversion is estimated at 0.56, the median discount rate is 21%, and the median individual makes mistakes 5% of the time. However, there is significant heterogeneity in risk and time preferences in the population and also in their individual-level stability.

Depending on the parameter in question, up to 50% of the variation in risk aversion, discount rates, and parameters governing their stability and individuals' rationality can be explained by cognitive ability and personality traits. Conscientiousness is the trait with the highest overall explanatory power, in line with previous results on the predictive potential of personality traits on real-world outcomes. It explains 45% of the cross-sectional variation in discount rates, 10% of the variation in risk aversion, and 20% of the variation in their individual-level stability. The à priori expected relationships (reported risk-seeking tendency and risk aversion, reported capacity to delay gratitude and discount rates, cognitive ability and the propensity to make mistakes) are all confirmed in the results, lending them further credibility. Nevertheless, individuals' preferences, their stability, and people's propensity to make mistakes remain to a large part a function of unobserved heterogeneity. One can thus conclude that economists' preferences and psychologists' personality traits are related but distinct concepts.

Establishing a precise mapping between the bodies of knowledge created by economists and psychologists (around what they each view as stable individual characteristics predictive of behavior in a wide array of situations) has interest beyond satisfying intellectual curiosity. First of all, it allows us to better understand the mechanism through which preferences, ability, and personality influence outcomes. The finding of a strong link between preferences and traits suggests that they work not only side by side but also through one another. It could be used to, for instance, disentangle the direct effect of personality on human capital investment through its impact on an individual's costs and benefits of schooling from its indirect effect due to its correlation with economic preferences. Second, I demonstrate that preferences have higher explanatory power in terms of observed choices under risk and delay than a standard set of demographic and socio-economic variables. While in reduced-form empirical work on outcomes it would often be ideal to add controls for preferences alongside this standard set of socio-demographics, I show that simply controlling for personality and ability could come a long way when information on preferences is not available. Indeed, this may be the practical solution in many contexts as psychological traits are generally cheaper and easier to elicit than economic preferences. Finally, the mapping of preferences to traits along with findings from psychology, biology, and neuroscience on the stability and heritability of personality and cognitive ability has implications for the inter-generational transmission of inequality and could enrich the burgeoning literature on the transmission and malleability of economic preference parameters in the population. The large estimated heterogeneity in individuals' propensity to make inconsistent or erroneous choices along with its implied negative impact on individual welfare may also induce policy-makers to protect at-risk individuals from sub-optimal choices.

In future work, it would be desirable to apply my methodology to a random sample of the US population. One the one hand this would be a test of the robustness of my results on the mapping between preferences to ability and personality traits in the wider population. On the other hand, it would enable the estimation of the general distributions of risk and time preferences and of their associated stochastic components which could then be used to calibrate structural microeconomic and macroecnomic models and to estimate the expected welfare impacts of policy. Furthermore, it would be nice to test the external validity of the estimated coefficients and see whether they can be used to better explain heterogeneity in economic outcomes. Finally, it could be useful to extend the model by incorporating behavioral elements such as probability weighting and allowing for time inconsistent behavior.

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9 Appendix

9.a Factor Measures

Factor	#	Measure	Type	Sign Reversal	Loading
Internal Locus of Control	1	When I make plans they work out as I expect.	binary		1,00
	2	Fate (luck) usually determines what happens to me.	binary	x	1,09
	3	Hard work is the key to success.	binary		0,61
	4	You have little control over the things that happen to you.	multi-valued	x	2,51
	5	There is really no way you can solve some of the problems you have.	multi-valued	x	3,12
	6	There is little you can do to change many of the important things in your life.	multi-valued	x	4,80
	7	You often feel helpless in dealing with the problems of life.	multi-valued	x	4,47
	8	Sometimes you feel that you are being pushed around in life.	multi-valued	x	2,17
	9	What happens to you in the future mostly depends on you	multi-valued		0,79
	10	You can do just about anything you really set your mind to do	multi-valued		1,31
Cognitive Ability	1	In your last year of high school, what was your overall grade average, as a percentage?	multi-valued		1,00
	2	How would you rate your ability to use a computer? For example, using software applications, programming, or using a computer to find or process information.	multi-valued		3,95
	3	How would you rate your writing abilities? For example, writing to get across information or ideas to others, or editing writing to improve it.	multi-valued		4,20
	4	How would you rate your reading abilities? For example, understanding what you read and identifying the most important issues, or using written material to find information.	multi-valued		1,94
	5	How would you rate your oral communication abilities? For example, explaining ideas to others, speaking to an audience, or participating in discussions.	multi-valued		2,13
	6	How would you rate your ability to solve new problems? For example, identifying problems and possible causes, planning strategies to solve problems, or thinking of new ways to solve problems.	multi-valued		1,42
	7	How would you rate your mathematical abilities? For example, using formulas to solve problems, interpreting graphs or tables, or using math to figure out practical things in everyday life.	multi-valued		2,00
	8	Numeracy Test Score	continuous		1,17
Openness to Experience		Likelihood of ...			
	1	Exploring an unknown city or section of town.	binary		1,00
	2	Speaking your mind about an unpopular issue at school.	binary		0,34
	3	Crossing a frozen lake with a car or a snowmobile.	multi-valued		0,69
	4	Eating "expired" food products that still "look okay."	multi-valued		0,29
	5	Going camping in the wild.	multi-valued		0,61
	6	Engaging in unprotected sex.	multi-valued		0,82
	7	Never wearing a seat belt.	multi-valued		0,38
	8	Periodically engaging in a dangerous sport (e.g., mountain climbing or sky diving).	multi-valued		0,24
	9	Regularly riding your bicycle without a helmet.	multi-valued		1,31
	10	Trying bungee jumping.	multi-valued		0,47
Conscientiousness	1	I am not good about preparing in advance for things, even if they have direct bearing upon my future.	binary	x	1,00
	2	I do things impulsively, making decisions on the spur of the moment.	binary	x	0,65
	3	I select activities in terms of how beneficial they are to my future.	binary		0,53
	4	I do not like to plan ahead.	binary	x	1,14
	5	I would rather enjoy what I am doing now than be concerned about having fun tomorrow.	binary	x	0,50
	6	I follow through with a course of action if it will get me where I want to be.	multi-valued		0,65
	7	I am able to resist temptations when I know there is work to be done.	multi-valued		0,55
	8	Generally, I am more focused on what is going on now than on what will happen in the future.	multi-valued	x	0,62
	9	I often think about what I will be doing 10 years from now.	multi-valued		0,53
	10	I try to live one day at a time.	multi-valued	x	0,54

9.b Indifference Thresholds

Figure 1: Indifference Thresholds and Observed Sample Proportions of Risky Choices on MPL Type Choice Tasks

Lottery Choice

Holt & Laury's MPL

	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10
Θ_{12}	-1,71	-0,95	-0,49	-0,14	0,15	0,41	0,68	0,97	1,37	Inf
% choosing risky MPL Set 1	0,7%	0,9%	2,2%	8,5%	24,6%	38,2%	58,9%	79,2%	91,2%	99,8%
% choosing risky MPL Set 2	0,3%	0,5%	1,2%	4,8%	15,6%	24,1%	43,1%	65,8%	85,9%	99,5%
% choosing risky MPL Set 3	0,8%	0,9%	2,2%	6,1%	17,3%	26,8%	45,8%	68,3%	87,8%	99,4%

Figure 2: Indifference Thresholds and Observed Sample Proportions of Risky Choices on OLS Type Choice Tasks

Lottery Choice

Binswanger's OLS

	Q1	Q2	Q3	Q4	Q5
Θ_{12} OLS Set 1	2,97	1,00	0,60	0,42	0,00
% choosing risky OLS Set 1	70,5%	67,7%	53,7%	38,1%	34,9%
Θ_{12} OLS Set 2	4,73	1,69	1,06	0,78	0,00
% choosing risky OLS Set 2	71,2%	72,8%	79,5%	65,3%	28,3%
Θ_{12} OLS Set 3	1,37	0,45	0,26	0,17	0,00
% choosing risky OLS Set 3	48,7%	39,4%	30,3%	26,3%	14,4%
Θ_{12} OLS Set 4	4,46	1,50	0,94	0,68	0,00
% choosing risky OLS Set 4	64,1%	79,8%	65,8%	45,8%	34,6%
Θ_{12} OLS Set 5	1,54	0,51	0,30	0,20	0,00
% choosing risky OLS Set 5	41,3%	54,7%	45,3%	30,7%	19,5%

Figure 3: Indifference Thresholds and Observed Sample Proportions of Distant Choices on Temporal Choice Tasks

Temporal Choice

	Q1	Q2	Q3	Q4	Q5	Q6
R_{12} at Θ=-0.3 Sets 1-4	0,067	0,141	0,297	0,902	2,519	10,282
R_{12} at Θ=0 Sets 1-4	0,051	0,107	0,222	0,641	1,638	5,477
R_{12} at Θ=0.7 Sets 1-4	0,015	0,032	0,063	0,164	0,347	0,774
R_{12} at Θ=1 Sets 1-4	0,000	0,001	0,002	0,005	0,010	0,019
% choosing distant Set 1	9,6%	10,1%	16,3%	25,7%	45,9%	68,9%
% choosing distant Set 2	8,2%	9,5%	13,6%	25,4%	46,4%	70,3%
% choosing distant Set 3	8,5%	9,7%	13,7%	24,0%	47,6%	70,5%
% choosing distant Set 4	11,7%	13,2%	17,7%	30,3%	52,7%	73,9%
R_{12} at Θ=-0.3 Sets 5-8	0,066	0,133	0,270	0,701	1,479	3,217
R_{12} at Θ=0 Sets 5-8	0,051	0,101	0,202	0,506	1,014	2,033
R_{12} at Θ=0.7 Sets 5-8	0,015	0,030	0,058	0,134	0,240	0,406
R_{12} at Θ=1 Sets 5-8	0,000	0,001	0,002	0,004	0,007	0,011
% choosing distant Set 5	6,0%	11,6%	29,7%	52,2%	76,4%	86,9%
% choosing distant Set 6	6,1%	11,5%	26,5%	48,9%	73,3%	86,2%
% choosing distant Set 7	5,9%	10,6%	25,6%	47,4%	72,7%	86,8%
% choosing distant Set 8	7,3%	11,2%	25,7%	46,0%	72,7%	86,8%

9.c Structural Results

Figure 4: Estimated Coefficients on Preference and Rationality Parameters Using the Full Structural Model with 5 Unobserved Types

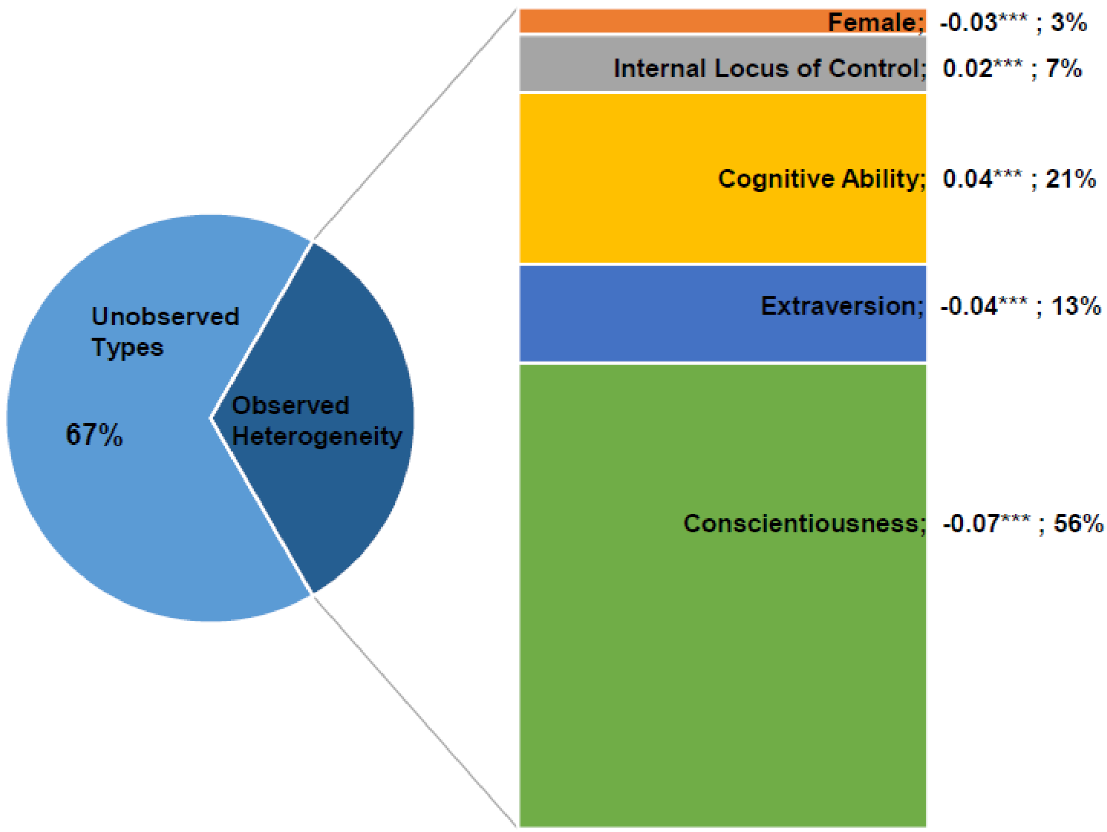
	Risk Aversion		Risk Aversion SD		Discount Rate		Discount Rate SD		% Hand Trembles	
Female	0,11	***	-0,07	***	-0,16	***	-0,18	***	0,09	***
	0,03		0,01		0,01		0,01		0,02	
Internal Locus of Control	0,25	***	0,17	***	0,79	***	0,82	***	0,07	***
	0,01		0,00		0,01		0,00		0,00	
Cognitive Ability	0,28	***	0,36	***	-0,25	***	-0,26	***	-0,34	***
	0,01		0,03		0,01		0,01		0,03	
Extraversion	-0,13	***	-0,10	***	-0,05	***	-0,01		0,01	
	0,02		0,00		0,01		0,01		0,01	
Conscientiousness	-0,20	***	-0,21	***	-1,41	***	-1,44	***	0,02	*
	0,05		0,00		0,01		0,01		0,01	

Figure 5: Explanatory Power of Individual Parameters with regards to Individual Choices

		# Safe Choices	# Immediate Payments	# Risk Reversals	# Time Reversals
Risk Aversion	R2	0,68	0,02	0,01	0,00
		86,8%	6,9%	1,6%	0,0%
Discount Rate	R2		0,29		0,00
			90,5%		9,6%
Risk Aversion SD	R2	0,09	0,01	0,00	0,00
		11,8%	1,9%	0,1%	1,3%
Discount Rate SD	R2		0,00		0,00
			0,2%		4,9%
% Hand Trembles	R2	0,01	0,00	0,47	0,02
		1,3%	0,5%	98,3%	84,2%

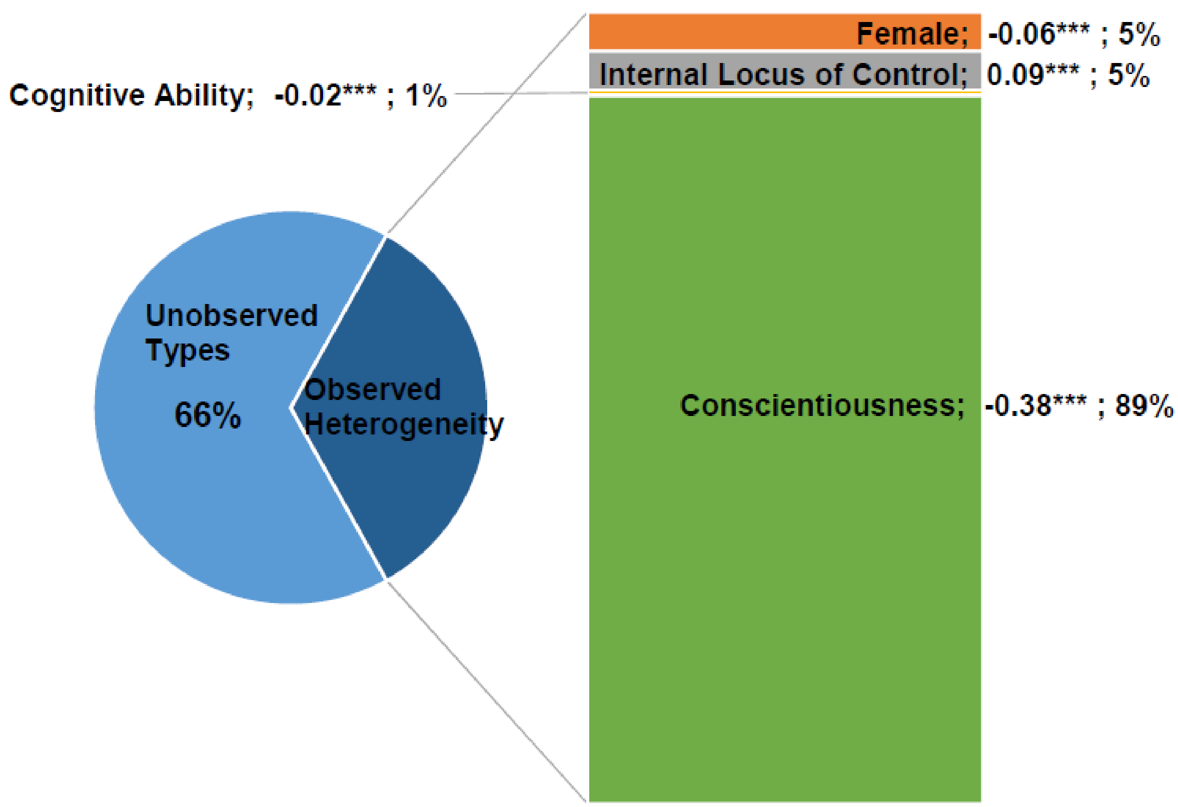
Notes: Rows labeled "R2" list the R2 of the regression of the moment listed in each column title on the parameter identified in the row title.
The row below represents the relative explanatory power of the identified parameter compared to that of all the other parameters, expressed as a percentage.

Figure 6: Heterogeneity in Individuals' Standard Deviation of the Coefficient of Risk Aversion



For observed heterogeneity, the first value corresponds to the marginal effect of changing each factor by 1 standard deviation (and sex from male to female) on the standard deviation of risk aversion; the second value gives the percentage contribution of each heterogeneity component to the overall explanatory power of observed heterogeneity.

Figure 7: Heterogeneity in Individuals' Standard Deviation of the Discount Rate



For observed heterogeneity, the first value corresponds to the marginal effect of changing each factor by 1 standard deviation (and sex from male to female) on the standard deviation of the discount rate; the second value gives the percentage contribution of each heterogeneity component to the overall explanatory power of observed heterogeneity.

10 For Online Publication

10.a Model

10.b Time Preferences

In case of time preference (delay-aversion) the parameter of interest will be the individual's discount rate R_i. Utility is still CRRA and has the same assumptions as before. Thus the utility of a proposed payoff of a \$ in τ years is:

If $\Theta_i \neq 1$

$$U_i = \beta_i^\tau \frac{a_1^{(1-\Theta_i)}}{1-\Theta_i} \tag{20}$$

If $\Theta_i = 1$

$$U_i = \beta_i^\tau * ln(a_1) \tag{21}$$

where β_i is the discount factor. It can be expressed as $\beta_i = \frac{1}{1+R_i}$ where R_i is the discount rate.[26]

Assume an individual is faced with two choices which differ in the payment they offer and the time at which the payment takes place. One can once again define a threshold level of the discount rate $R_{12,i,t}$ at which the discounted utilities of the two options will be equal for individual i in temporal choice task t. As with lotteries described in the previous section, the threshold will vary by choice task, depending on the exact parameters of the two options. However, with delay aversion, the threshold of a particular choice task is no longer common to all individuals. Notably, it will depend on each individual's level of risk aversion, Θ_i, as this affects the curvature of his utility function. Thus each individual will now have a series of associated discount rate thresholds, one for each temporal choice task. His discount rate in temporal choice task l will be compared to his indifference threshold for that particular temporal choice task. In each temporal choice task, agents with a lower discount rate than the associated threshold of indifference will choose the later option while those with a higher one will choose the earlier option.

Figure 3 of Section 9.b of the Appendix shows the calculated indifference thresholds for the temporal choice tasks along with the percentage of the individuals who picked the later option on each task. The $R_{12,i,t}$ are monotonically increasing between Q1 and Q6 in each set of temporal questions reflecting the increasing attractiveness of the distant option. They are shown for 4 different levels of risk aversion, between risk seeking behavior up to a logarithmic utility function

[26]The formulation of the discount rate as $\frac{1}{1+R_i}$ only holds for $\Theta_i \leq 1$ as otherwise ordinal utility is negative under CRRA. When ordinal utility is positive, the discount rate functions as usual. Under the indifference threshold framework, it will serve to equilibrate the utility of a smaller immediate payment with the utility of a larger later payment. A higher discount rate translates to a smaller discount factor which brings down the value of discounted utility of the later payment until it reaches, at the threshold level of discount rate, the value of the immediate payment. When ordinal utility is negative, this mechanism no longer works with a traditionally defined discount factor. In fact, in this situation, higher payoffs provide a less negative (and thus larger) utility, correctly preserving the order of preferences, which is all that ordinal utility requires. However, the absolute value of the larger payoff is now smaller. It is easy to see, that applying a standard discount rate (with a value between 0 and 1) on the utility of the larger later payoff no longer brings it closer to the utility of the smaller immediate payoff. This is so as standard discounting lowers the absolute value of utility which in the case of negative utilities makes it less negative and thus in fact higher. There is no simple fix to this problem. While unlike Apesteguia and Ballester (2018) I shall allow $\Theta_i > 1$ as these are still reasonable levels of risk aversion, I shall only estimate indifference thresholds for the discount rate up to logarithmic risk aversion. As seen in Figure 3 of the Appendix, at these levels of risk aversion, indifference thresholds for the discount rate already approach zero.

(as explained before, $R_{12,i,t}$ for individuals with estimated $\Theta_i > 1$ will be assigned this threshold as the limit). One can observe large differences in indifference thresholds depending on assumed risk aversion, confirming the importance of joint estimation of the two preference parameters. As predicted by the RPM model, the percentage of individuals choosing the later option is also monotonically increasing. It is more stable for questions with a common indifference threshold than was the case with the tasks designed to elicit risk preferences. However, it still varies even among such questions, confirming the necessity of using stochastic shocks to model temporal choices as well (in this case, the stochastic shocks could be on risk aversion, discount rates, or both).

As with risk aversion in the previous section, an individual's average deterministic part of the discount rate will be hit with a random shock in each temporal choice task thus making R_i a random variable. As the discount rate has to always stay positive, I shall assume a lognormal distribution for time preferences. Thus the discount rate is a lognormally distributed random variable with mean R_i and standard deviation $\sigma_{R,i}$. The higher an individual's $\sigma_{R,i}$, the less stable are his time preferences over a set of choices he has to make. Thus $\sigma_{R,i}$ can be interpreted as a parameter governing the stability of an individual's delay aversion.

Individual i will prefer the later option in temporal choice task t if his realization of the discount rate, $\Psi_{R,i,t}$, is below his threshold of indifference between the earlier and later option $R_{12,i,t}$. More formally and after taking logs, the later option is preferred if:

$$ln(\Psi_{R,i,t}) \sim \mathcal{N}\left(ln\left(\frac{R_i^2}{\sqrt{(\sigma_{R,i})^2 + R_i^2}}\right), ln\left(1 + \frac{(\sigma_{R,i})^2}{R_i^2}\right)\right) < ln(R_{12,i,t}) \tag{22}$$

where the two arguments in parentheses are respectively the mean and standard deviation of the log of the discount rate random variable which is normally distributed.

Rearranging:

$$\epsilon_{i,t} \sim \mathcal{N}(0,1) < \frac{ln(R_{12,i,t}) - ln\left(\frac{R_i^2}{\sqrt{(\sigma_{R,i})^2+R_i^2}}\right)}{\sqrt{ln\left(1 + \frac{(\sigma_{R,i})^2}{R_i^2}\right)}} \tag{23}$$

where $\epsilon_{i,t}$ is a standard normal random variable.

The resulting probability of preferring the later option thus has a closed form expression:

$$P(LP_{i,t} = 1) = \Phi\left[\frac{ln(R_{12,i,t}) - ln\left(\frac{R_i^2}{\sqrt{(\sigma_{R,i})^2+R_i^2}}\right)}{\sqrt{ln\left(1 + \frac{(\sigma_{R,i})^2}{R_i^2}\right)}}\right] \tag{24}$$

where $LP_{i,t}$ is a binary variable which takes on the value of 1 if individual i derives higher discounted utility from the later option in temporal choice task t than from the earlier one.

The probability of choosing the earlier option is simply:

$$P(LP_{i,t} = 0) = 1 - P(LP_{i,t} = 1) \tag{25}$$

As in the previous section on risk aversion, an individual's final choice in the temporal choice tasks will be driven not only by his *pure* preference but also by his *trembling* hand. The logic does not change and I shall assume that the tremble parameter K_i applies to all choice tasks individual i faces - whether they be lottery based or temporal in nature.

Incorporating the tremble parameter, I can get the expression for the probability that individual i *chooses* the later option in choice task t.

$$P(LC_{i,t}=1)=P(LP_{i,t}=1)*(1-K_i)+[1-P(LP_{i,t}=1)]*K_i \tag{26}$$

where $LC_{i,t}$ is a binary variable which takes on the value of 1 if individual i *chooses* the later option in temporal choice task t.

An individual's contribution to the likelihood based on his choice on choice task t thus becomes:

$$P(LC_{i,t}=LC_{i,t})=P(LC_{i,t}=1)^{LC_{i,t}}*P(LC_{i,t}=0)^{1-LC_{i,t}} \tag{27}$$

or, in full:

$$\begin{aligned}
&P(LC_{i,t}=LC_{i,t})= \\
&=\left\{\Phi\left[\frac{ln(R_{12,i,t})-ln\left(\frac{R_i^2}{\sqrt{(\sigma_{R,i})^2+R_i^2}}\right)}{\sqrt{ln\left(1+\frac{(\sigma_{R,i})^2}{R_i^2}\right)}}\right]*(1-K_i)+\left\langle 1-\Phi\left[\frac{ln(R_{12,i,t})-ln\left(\frac{R_i^2}{\sqrt{(\sigma_{R,i})^2+R_i^2}}\right)}{\sqrt{ln\left(1+\frac{(\sigma_{R,i})^2}{R_i^2}\right)}}\right]\right\rangle *K_i\right\}^{LC_{i,t}}* \\
&*\left\{\left\langle 1-\Phi\frac{ln(R_{12,i,t})-ln\left(\frac{R_i^2}{\sqrt{(\sigma_{R,i})^2+R_i^2}}\right)}{\sqrt{ln\left(1+\frac{(\sigma_{R,i})^2}{R_i^2}\right)}}\right\rangle *(1-K_i)+\Phi\left[\frac{ln(R_{12,i,t})-ln\left(\frac{R_i^2}{\sqrt{(\sigma_{R,i})^2+R_i^2}}\right)}{\sqrt{ln\left(1+\frac{(\sigma_{R,i})^2}{R_i^2}\right)}}\right]*K_i\right\}^{1-LC_{i,t}}
\end{aligned} \tag{28}$$

where R_i, $\sigma_{R,i}$, and K_i are assumed to be functions of observed characteristics and unobserved factors.

10.c Heterogeneity

$$\Theta_i=\theta_0+\theta_1{}'X_i+\theta_2{}'F_i \tag{29}$$

$$\sigma_{\Theta,i}=\Phi(s_{\theta,0}+s_{\theta,1}{}'X_i+s_{\theta,2}{}'F_i) \tag{30}$$

$$R_i=\Phi(r_0+r_1{}'X_i+r_2{}'F_i) \tag{31}$$

$$\sigma_{R,i}=\Phi(s_{r,0}+s_{r,1}{}'X_i+s_{r,2}{}'F_i) \tag{32}$$

$$K_i=\Phi(\kappa_0+\kappa_1{}'X_i+\kappa_2{}'F_i) \tag{33}$$

where θ_0 is the type-dependent intercept, X_i is a vector of individual i's characteristics which influence his preference parameters and F_i is a vector of values of his unobserved factors. These factors are: internal locus of control, cognitive ability, extraversion, and conscientiousness. The normal cdf is applied to the discount rate and to the rationality parameters. The trembling hand parameter, K_i, represents the percentage of time that an individual chooses his less preferred option and thus needs to be constrained between 0 and 1. While $\sigma_{\Theta,i}$, R_i, and $\sigma_{R,i}$ are not necessarily bound from above, it makes economic sense to also restrict their values between 0 and 1.

10.d Factor Measures

10.d.i Ordered Multi-Valued Measures

A measure is multi-valued ordered if it contains values k=0,1,...,K which have a natural monotonic ordering. One can then define a series of K ordered thresholds t_k which will map the underlying latent variable into the observed discrete values. The measure's contribution to the likelihood function then follows:

For value *k*=0

$$P(M_{i,j,f} = m_{i,j,f} = k = 0) = \Phi(t_k - \gamma_{0,j,f} - \gamma_{1,j,f} * F_{i,f}) \tag{34}$$

For values *k*=1,...,K-1

$$P(M_{i,j,f} = m_{i,j,f} = k) = \Phi(t_{k+1} - \gamma_{0,j,f} - \gamma_{1,j,f} * F_{i,f}) - \Phi(t_k - \gamma_{0,j,f} - \gamma_{1,j,f} * F_{i,f}) \tag{35}$$

For value *k*=K

$$P(M_{i,j,f} = m_{i,j,f} = k = K) = 1 - \Phi(t_k - \gamma_{0,j,f} - \gamma_{1,j,f} * F_{i,f}) \tag{36}$$

10.d.ii Continuous Measures

In case of a continuous measure, the underlying latent variable defined above is directly observed. This time the error term $\epsilon_{i,j,f}$ follows a Normal distribution with mean 0 and standard deviation σ_j^2 which is proper to each continuous measure and can be estimated. The measure's contribution to the likelihood function becomes:

$$P(M_{i,j,f} = m_{i,j,f}) = \frac{1}{\sigma_j} * \phi(\frac{m_{i,j,f} - \gamma_{0,j,f} - \gamma_{1,j,f} * F_{i,f}}{\sigma_j}) \tag{37}$$

11 Full Experimental Instructions

Choices

Part I

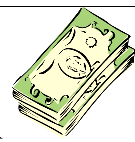
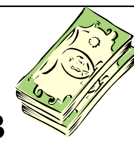
□□-□□-□□-□□□
SAMPLE ID

The first series of choices are offers of money at different dates. Choice A is always closer to the present than Choice B.

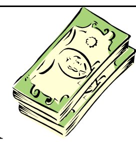
Choice B is always *one month* later than choice A.

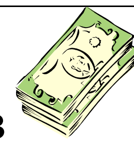
If one of these decisions is picked with your random draw at the end of today’s session, the money will be paid to you by cheque on the promised date.

You must choose A or B:

	CHOICE A 	CHOICE B 
	$75 Tomorrow	$$ One month from tomorrow
Decision 1	❒ $75 Tomorrow	❒ $75.31 One month from tomorrow The additional **$0.31** represents the money you would have earned in a savings account for one month at **5%** annual interest.
Decision 2	❒ $75 Tomorrow	❒ $75.63 One month from tomorrow The additional **$0.63** represents the money you would have earned in a savings account for one month at **10%** annual interest.
Decision 3	❒ $75 Tomorrow	❒ $76.25 One month from tomorrow The additional **$1.25** represents the money you would have earned in a savings account for one month at **20%** annual interest.
Decision 4	❒ $75 Tomorrow	❒ $78.13 One month from tomorrow The additional **$3.13** represents the money you would have earned in a savings account for one month at **50%** annual interest.
Decision 5	❒ $75 Tomorrow	❒ $81.25 One month from tomorrow The additional **$6.25** represents the money you would have earned in a savings account for one month at **100%** annual interest.
Decision 6	❒ $75 Tomorrow	❒ $87.50 One month from tomorrow The additional **$12.50** represents the money you would have earned in a savings account for one month at **200%** annual interest.

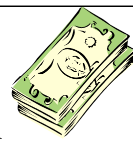
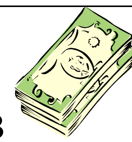
You must choose A or B:



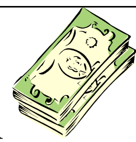
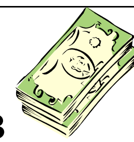


	CHOICE A $75 One week from today	CHOICE B $$ One week and one month from today
Decision 7	❒ $75 in one week	❒ $75.31 in one week and one month The additional **$0.31** represents the money you would have earned in a savings account for one month at **5%** annual interest.
Decision 8	❒ $75 in one week	❒ $75.63 in one week and one month The additional **$0.63** represents the money you would have earned in a savings account for one month at **10%** annual interest.
Decision 9	❒ $75 in one week	❒ $76.25 in one week and one month The additional **$1.25** represents the money you would have earned in a savings account for one month at **20%** annual interest.
Decision 10	❒ $75 in one week	❒ $78.13 in one week and one month The additional **$3.13** represents the money you would have earned in a savings account for one month at **50%** annual interest.
Decision 11	❒ $75 in one week	❒ $81.25 in one week and one month The additional **$6.25** represents the money you would have earned in a savings account for one month at **100%** annual interest.
Decision 12	❒ $75 in one week	❒ $87.50 in one week and one month The additional **$12.50** represents the money you would have earned in a savings account for one month at **200%** annual interest.

You must choose A or B:

	CHOICE A 	CHOICE B 
	$75 One month from today	$$ Two months from today
Decision 13	❒ $75 One month from today	❒ $75.31 Two months from today The additional **$0.31** represents the money you would have earned in a savings account for one month at **5%** annual interest.
Decision 14	❒ $75 One month from today	❒ $75.63 Two months from today The additional **$0.63** represents the money you would have earned in a savings account for one month at **10%** annual interest.
Decision 15	❒ $75 One month from today	❒ $76.25 Two months from today The additional **$1.25** represents the money you would have earned in a savings account for one month at **20%** annual interest.
Decision 16	❒ $75 One month from today	❒ $78.13 Two months from today The additional **$3.13** represents the money you would have earned in a savings account for one month at **50%** annual interest.
Decision 17	❒ $75 One month from today	❒ $81.25 Two months from today The additional **$6.25** represents the money you would have earned in a savings account for one month at **100%** annual interest.
Decision 18	❒ $75 One month from today	❒ $87.50 Two months from today The additional **$12.50** represents the money you would have earned in a savings account for one month at **200%** annual interest.

You must choose A or B:

	CHOICE A 	CHOICE B 
	$75 Three months from today	$$ Four months from today

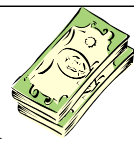
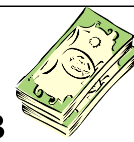
Decision 19	❒ $75 Three months from today	❒ $75.31 Four months from today The additional **$0.31** represents the money you would have earned in a savings account for one month at **5%** annual interest.
Decision 20	❒ $75 Three months from today	❒ $75.63 Four months from today The additional **$0.63** represents the money you would have earned in a savings account for one month at **10%** annual interest.
Decision 21	❒ $75 Three months from today	❒ $76.25 Four months from today The additional **$1.25** represents the money you would have earned in a savings account for one month at **20%** annual interest.
Decision 22	❒ $75 Three months from today	❒ $78.13 Four months from today The additional **$3.13** represents the money you would have earned in a savings account for one month at **50%** annual interest.
Decision 23	❒ $75 Three months from today	❒ $81.25 Four months from today The additional **$6.25** represents the money you would have earned in a savings account for one month at **100%** annual interest.
Decision 24	❒ $75 Three months from today	❒ $87.50 Four months from today The additional **$12.50** represents the money you would have earned in a savings account for one month at **200%** annual interest.

The next series of choices are once again offers of money at different dates. As before, Choice A is always closer to the present than Choice B.

However, this time Choice B is always *one year* later than Choice A.

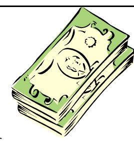
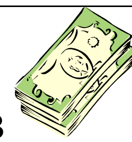
If one of these decisions is picked with your random draw at the end of today’s session, the money will be paid to you by cheque on the promised date.

You must choose A or B:

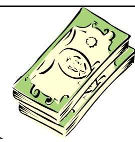
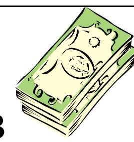
	CHOICE A 	CHOICE B 
	$75 Tomorrow	$$ One year from tomorrow

Decision 25	❒ $75 Tomorrow	❒ $78.75 One year from tomorrow The additional **$3.75** represents the money you would have earned in a savings account for one year at **5%** annual interest.
Decision 26	❒ $75 Tomorrow	❒ $82.50 One year from tomorrow The additional **$7.50** represents the money you would have earned in a savings account for one year at **10%** annual interest.
Decision 27	❒ $75 Tomorrow	❒ $90.00 One year from tomorrow The additional **$15.00** represents the money you would have earned in a savings account for one year at **20%** annual interest.
Decision 28	❒ $75 Tomorrow	❒ $112.50 One year from tomorrow The additional **$37.50** represents the money you would have earned in a savings account for one year at **50%** annual interest.
Decision 29	❒ $75 Tomorrow	❒ $150.00 One year from tomorrow The additional **$75.00** represents the money you would have earned in a savings account for one year at **100%** annual interest.
Decision 30	❒ $75 Tomorrow	❒ $225.00 One year from tomorrow The additional **$150.00** represents the money you would have earned in a savings account for one year at **200%** annual interest.

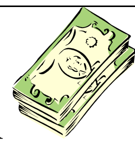
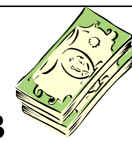
You must choose A or B:

	CHOICE A 	CHOICE B 
	$75 in one week	$$ One week and one year
Decision 31	❒ $75 in one week	❒ $78.75 in one week and one year The additional **$3.75** represents the money you would have earned in a savings account for one year at **5%** annual interest.
Decision 32	❒ $75 in one week	❒ $82.50 in one week and one year The additional **$7.50** represents the money you would have earned in a savings account for one year at **10%** annual interest.
Decision 33	❒ $75 in one week	❒ $90.00 in one week and one year The additional **$15.00** represents the money you would have earned in a savings account for one year at **20%** annual interest.
Decision 34	❒ $75 in one week	❒ $112.50 in one week and one year The additional **$37.50** represents the money you would have earned in a savings account for one year at **50%** annual interest.
Decision 35	❒ $75 in one week	❒ $150.00 in one week and one year The additional **$75.00** represents the money you would have earned in a savings account for one year at **100%** annual interest.
Decision 36	❒ $75 in one week	❒ $225.00 in one week and one year The additional **$150.00** represents the money you would have earned in a savings account for one year at **200%** annual interest.

You must choose A or B:

	Choice A 	Choice B 
	$75 in one month	$$ One year and one month
Decision 37	❒ $75 in one month	❒ $78.75 in one month and one year The additional **$3.75** represents the money you would have earned in a savings account for one year at **5%** annual interest.
Decision 38	❒ $75 in one month	❒ $82.50 in one month and one year The additional **$7.50** represents the money you would have earned in a savings account for one year at **10%** annual interest.
Decision 39	❒ $75 in one month	❒ $90.00 in one month and one year The additional **$15.00** represents the money you would have earned in a savings account for one year at **20%** annual interest.
Decision 40	❒ $75 in one month	❒ $112.50 in one month and one year The additional **$37.50** represents the money you would have earned in a savings account for one year at **50%** annual interest.
Decision 41	❒ $75 in one month	❒ $150.00 in one month and one year The additional **$75.00** represents the money you would have earned in a savings account for one year at **100%** annual interest.
Decision 42	❒ $75 in one month	❒ $225.00 in one month and one year The additional **$150.00** represents the money you would have earned in a savings account for one year at **200%** annual interest.

You must choose A or B:

	CHOICE A 	CHOICE B 
	$75 in three months	$$ One year and three months
Decision 43	❒ $75 in three months	❒ $78.75 in three months and one year The additional **$3.75** represents the money you would have earned in a savings account for one year at **5%** annual interest.
Decision 44	❒ $75 in three months	❒ $82.50 in three months and one year The additional **$7.50** represents the money you would have earned in a savings account for one year at **10%** annual interest.
Decision 45	❒ $75 in three months	❒ $90.00 in three months and one year The additional **$15.00** represents the money you would have earned in a savings account for one year at **20%** annual interest.
Decision 46	❒ $75 in three months	❒ $112.50 in three months and one year The additional **$37.50** represents the money you would have earned in a savings account for one year at **50%** annual interest.
Decision 47	❒ $75 in three months	❒ $150.00 in three months and one year The additional **$75.00** represents the money you would have earned in a savings account for one year at **100%** annual interest.
Decision 48	❒ $75 in three months	❒ $225.00 in three months and one year The additional **$150.00** represents the money you would have earned in a savings account for one year at **200%** annual interest.

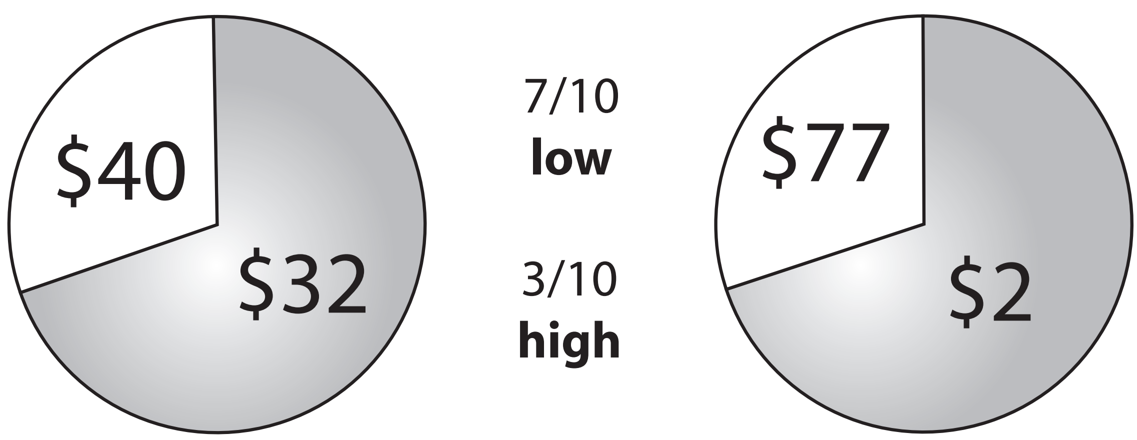
The next series of choices are offers of money with different levels of risk. If of these decisions is picked with your random draw at the end of today's session, the money will be paid to you by cheque today.

Remember that at the end of today's session, one decision will be chosen randomly, and you will be paid for your decision. Therefore, your best strategy is to treat each decision as if it could be the one you get paid for.

In this next set of decisions, you are given a chance to earn a cash prize today. For each decision, you will choose between playing the choice on the left and the choice on the right. The outcome of these choices is uncertain, meaning you have to roll a die to determine the outcome. For this activity, we will ask you to roll a 10-sided die.

Example:

Mark the circle of your choice



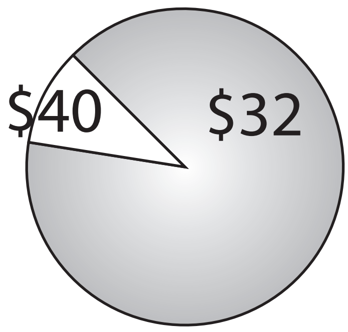
Each of the options above is composed of two outcomes.
Which outcome occurs depends on the roll of a ten-sided die.

For instance, let's look at the option on the left. You have 7 out of 10 chances to win $32 and 3 out of 10 chances to win $40. If you roll a 1, 2 ,3,4,5,6 or 7 (7 sides out of 10 sides) then you win $32. If you roll a 8, 9, 0, (3 sides out of 10 sides) then you win $40.

Now let's look at the options on the right. If you roll a 1, 2,3,4,5,6, or 7 (7 sides out of 10 sides) then you win $2. If you roll a 8, 9, 0, (3 sides out of 10 sides) then you win $77.

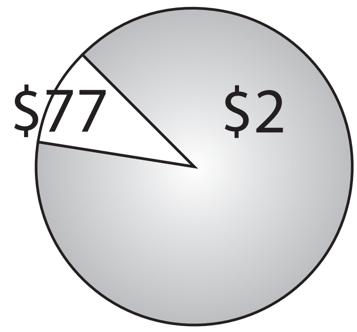
Mark the circle of your choice for each pair

Decision
49

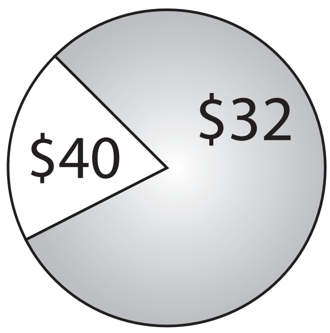


9/10
low

1/10
high

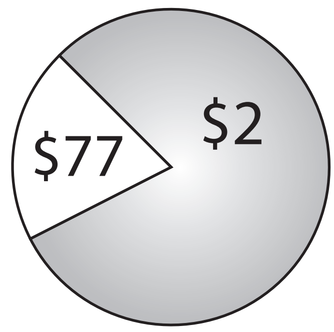


Decision
50

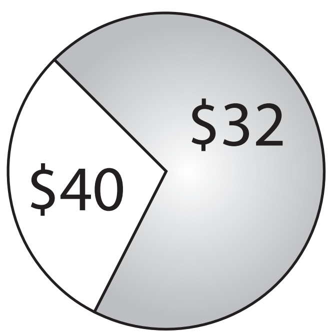


8/10
low

2/10
high

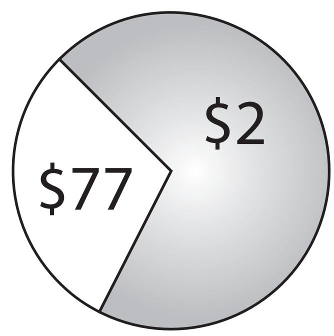


Decision
51

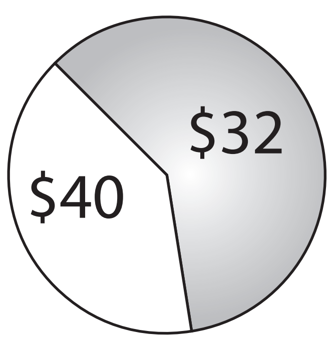


7/10
low

3/10
high

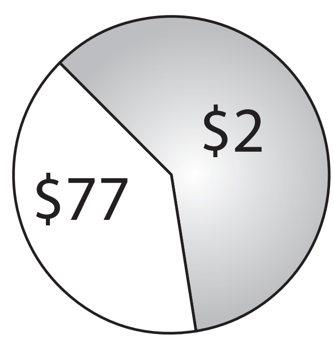


Decision
52

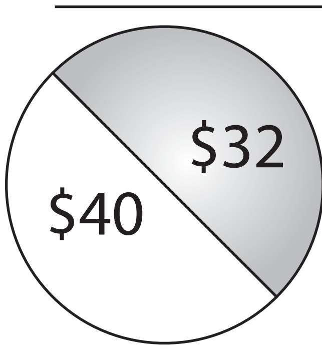


6/10
low

4/10
high

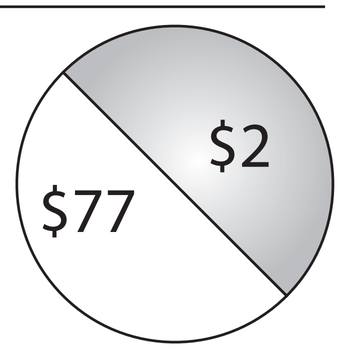


Decision
53

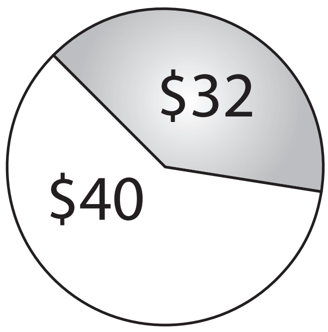


5/10
low

5/10
high

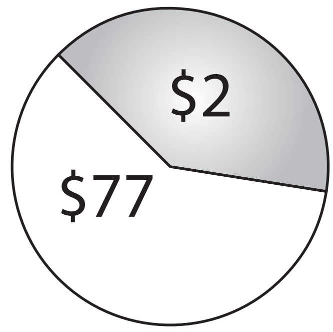


Decision
54

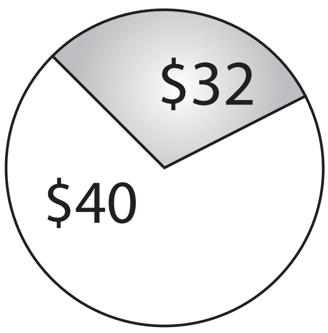


4/10
low

6/10
high

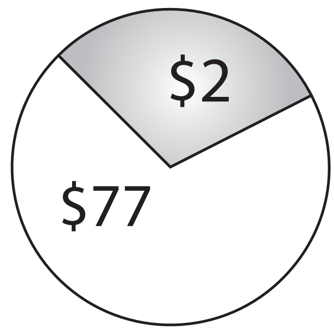


Decision
55

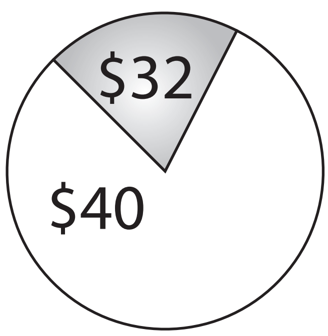


3/10
low

7/10
high

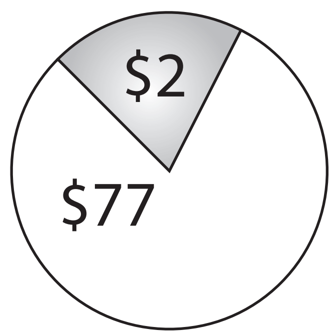


Decision
56

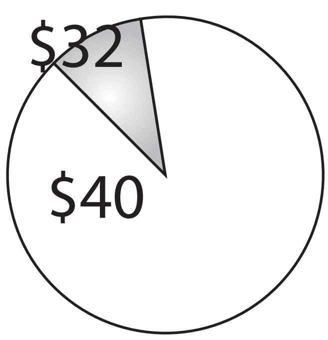


2/10
low

8/10
high

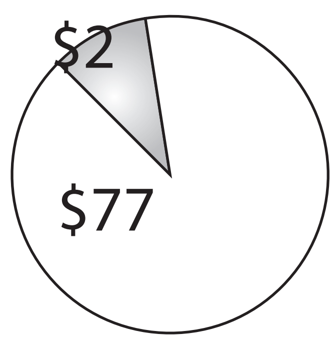


Decision
57

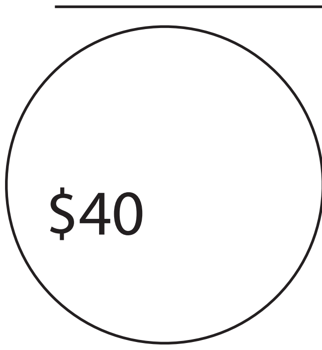


1/10
low

9/10
high

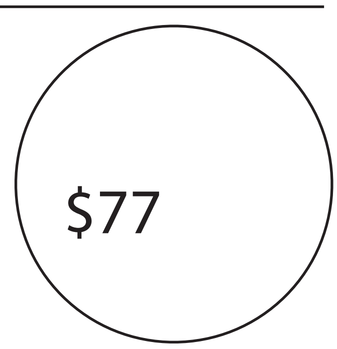


Decision
58



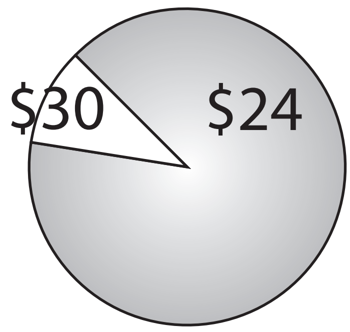
0/10
low

10/10
high



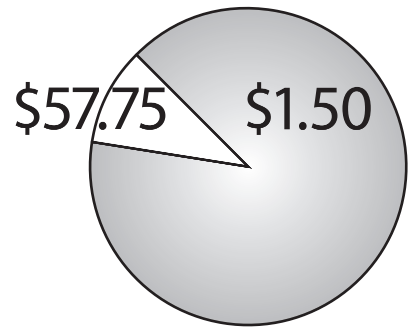
Mark the circle of your choice for each pair

Decision
59

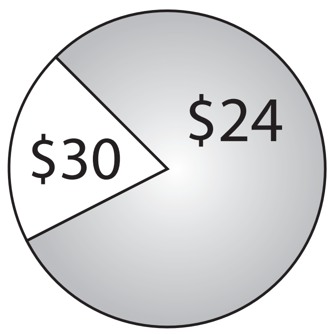


9/10
low

1/10
high

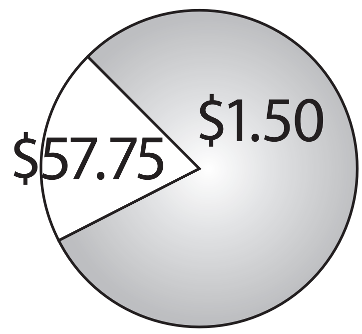


Decision
60

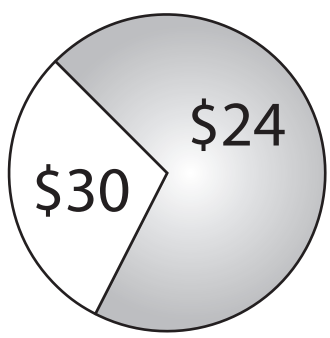


8/10
low

2/10
high

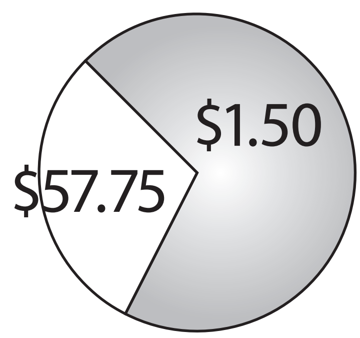


Decision
61

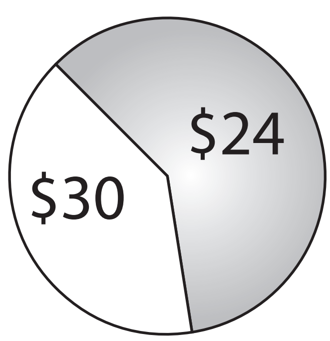


7/10
low

3/10
high

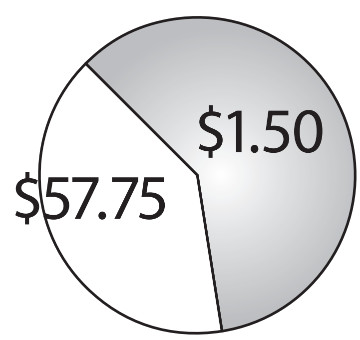


Decision
62

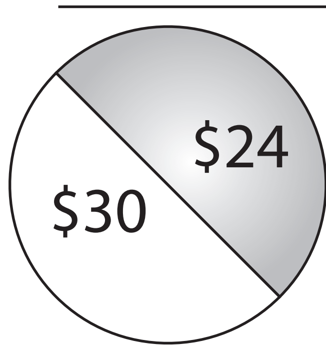


6/10
low

4/10
high

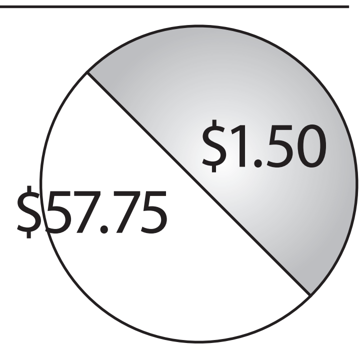


Decision
63

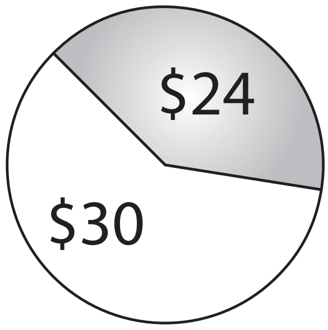


5/10
low

5/10
high



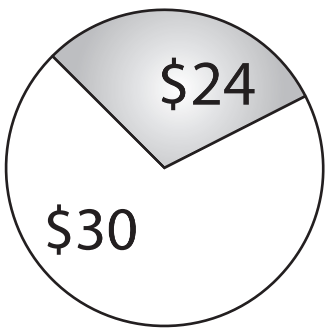
Decision
64



4/10
low

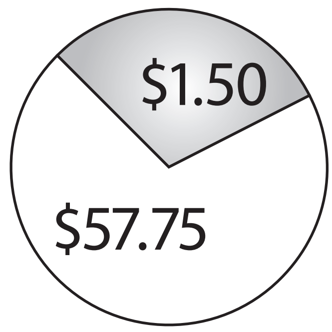
6/10
high

Decision
65

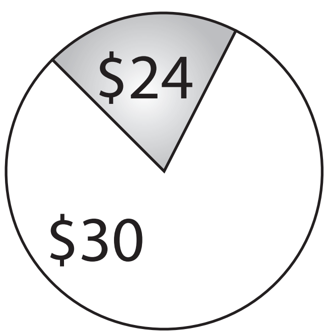


3/10
low

7/10
high

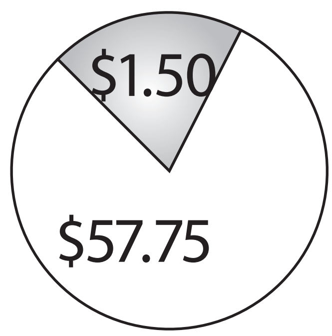


Decision
66

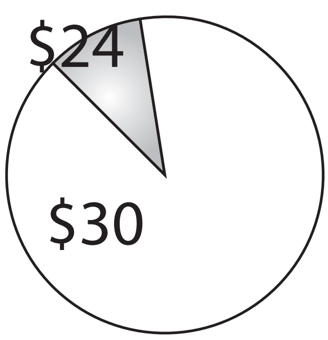


2/10
low

8/10
high

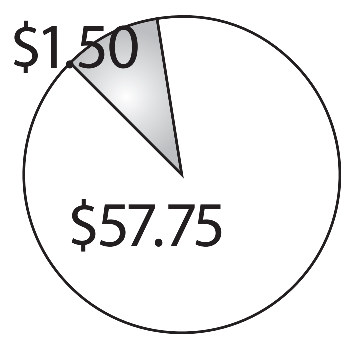


Decision
67

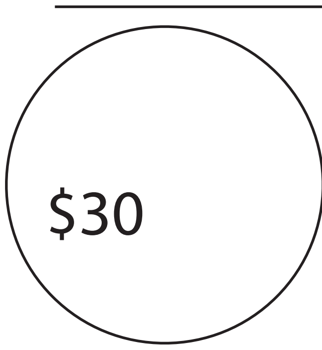


1/10
low

9/10
high



Decision
68

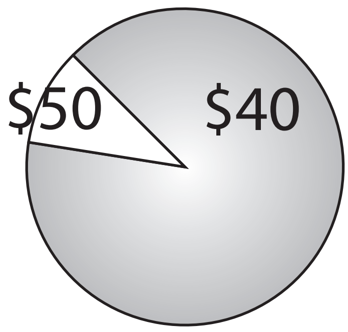


0/10
low

10/10
high

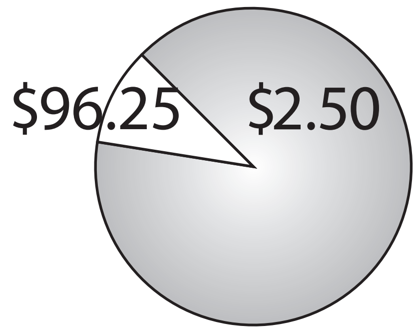
Mark the circle of your choice for each pair

Decision
69

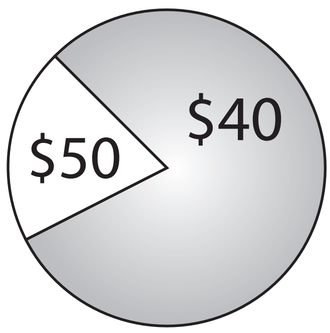


9/10
low

1/10
high

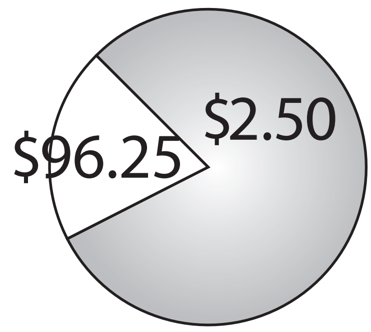


Decision
70

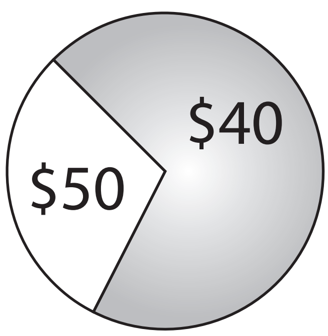


8/10
low

2/10
high

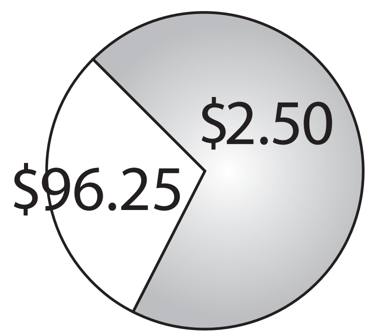


Decision
71

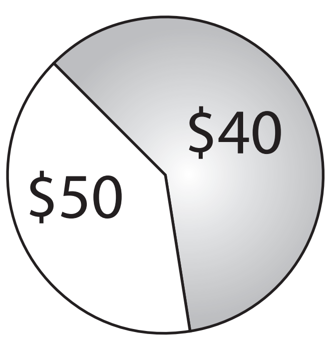


7/10
low

3/10
high

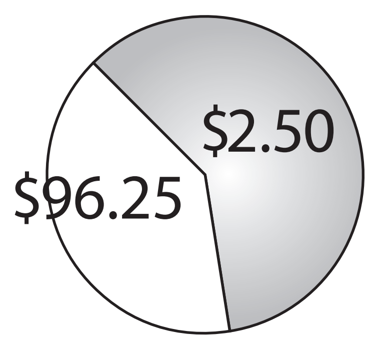


Decision
72

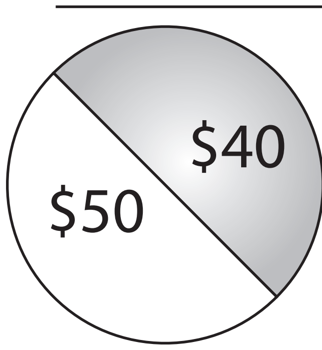


6/10
low

4/10
high

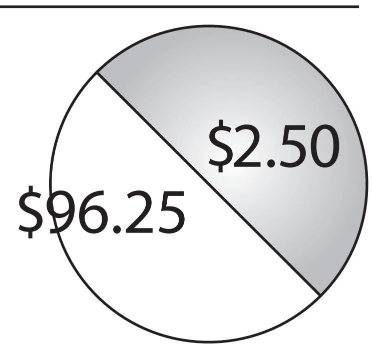


Decision
73

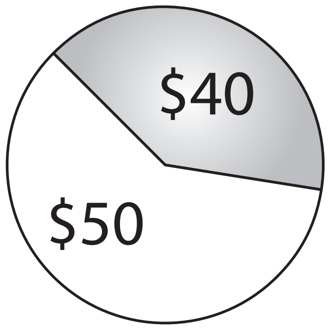


5/10
low

5/10
high

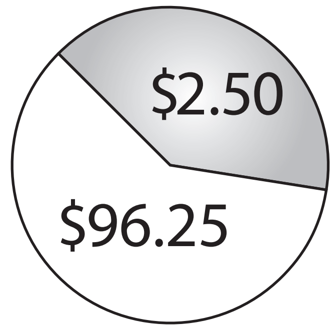


Decision
74

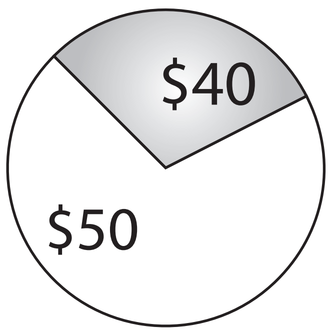


4/10
low

6/10
high



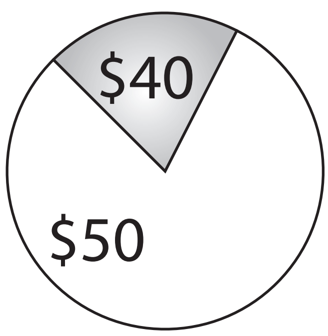
Decision
75



3/10
low

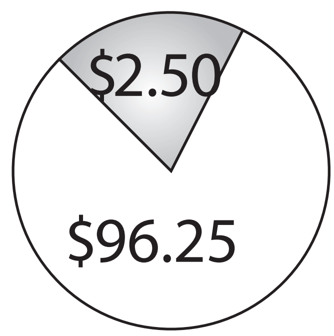
7/10
high

Decision
76

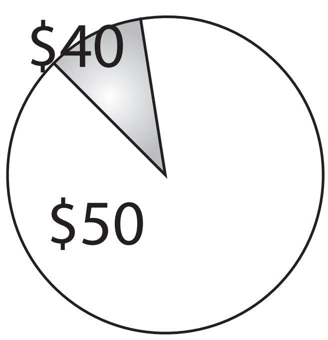


2/10
low

8/10
high

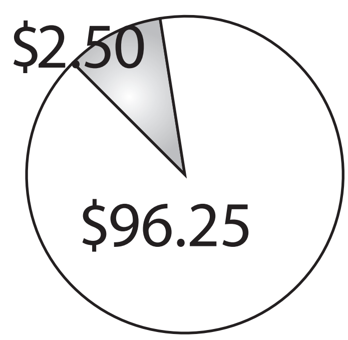


Decision
77

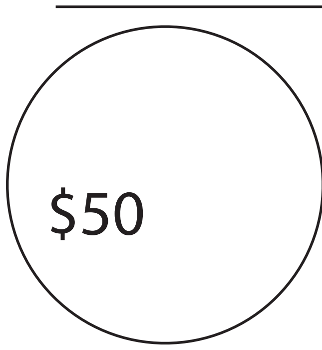


1/10
low

9/10
high



Decision
78



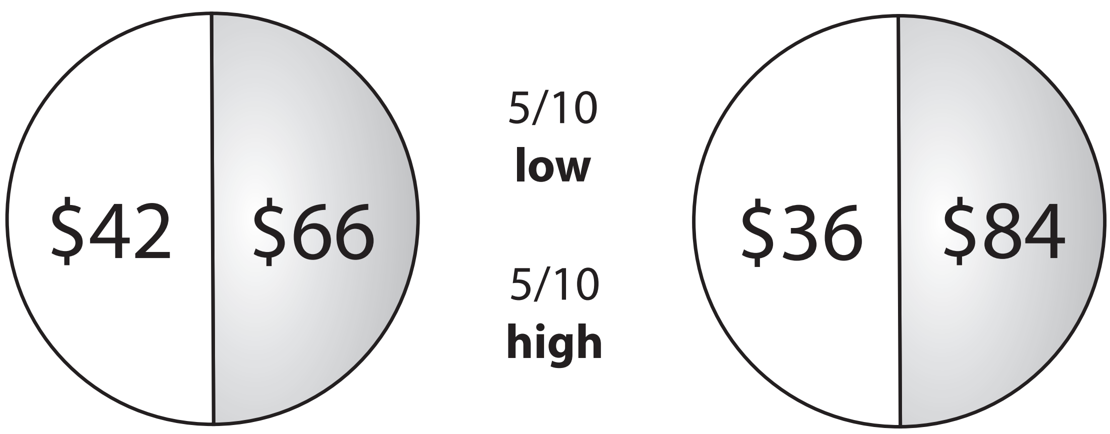
0/10
low

10/10
high

In this next set of decisions, you are given a chance to earn a cash prize today. For each decision, you will choose between playing the choice on the left and the choice on the right. The outcome of these choices is uncertain, meaning you have to roll a die to determine the outcome. For this activity, we will ask you to roll a 10-sided die.

Example:

Mark the circle of your choice



Each of the options above is composed of two outcomes.
Which outcome occurs depends on the roll of a ten-sided die.

For instance, let's look at the option on the left. You have 5 out of 10 chances to win $42 and 5 out of 10 chances to win $66. If you roll a 1, 2,3,4 or 5, (5 sides out of 10 sides) then you win $42. If you roll a 6, 7, 8, 9, 0, (5 sides out of 10 sides) then you win $66.

Now let's look at the options on the right. If you roll a 1, 2, 3, 4 or 5 (5 sides out of 10 sides) then you win $36. If you roll a 6, 7, 8, 9, 0, (5 sides out of 10 sides) then you win $84.

Mark the circle of your choice for each pair

	Left circle: 5/10 **low**	Left circle: 5/10 **high**	Right circle: 5/10 **low**	Right circle: 5/10 **high**
Decision 79	$48	$48	$40	$64
Decision 80	$40	$64	$32	$80
Decision 81	$32	$80	$24	$96
Decision 82	$24	$96	$16	$112
Decision 83	$16	$112	$8	$120

Mark the circle of your choice for each pair

	Left circle			Right circle	
			5/10 **low** / 5/10 **high**		
Decision 84	$48	$48		$42	$66
Decision 85	$42	$66		$36	$84
Decision 86	$36	$84		$30	$102
Decision 87	$30	$102		$24	$120
Decision 88	$24	$120		$16	$128

Mark the circle of your choice for each pair

Decision 89	$48 | $48	5/10 **low** 5/10 **high**	$38 | $62
Decision 90	$38 | $62		$28 | $76
Decision 91	$28 | $76		$18 | $90
Decision 92	$18 | $90		$8 | $104
Decision 93	$8 | $104		$0 | $112

Mark the circle of your choice for each pair

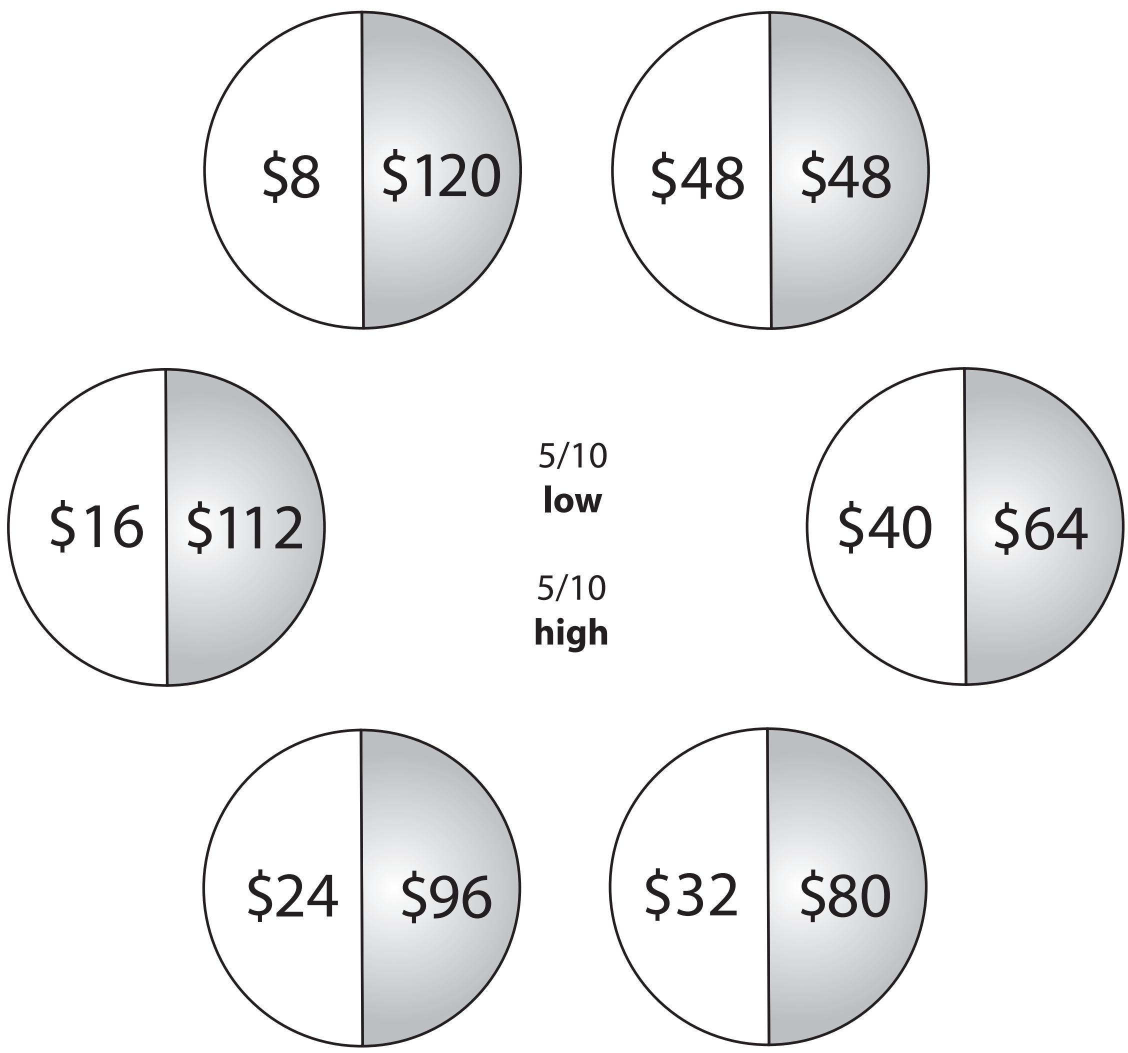
	Option A (low)	Option A (high)		Option B (low)	Option B (high)
Decision 94	$42	$42	5/10 **low** / 5/10 **high**	$36	$60
Decision 95	$36	$60		$30	$78
Decision 96	$30	$78		$24	$96
Decision 97	$24	$96		$18	$114
Decision 98	$18	$114		$10	$122

Mark the circle of your choice for each pair

Decision 99	$54 | $54	5/10 **low** 5/10 **high**	$44 | $68
Decision 100	$44 | $68		$34 | $82
Decision 101	$34 | $82		$24 | $96
Decision 102	$24 | $96		$14 | $110
Decision 103	$14 | $110		$6 | $118

Decision
104

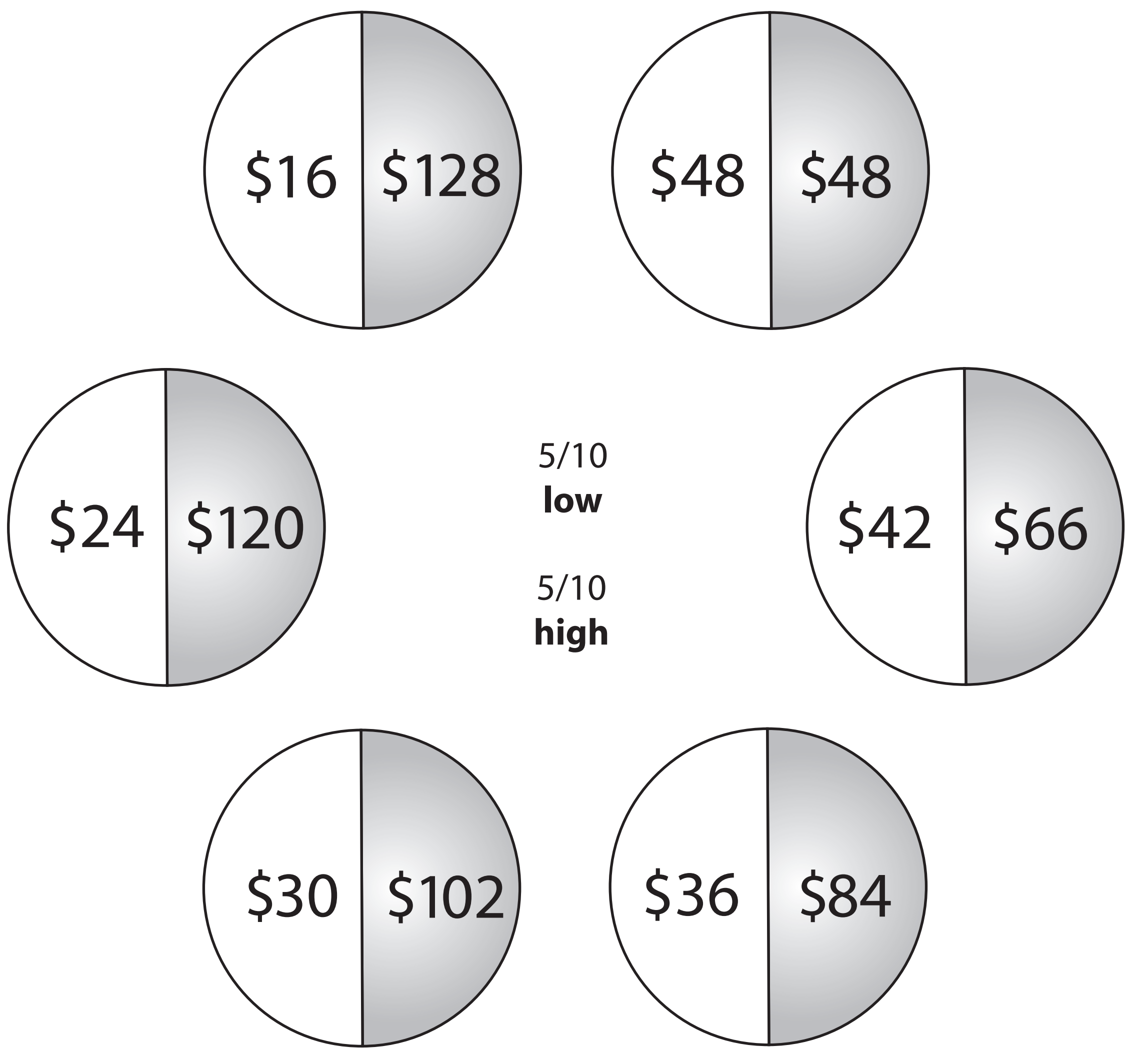
Mark the circle of your choice



Mark the circle of your choice

Decision

105



Mark the circle of your choice

Decision
106

$0 | $112

$48 | $48

$8 | $104

5/10
low

5/10
high

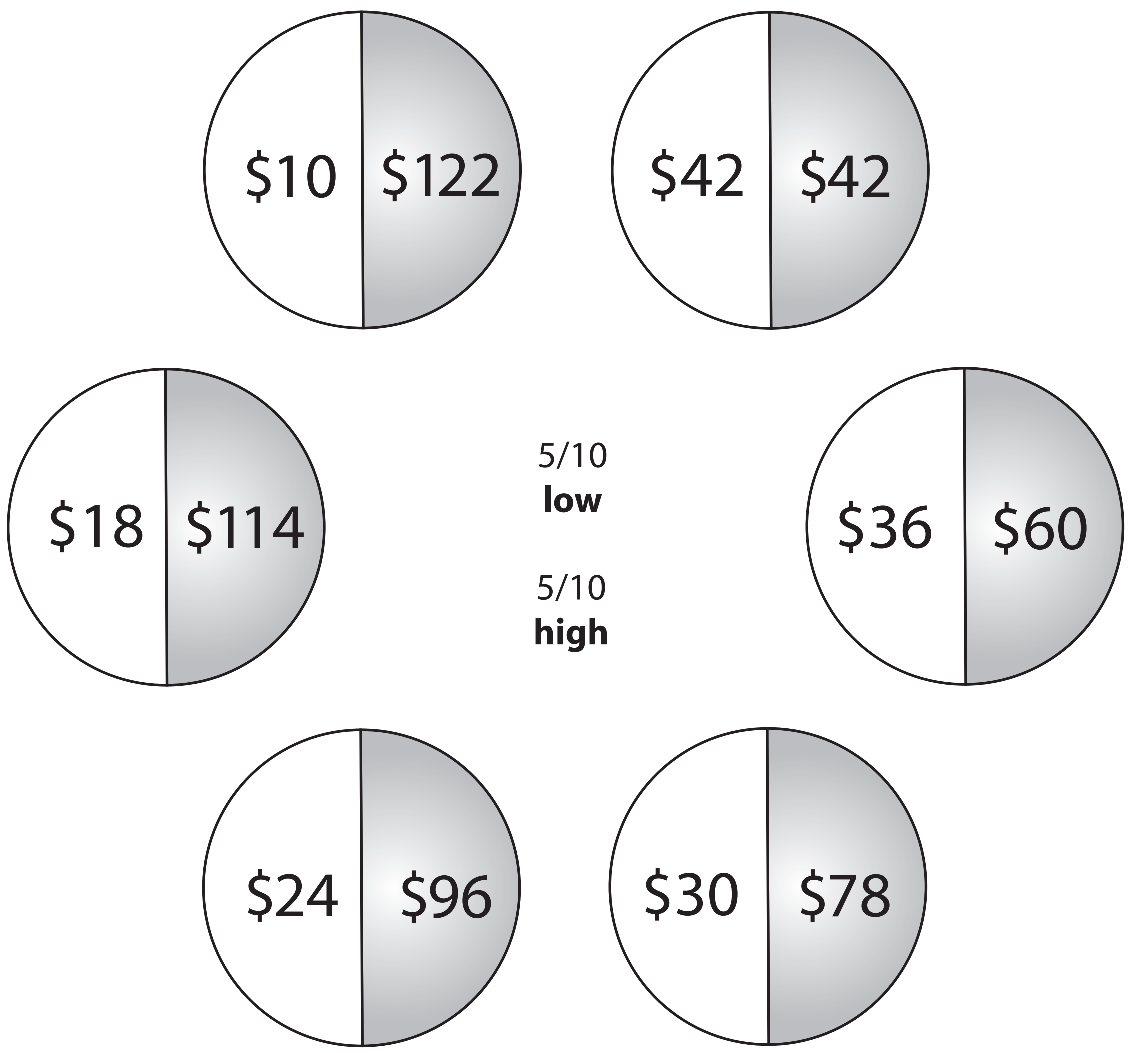
$38 | $62

$18 | $90

$28 | $76

Mark the circle of your choice

Decision
107



Mark the circle of your choice

Decision
108

$6 | $118

$54 | $54

$14 | $110

5/10
low

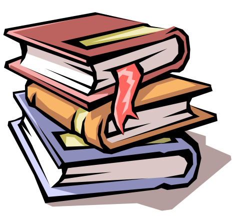
5/10
high

$44 | $68

$24 | $96

$34 | $82

The following 22 decisions are choices between **CASH** and **FULL-TIME** educational expenses.



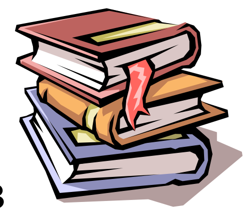
FULL-TIME study means that you will devote most of your weekdays to classes and studying. In other words, your main activity is to attend training or education full-time.

The **CASH** offered will be paid **one week from today.**

You must choose A or B:

CHOICE A

$$ one week from today

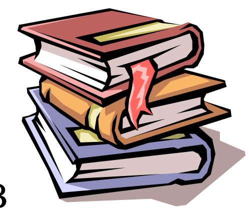


CHOICE B

A LOAN for FULL-TIME Education or Training

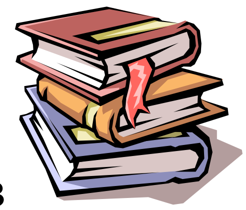
Decision 109	❐ $25	❐ $2000 LOAN
Decision 110	❐ $300	❐ $2000 LOAN
Decision 111	❐ $700	❐ $2000 LOAN

You must choose A or B:

 CHOICE A $$ one week from today	 CHOICE B A LOAN for FULL-TIME Education or Training

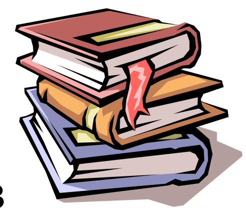
Decision 112	❒ $300	❒ $1000 LOAN
Decision 113	❒ $300	❒ $4000 LOAN

You must choose A or B:

 CHOICE A $$ one week from today	 CHOICE B Part GRANT and Part LOAN for FULL-TIME Education or Training

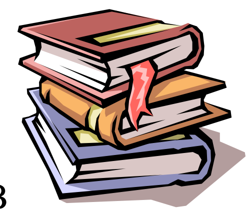
Decision 114	❐ $25	❐ $1000 LOAN + $1000 GRANT
Decision 115	❐ $300	❐ $1000 LOAN + $1000 GRANT
Decision 116	❐ $700	❐ $1000 LOAN + $1000 GRANT

You must choose A or B:

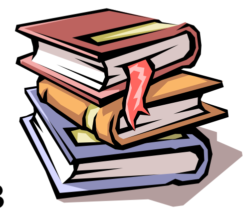
CHOICE A	CHOICE B
	
$$ one week from today	Part GRANT and Part LOAN for FULL-TIME Education or Training

Decision 117	❒ $300	❒ $400 LOAN + $400 GRANT
Decision 118	❒ $300	❒ $2000 LOAN + $2000 GRANT

You must choose A or B:

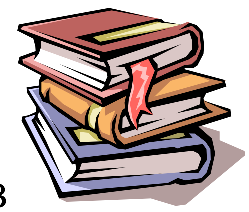
	CHOICE A 	CHOICE B 
	$$ one week from today	Part GRANT and Part Income Contingent Repayment (ICR) LOAN for FULL-TIME Education or Training
Decision 119	❐ $25	❐ $1000 ICR LOAN + $1000 GRANT
Decision 120	❐ $300	❐ $1000 ICR LOAN + $1000 GRANT
Decision 121	❐ $700	❐ $1000 ICR LOAN + $1000 GRANT

You must choose A or B:

CHOICE A	CHOICE B
 CHOICE A $$ one week from today	 CHOICE B Part GRANT and Part Income Contingent Repayment (ICR) LOAN for FULL-TIME Education or Training

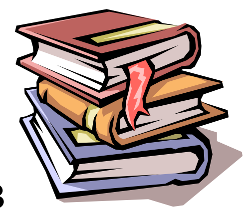
Decision 122	❐ $300	❐ $400 ICR LOAN + $400 GRANT
Decision 123	❐ $300	❐ $2000 ICR LOAN + $2000 GRANT

You must choose A or B:

CHOICE A	CHOICE B
	
$$ one week from today	FULL-TIME Education or Training (Expenses refunded)

Decision 124	❒ $25	❒ $1000 GRANT
Decision 125	❒ $100	❒ $1000 GRANT
Decision 126	❒ $300	❒ $1000 GRANT
Decision 127	❒ $700	❒ $1000 GRANT

You must choose A or B:

CHOICE A 	CHOICE B 
$300 one week from today	FULL-TIME Education or Training (Expenses refunded)

Decision 128	❒ $300	❒ $500 GRANT
Decision 129	❒ $300	❒ $2000 GRANT
Decision 130	❒ $300	❒ $4000 GRANT

After you have finished these decisions you may raise your hand and the experimenter will bring you Part II.