ECONtribute
MARKETS & PUBLIC POLICY

ECONtribute
Discussion Paper No. 014

Are Economists' Preferences Psychologists' Personality Traits? A Structural Approach

Tomáš Jagelka

July 2020

www.econtribute.de

UNIVERSITÄT BONN
Universität zu Köln

Funding by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) under Germany´s Excellence Strategy – EXC 2126/1– 390838866 is gratefully acknowledged.

WORKING PAPER

Are Economists' Preferences Psychologists' Personality Traits? A Structural Approach

Author:

Tomáš JAGELKA[‡]

May 26, 2020

I would like to give special thanks to Christian Belzil, James Heckman, Douglas Staiger, John Rust and four anonymous referees for their detailed feedback and to Frederik Bennhoff, Raicho Bojilov, Alexandre Cazenave-Lacroutz, Femke Cnossen, Thomas Dohmen, Armin Falk, Erzo Luttmer, Julie Pernaudet, Andrew Samwick, Sieuwerd Gaastra and Jonathan Zinman for their helpful comments. I also thank participants at seminars at Dartmouth College, École Polytechnique - CREST, Georgetown University, the University of Chicago, the University of Bonn, CERGE-EI, at the RES annual conference, the RES PhD meetings, the RES junior symposium, and at the annual conference of the Slovak Economic Association for their feedback. I gratefully acknowledge the receipt of the Student Travel Grant for the IAAE 2019 conference and of the prize for the "Best paper presented by a graduate student" at the conference. This research is funded by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) under Germany´s Excellence Strategy – EXC 2126/1– 390838866.

[‡]ECONtribute Cluster of Excellence, IZA, Institute for Applied Microeconomics at the University of Bonn, and CEHD at the University of Chicago. Email: tjagelka@uni-bonn.de.

Abstract

This paper proposes a method for empirically mapping psychological personality traits to economic preferences. Careful modelling of random components of decision making is crucial to establishing the long supposed but empirically elusive link between economic and psychological systems for understanding differences in individuals' behavior. I use factor analysis to extract information on individuals' cognitive ability and personality and embed it within a Random Preference Model to estimate distributions of risk and time preferences, of their individual-level stability, and of people's propensity to make mistakes. I explain up to 50% of the variation in both average risk and time 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. True differences in desired outcomes are related to differences in personality whereas actual mistakes in decisions are related to cognitive skill.

1 Introduction

There is extensive evidence that economic preferences, cognitive ability, and personality predict a wide range of economic outcomes (see Heckman, Jagelka, and Kautz, 2019 for a recent summary of the literature). 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 determine the dimension of attributes which constitute human capital and explain differences in life outcomes.[1] I demonstrate that careful modelling of random errors allows one to establish the long supposed but empirically elusive link (see Almlund et al., 2011 and Becker et al., 2012) between economic and psychological frameworks for understanding differences in individuals' behaviors.

I estimate a structural model of decision making under uncertainty and delay 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. There are 5 estimated structural parameters of interest: the coefficient of risk aversion and the discount rate which measure true (or average) risk and time preferences respectively; two parameters which describe the degree of instability of an individual's risk and time preferences respectively; and a "mistake" parameter which allows an individual to choose his less preferred option some percentage of the time. I use the extensive associated survey data to map both true economic preferences and the stochastic components of decision-making onto cognitive ability and factors related to three of the *Big Five* personality traits.

Both true risk and time preferences and their associated stochastic components map robustly onto cognitive ability and personality. Overall, the conscientiousness trait exhibits the strongest links. It explains a third of the cross-sectional variation in discount rates, 9% of the variation in risk aversion, and 23% of the variation in their individual-level stability. Furthermore, extraversion is strongly related to risk aversion and discount rates while high cognitive ability reduces an individual's propensity to make mistakes. 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 likely resulted in biased estimates of both risk aversion and of its relationship with characteristics such as cognitive ability in previous research.

My results show that heterogeneity in preferences explains a majority of the variation in observed choices between risky lotteries and between payments occurring at different points in time. Indeed, the five estimated structural parameters alone have explanatory power which is an order of magnitude larger than that of nearly two dozen demographic and socio-economic

[1] There is an increasing recognition in educational systems and beyond that characteristics other than cognitive ability are important. However, there is currently a lack of consensus on which ones truly matter and how to measure them.

variables. While risk and time preferences account for a vast majority of the explained variation in the overall number of risky or intertemporal choices, parameters related to randomness in decision making also have a non-negligible influence and predict inconsistencies in individual behavior. I thus call them *consistency parameters*.

My structural model has two main parts: a factor model used to derive latent cognitive ability and personality traits from multiple noisy observed indicators; and a model of decision-making under uncertainty and delay based on the assumption that decisions are driven by expected utility maximizing behavior which itself depends on an individual's risk and time preferences but is subject to random errors. I allow preferences to depend both on observed heterogeneity and on unobserved factors related to cognitive 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 using data from "The Millenium Foundation Field Experiment on Education Financing" based on a representative sample of 1,224 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, all given his observed characteristics, the four unobserved latent factors[2], and five unobserved types.[3]

My approach generalizes to settings in which one wishes to relate parameters of economic models to observables with multiple available noisy measures. It incorporates a flexible error structure which accounts for errors in both decision making and in measurement, and thus allows to separate signal from noise in observed choices.

The rest of the paper is organized as follows: Section 2 situates my contribution within the broader economic and psychological literature, Section 3 describes the data, Section 4 presents the theoretical underpinnings of the structural model, Section 5 details the empirical methodology, Section 6 presents the empirical results, Section 7 provides a general discussion of the broader implications of the findings presented in this article, and Section 8 concludes.

[2]The factors of interest are: an individual's cognitive skills and his personality traits. The latter consist of factors related to emotional stability, extraversion, and conscientiousness: stable personality traits identified by 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 given measures available in the data.

[3]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).

2 Background

2.a Relating Preferences and Personality

This paper builds on previous research in both economics and psychology. Walter Mischel's work on the "Marshmallow Test" brought attention to the importance of enduring traits in life outcomes. He found that children who were able to resist temptation to immediately eat one marshmallow and instead wait 15 minutes to get several, had better SAT scores, educational attainment, etc. later in life. Their choice to defer immediate gratification thus seemed to reflect some characteristic - preference or skill - which is valuable in other contexts. It would be explained by a low discount factor in neoclassical economic models and associated with the conscientiousness personality trait in the psychological literature. Similar intuitive correspondences can be drawn between diverse economic preferences[4] and personality traits[5]. In their 2017 review of the literature, Golsteyn and and Shildberg-Horisch note that "research on preferences and personality traits is a blossoming field in economic and psychological science. Economic preferences and personality traits are related concepts in the sense that both are characteristics of an individual that have been shown to predict individual decision making and life outcomes across a wide variety of domains."

Attempts to relate economic preferences and psychological traits can be understood as part of a broader effort to determine the dimensionality of attributes - skills, preferences, or behavioral biases - required to characterize essential human differences. One strand of the literature attempts to create "an empirical basis for more comprehensive theories of decision-making" by correlating various behavioral measures and sorting them into clusters (e.g. Chapman et al., 2018 and Dean and Ortoleva, 2019). A second strand concerns itself with summarizing the various documented behavioral tendencies in a simplified measure like a sufficient statistic (e.g. Chetty, 2015) or a sparsity model (e.g. Gabaix, 2014). Stango and Zinman (2019) empirically test such "B-counts" constructed from various behavioral biases relevant in consumer finance and find that they are correlated with cognitive ability and predictive of financial outcomes.

[4]Risk and time preference are the most basic economic preferences. Along with differences in constraints, they explain heterogeneity in behavior in neoclassical economic models. They are standardly embodied by the coefficient of risk aversion and by the discount factor respectively. More recent economic theory also incorporates social preferences and behavioral biases.

[5]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." While various classifications exist, the *Big Five* is the most prominent. It consists of: Extraversion associated with excitement-seeking and active, sociable behavior; Conscientiousness associated with ambition, self-discipline, and the ability to delay gratification; Emotional stability associated with confidence, high self-esteem, and consistency in emotional reactions; Agreeableness associated with warmth, trust, and generosity; and Openness to experience associated with imagination and creativity.

My contribution is to show that up to 50% of the heterogeneity in both the true (or average) risk and time preferences, in their individual-level stability, and in people's propensity to make mistakes can be explained by cognitive ability and factors related to three of the *Big Five* personality traits: extraversion, conscientiousness, and emotional stability.[6] 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 (see Heckman, Jagelka, and Kautz, 2019). 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)[7]

This paper is the first attempt to establish such a mapping in a full structural framework of decision-making under uncertainty and delay.[8] The amount of explained cross-sectional variation is large compared to previous research (see for example Becker et al, 2012). My results suggest that preferences and personality do not simply function side by side as previously claimed but that they are strongly related. I believe that I find a stronger relationship than previous studies because I estimate each trait from multiple noisy indicators using a factor model embedded in a full structural model of decision-making. This makes optimal use of available information and should address *attenuation bias* resulting from measurement error (see for example Carneiro, Hansen, and Heckman, 2003; Cunha and Heckman, 2009; and Cunha, Heckman, and Schennach, 2010) as well as *decision error bias* (see Andersson et al., 2016). Because preferences and traits as well as the quality of decision making have been shown to predict outcomes and to be highly heritable, this finding also has ramifications for understanding inequality and the mechanisms underlying the inter-generational transmission of socio-economic status.[9]

[6]While this dataset did not measure the *Big Five* personality traits using a questionnaire specifically developed for this purpose, the available survey questions listed in Section 10.b of the Appendix provide reasonable proxies for the first three traits. This assumption is supported by the fact that I obtain similar results - low correlations between preferences and personality - as those reported in previous research (e.g. Becker et al., 2012) when relying on reduced form measures used in that research i.e. on the average numbers of safe or patient choices to proxy for risk and time preferences respectively and on measures of cognitive ability and personality constructed as a simple sum of the constituent indicators.

[7]The question is as valid now as it was nine 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."

[8]In a contemporaneous project, Andersson et al. (2018) employ a similar theoretical model. As the focus of their study is on de-biasing inference based on lottery choice tasks, their work is limited to the study of risk preferences. The correlations between risk aversion and personality which they obtain point to the same general direction as my results. My framework and rich data allow me to dig deeper and establish a comprehensive mapping showing the percentage of cross-sectional variation in risk preference (and in time preference as well as in parameters governing decision instability) explained by cognitive ability and three factors related to personality.

[9]Heritability estimates are about 50% for cognitive skills and personality (see for example Bouchard and Loehlin, 2001; and Bergen, Gardner, and Kendler, 2007). Evidence is more mixed regarding the heritability

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, Van Soest, and Wengstrom'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. 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 when properly measured. Using only the coefficients from my structural model, information on observed heterogeneity, and my estimates of the prevalence of unobserved types, I am able to simulate as rich a distribution of preferences and of the random components of decision-making as can be obtained from estimates based on the full set of observed individual choices. For comparison purposes, using observed and unobserved heterogeneity, Von Gaudecker, Van Soest, and Wengstrom (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.

Nevertheless, I find that a large part of the cross-sectional variation is attributable to unobserved heterogeneity embodied by unobserved types. Establishing a more complete mapping between economic and psychological measures of human differences will require further research relying on enhanced datasets with an expanded array of economic preferences and the full *Big Five*.

2.b Separating Signal From Noise in Observed Measures

When elicited within laboratory experiments, risk and time preferences are difficult to estimate without introducing a stochastic element capturing a form of seemingly erratic behavior. For instance, take a classical Multiple Price List (MPL) approach popularized by Holt and Laury (2002) in which individuals face a sequence of binary choices between lotteries. Typically, the attractiveness of the riskier alternative increases as one proceeds down a set of tasks of an MPL. Certain individuals who at some point switch to the riskier option revert back to the safer one in subsequent choices even if those offer an even more attractive riskier alterna-

of preferences although recent research has shown that they may be as heritable as cognitive and non-cognitive traits (see for example Beauchamp, Cesarini, and Johannesson, 2017). Little is known regarding the heritability of decision-making quality. My results documenting a strong link between preferences, random components of decision-making, cognitive skill, and personality combined with extensive psychological research on the heritability of personality suggest that all of the above may be heritable to a large degree.

tive. Furthermore, when faced with multiple sets of questions designed to elicit risk (or time) preferences, individuals rarely make choices consistent with having one precise parameter for risk (or delay) aversion. For this reason, individual behavior can be naturally characterized by structural **preference parameters** such as the coefficient of relative risk aversion or the discount factor but also by parameters representing the propensity to deviate from their true (or average) preferences. Let us call the latter **consistency parameters**.

Accordingly, economists developed stochastic choice models that introduce a noise element into individual decisions. The Random Utility Model (RUM) includes the often used Fechner and Luce error specifications and has been largely favoured by experimentalists (e.g. Hey and Orme, 1994; Holt and Laury, 2002; Andersen et al., 2008). While there are multiple variations of the framework (see Becker, DeGroot, and Marschak, 1963), it can be modeled as an error term appended to the utility that a decision maker derives from selecting a particular alternative, thus making choices probabilistic. Under RUM, noise is standardly assumed to be independent of the structural expected utility component driving decisions. Choice probabilities derived using the RUM thus exhibit non-monotonicities which are at odds with a basic theoretical definition of risk and time preferences, calling into question its continued use in preference estimation. Recent papers by Wilcox (2011) and Aspesteguia and Ballester (2018) have pointed out the benefits of using a different type of stochastic model in which the error term directly impacts individual preference parameters. This type of error specification was proposed by Loomes and Sugden (1995). While it can be considered a particular interpretation of the broad random utility framework, for the sake of clarity of terminology, I will refer to it as the Random Preference Model (RPM) following its authors. Bruner (2017) provides empirical support for the use of monotone models in risk preference estimation by documenting a negative relationship between risk aversion and stochastic decision error as predicted by this class of models (RUM has the opposite prediction).[10] Aspesteguia and Ballester (2018) compared the RUM to the RPM model with decision errors[11] within a *representative agent* framework using Danish data. Their estimates indicate that the degree of relative risk aversion obtained from a RUM specification is lower than the estimate obtained using a RPM, especially for individuals who are highly risk-averse. However, they do not investigate the *distributions* of preference parameters using the RPM. Indeed, a structural estimation of the distributions of preference (let alone consistency) parameters, has not yet been performed within this framework.

I contribute to this active area of research by estimating distributions of risk and time preferences using the Random Preference Model (RPM). I am the first to jointly estimate full popu-

[10]The predicted general relationship between decision errors and risk aversion under RPM is actually more complex. However, in choices in which both alternatives have the same expected return and differ only in its variance (such as those used by Bruner, 2017, to detect mistakes), the predicted relationship is indeed negative.

[11]Incorporating a "mistake" parameter within the RPM framework allows for "processing error" on the part of the decision-maker. It relaxes the otherwise strong rationality requirements of the RPM which for example excludes choosing dominated options.

lation distributions of risk and time preference parameters and of their associated stochastic components using the RPM framework. 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 preference parameters 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.

My approach offers a comprehensive treatment of random errors associated with both the stability of preferences and with the propensity to make random mistakes. While the addition of various types of stochastic components to models of decision-making is not new, my approach is unique in that I introduce a total of three distinct consistency 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. Beauchamp, Cesarini, and Johannesson (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. Bruner (2017) finds that errors decrease with risk aversion. He estimates risk preferences from standard MPLs and error propensity from the number of choices of a stochastically dominated option in separate choice tasks. In the absence of a structural model he is not able to use the individual noise estimates to correct estimated risk aversion and thus simply takes the average switching point from two MPL lists to reduce measurement error, a commonly used but imprefect solution. Several recent papers (e.g. Stango and Zinman, 2019 and Chapman et al., 2018) refer to Gillen et al. (2019) to use multiple measures of a variable as instruments for one another to reduce *measurement error*. While this approach is valid, it is not as original as claimed.[12] Moreover, it does not deal with *decision error* mentioned by Andersson et al. (2016) who suggest that random mistakes, if not properly accounted for, may bias preference estimates.[13]

Insofar as decision errors depend on observed and unobserved heterogeneity, they can also lead to the detection of spurious correlations between estimated preferences and explanatory variables (e.g. between risk aversion and cognitive ability). Andersson et al. (2018) empir-

[12]The estimation system follows directly from Hansen (1982) or Sargan (1958).

[13]E.g. if an average person tends to choose the risky option on 8 out of 10 MPL tasks, random mistakes will more likely turn his choice to safe than to risky, leading to an overestimation of risk aversion. This will be true also in repeated measurements making errors in the risky behavior variable correlated between the measure and its instrument, thus invalidating the instrument.

ically document the existence of decision error bias using two MPLs calibrated such that a risk neutral decision maker switches at a different point in each MPL.[14] They find that only a combination of their "balanced" design and of the use of an RPM with heterogeneous noise eliminates the spurious negative correlation between risk aversion and cognitive ability induced by a standard MPL (such as those studied in this paper).[15] In contrast, my results suggest that given enough observed lottery choices per individual, a more sophisticated RPM framework which I develop in this paper and which includes unobserved heterogeneity and a factor model, is in itself sufficient to eliminate the spurious negative correlation between risk aversion and cognitive ability.

Von Gaudecker, Van Soest, and Wengstrom (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, *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 risk and time respectively. 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. Accordingly inconsistent switching points *across* MPLs are best explained by the estimated stability parameters whereas actual choice reversals *within* a given MPL (a much stronger violation of choice consistency) are best explained by the estimated trembling hand parameter.

I document a relationship between *preference instability* and conscientiousness, and between the *propensity to make mistakes* and cognitive ability supporting the notion that these two types of choice inconsistency are fundamentally separate. More conscientious individuals exhibit more stable risk and time preferences while higher ability individuals make errors in decisions less frequently.

[14] Their logic behind such a "balanced design" is that in each MPL, the bias on estimated risk aversion due to the existence of random mistakes (e.g. a person picks the riskier option when in fact the safe one is truly preferred) should go in a different direction and thus balance out. In order for this to work in practice, one would need an MPL design balanced at the individual level according to each individual's true level of risk aversion.

[15] This design is characterized by a relatively early switching point to the risky lottery. If lower cognitive ability individuals make more mistakes, the spurious negative correlation between risk aversion and cognitive ability emerges.

The *stability parameters* allow individuals' tastes to vary. 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 estimated preference instability does not necessarily point to irrational behavior. For example, in my 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. Revealed 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 and thus he may choose to randomize within this interval) or they could vary due to external factors such as rising temperature in the room. Alternatively, these stability parameters can be viewed as akin to measurement error describing the degree of precision to which I can measure a person's true (or average) preferences from his observed choices.[16] 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 fully explained by variation alone in task parameters.

The *trembling hand* parameter allows for individuals to make mistakes and actually *pick their less preferred alternative* some percentage of the time. This can be due some individuals having a level of cognitive ability which is either insufficient to correctly process the parameters of the choice task at hand or which would require too much effort relative to the experimental payoffs. This hypothesis is supported by my finding that heterogeneity in the trembling hand parameter is best explained through variation in cognitive ability. In contrast, heterogeneity in both true preferences and in preference instability (which leads to choosing the *currently preferred* option although this may be inconsistent with the individual's true underlying preference) is best explained by personality traits. A pattern emerges: Differences in desired outcomes (which themselves may vary) are related to differences in personality whereas mistakes in decisions which result in actually choosing the less preferred option are related to cognitive skill.

The existence of heterogeneity in consistency parameters which characterize the stochastic components of decision-making may have a large impact on economic outcomes. Since El-Gamal and Grether's finding that students from better colleges behave in a more bayesian way, a body of evidence has accumulated showing a link between cognitive ability and various types of behavioral biases and inconsistencies (e.g. Benjamin, Brown, and Shapiro, 2013;

[16] Or, in the words of Loomes and Sugden (1995): "the stochastic element derives from the inherent variability or imprecision of the individual's preferences, whereby the individual does not always know exactly what he or she prefers. Alternatively, it might be thought of as reflecting the individually small and collectively unsystematic impact on preferences of many unobserved factors."

Choi et al., 2014; and Stango and Zinman, 2019). 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 consistency 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 through (or 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.

3 Data

The data comes from "The Millenium Foundation Field Experiment on Education Financing" which involved a representative sample of 1,224 Canadian citizes who were full time students in their last year of high school. The students were between 16 and 18 years old at the time of the experiment.

The experiment was conducted using pen and paper choice booklets as well as simple random sampling devices like bingo balls and dice. Project cost considerations suggested that participants be drawn from locations with convenient travel connections from the SRDC Ottawa and CIRANO Montreal offices. Manitoba, Saskatchewan, Ontario and Quebec were the selected provinces. The implementation team was able to carry out work in urban and rural schools in each of the four provinces.

The experiment contains 103 choice tasks designed to elicit risk and time preferences. Choices were incentivized and students were paid for one randomly drawn decision at the end of the session. The full experimental setup is included in Section 2 of the Online Appendix.

3.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 introduced by Miller, Meyer, and Lanzetta (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.[17] 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 on the 3 sets of H&L questions.[18]

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

The remaining 25 tasks designed to measure risk aversion used in this study are a binarized version of the ordered lottery selection (OLS) design developed by Binswanger (1980) and popularized 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. It should vary among the 5 sets of OLS type questions for a given individual, unlike in the H&L design. However, a risk neutral individual should always at least weakly prefer the riskier alternative. 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 under CRRA utility), OLS tasks let us identify highly risk-averse individuals.

[17] 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.

[18] This prediction holds for the popular constant relative risk aversion (CRRA) utility function but not for alternatives such as constant absolute risk aversion (CARA) utility.

Harisson and Rutstrom (2008) compare estimates based on H&L type tasks and OLS type tasks for the same sample of individuals. They conclude that "[t]he results indicate consistency in the elicitation of risk attitudes, at least at the level of the inferred sample distribution". I thus treat both types of lottery choice tasks symmetrically in the structural model.

3.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 with variations on front-end delay (1 day to three months) and time-horizon (1 month to 1 year). In each group of questions, subjects are presented with an ordered array of binary choices. In each choice task they choose between an earlier payment and a later payment. In each subsequent row the magnitude of the later payment increases. Most individuals are thus expected to switch to the later payment at some point. The "switching point" should be indicative of each individual's time preference.

3.d Observed Individual Choices

Figure 1 plots the distributions of individuals' choices on tasks designed to elicit their risk and time preferences. There is significant heterogeneity in choices and that extremes of both distributions (choosing all risky or all safe alternatives in lottery tasks and all earlier or all later payments in temporal tasks) have non-zero mass.[19] 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 earlier payments or all later payments. Particularly striking is the large share of seemingly very impatient people. However, one needs to have estimates of individuals' risk aversion in order to be able to draw conclusions about their discount rates.

[19] A "safe" choice is defined as picking the less risky of two lotteries in a given lottery choice task and an "impatient" choice is defined as picking the earlier of two options in a given temporal choice task.

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

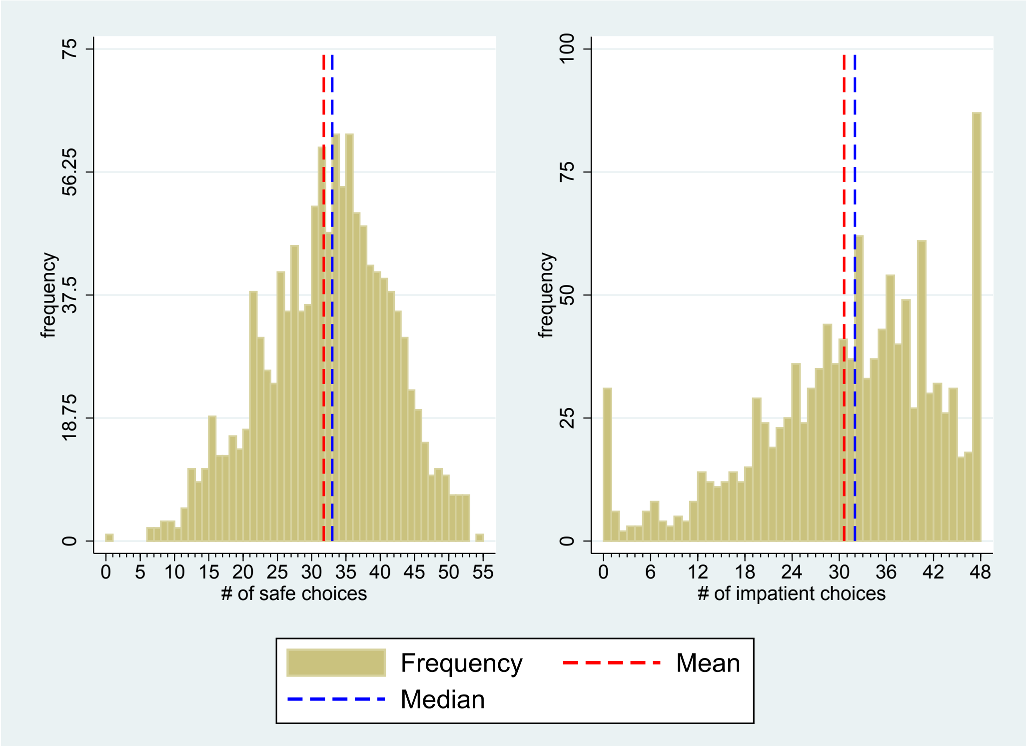
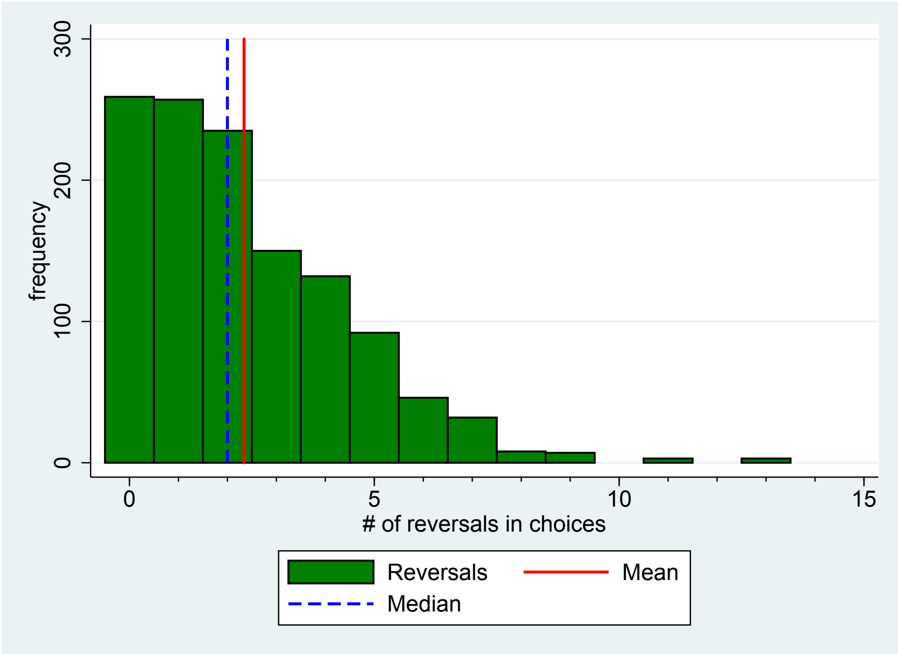


Figure 2 shows that contrary to standard predictions, some individuals exhibit reversals in their choices within a set of choice tasks.[20] This shows the utility of analyzing data on the full set of tasks as opposed to assuming that each individual will maintain his choice after his "switching point" (as is often done in the literature, see Bruner, 2017 for a recent example). Observed reversals in choices within a set of questions allow for the identification of the trembling hand parameter which embodies the propensity to make mistakes. In contrast, an individual's inconsistent switching points across MPLs allow for the identification of the stability parameters, see Figure 10.

[20]A reversal is defined as follows. Take for example one set of 10 H&L lottery choice tasks. If an individual starts 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 he then reverts back to the safer option within the same set of tasks, despite the riskier option becoming even more attractive, this is considered a reversal. The definition is analogous for OLS type lottery tasks and for temporal choice tasks.

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



3.e Background Information

The experiment also solicits a large amount of background information collected both from students and from their parents. The collected information includes grades, a measure of numeracy, measures of non-verbal ability, personality, finances, school and job aspirations, etc. Detailed descriptive statistics including demographic and socioeconomic variables for test subjects and their families are in Section 10.a of the Appendix.

Section 10.b of the Appendix lists measures selected to approximate cognitive ability and 3 of the *Big Five* personality traits. Cognitive ability is proxied for by various indicators related to cognitive skills – grades, a numeracy test, and self-reports of skills: oral, written, mathematical, etc. Conscientiousness is proxied for by self-reported ambition, ability to delay gratification, and diligence. Extraversion is proxied for by questions related to self-reported tendencies for active, sociable behavior and excitement-seeking. Emotional stability is proxied for by questions related to confidence, self-esteem, and a perceived internal locus of control.[21] While the survey does not include a full validated Big 5 questionnaire, evidence presented in Figure 3 suggests that the included indicators may indeed approximate emotional stability, extraversion, and conscientiousness. I restrict my analysis to these 3 personality traits as the data does not have proxies for the remaining *Big Five* personality traits: agreeableness and openness to experience.

[21]Previous research found locus of control to be strongly related to emotional stability - see Judge et al. (2002) and Almlund et al. (2011).

Section 10.b of the Appendix includes estimated loadings and calculated signal to noise ratios associated with each indicator for cognitive ability and personality. The magnitudes of the loadings and the informational content of the measures 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).

There are several recent working papers which analyze this dataset using a structural model. Belzil and Sidibe (2016) estimate individual preference over risk and time and study heterogeneity using various specifications of preferences, which include hyperbolic, quasi-hyperbolic discounting as well as subjective failure probability over future payments. They investigate the predictive power (transportability) of the estimated preference parameters. Belzil, Maurel and Sidibe (2017) make use of the portion of the experiment devoted to preference elicitation in conjunction with the higher education financing segment to estimate the distribution of the value of financial aid for prospective students.

3.f Correlational Evidence

To illustrate the contribution of my proposed structural framework, it is useful to examine correlations between simple measures of preferences, cognitive ability, and personality contained in the data. To this end I construct for each individual variables which represent: the total number of times that he chose the riskier of two lotteries on the 55 tasks designed to elicit risk preferences (a proxy for risk aversion); the total number of times that he chose the later of two payments on the 48 tasks designed to elicit time preferences (a proxy for impatience); and score variables for cognitive ability and proxies for the three personality traits obtained as a simple sum of the respective underlying measures.[22] Figure 3 shows correlational evidence of the link between between safe or impatient choices and cognitive ability and personality. It compares correlations obtained in this dataset to those presented in Becker et al. (2012).[23] One can see, that I replicate the previously established null result on the relationship between preferences and personality when using measures and techniques common in past research on the topic.

[22]Categorical measures are normalized to lie on the 0-1 interval, continuous measured are normalized to have 0 mean and a standard deviation of 1.

[23]Neuroticism is the inverse of emotional stability. The sign on the correlations presented in Becker et al. are reversed in accord with the direction of the risk and time measure as used in my paper: higher values reflect higher risk aversion and discount rates respectively.

Figure 3: Correlational Evidence on the Link Between Risky and Impatient Choices and Personality

	Safe Choices			Impatient Choices		
	Becker et al. (2012)		Jagelka (2018)	Becker et al. (2012)		Jagelka (2018)
	Table 2	Table 3		Table 2	Table 3	
Neuroticism	0.12	-0.03	0.05	0.05	0.06	0.04
Extraversion	-0.08	-0.08	-0.10	0.01	0.07	0.06
Conscientiousness	0.06	0.07	0.00	-0.01	0.07	-0.11
Cognitive Ability	NA	NA	-0.04	NA	NA	-0.18

Source: Becker et al. (2012), Table 2 and 3

One can go a step further and conduct a linear regression of observed choices on gender and simple score indices of cognitive ability and personality traits. These results are summarized in Figure 1 of the Online Appendix. Being female is associated with making more safe choices and fewer impatient ones. Cognitive ability is related to fewer impatient choices and fewer choice reversals. Its coefficient on risk aversion is negative in line with the raw correlation presented above and with the results of Anderssen et al. (2018) obtained using their first MPL design in which a risk-neutral decision-maker is expected to pick relatively many risky options, such as in the MPLs used here. The sign reversal obtained through my structural model (see Table 2 of the Appendix) supports their claim that the supposed negative relationship between risk aversion and cognitive ability is an artefact of a particular MPL design and thus spurious. Extraversion is associated with picking fewer safe choices. Conscientiousness and emotional stability show no statistically significant links. The low R2 documented here would suggest that the link between preferences and personality is at best weak as even the marginal explanatory power comes largely from gender.

The limitations of these simple analytical techniques are readily apparent. Estimated coefficients can be biased by random mistakes in decisions as discussed in Andersson et al. (2016). Insignificant results can be an artefact of measurement error in proxies for economic preferences and personality traits. A reduced form analysis does not allow one to determine whether personality traits influence choices through preference or consistency parameters.

The full structural model described in the next section addresses these shortcomings.

4 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 risk aversion parameter. In other cases, the choice is between an earlier payment 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 a preference parameter is hit by one of the possible realizations of these shocks every time a task is performed. The shocks are independent across tasks. 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 needs to be made. This can reflect 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 the choice tasks, I can map individual-specific preference parameters onto psychological traits using a factor model.[24] I also incorporate heterogeneity in the stability of individual preferences and in the propensity to make mistakes. 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.

Cognitive 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 relate all components of the model in a structural framework where preference and consistency 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.

[24]This approach allows me to stay within a standard economic framework for decision-making under uncertainty and delay. Decisions depend on the coefficient of risk aversion and on the discount rate, primitives of classical economic models. The mapping as presented is not a statement on the direction of causality, if any, between preferences on the one hand and ability and personality on the other hand but rather on the existence of a correspondence between the two concepts. The mapping could well be performed in the opposite direction as well.

4.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.

4.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 decreasing relationship between the probability of choosing the riskier option and aversion to risk. Apesteguia and Ballester (2018) point out 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.[25]

Assume constant relative risk aversion (CRRA) utility and no background consumption.[26,27] 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 $\Theta_i \neq 1$

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

[25]As pointed out in the background section, the RPM used here can be viewed as an alternative random utility specification which still reflects a degree of randomness in observed choices but has more sound theoretical properties. The difference lies in the placement of the error term and in the inclusion of an additional "mistake" parameter.

[26]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". When they estimate individual coefficients on the parameter, they discover that "a vast majority" of the subjects in the sample uses a background consumption reference point that approaches 0.

The CRRA utility function is undefined for 0 payoffs when the coefficient of risk aversion is greater than 1. All lotteries used in this experiment involve non-zero payoffs, so this is not an issue in risk-estimation. In time preference estimation where choice tasks do involve 0 payoffs in either the earlier or in the later period, the coefficient of risk aversion is capped at +1 as explained in Section 4.a.ii.

[27]The obtained mapping between preferences and ability and personality is robust to an alternative assumption of constant absolute risk aversion (CARA) utility. The functional form then becomes $U(a_1)_i = \frac{1-\exp(-\Theta_i * a_1)}{\Theta_i}$ if $\Theta_i \neq 0$ and $U(a_1)_i = a_1$ if $\Theta_i = 0$.

If $\Theta_i = 1$

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

where $\Theta_i \in (-\infty; +\infty)$ is individual i's coefficient of risk aversion.

The expected utility of the second option $E(U_{i,2})$ 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.

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 $\sigma_{\Theta,i} \in [0;1]$ is the standard deviation of his risk aversion. It is restricted to the unit interval as values above one make little economic sense.[28] Standard deviation of an individual's risk aversion has Θ as subscript to distinguish it from the standard deviation 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.

[28]To reflect the different scale of risk aversion under CARA utility (roughly 20 times smaller than comparable coefficients under CRRA), the scale of $\sigma_{\Theta,i}$ is adjusted accordingly in the CARA robustness check.

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 imposes strong rationality requirements and predicts that dominated choices are never chosen.[29] Yet in reality some individuals do choose such dominated options.

This is when the *trembling hand* concept comes in. One can assume that each individual's hand will *tremble* some percentage of the time and he mistakenly picks his less preferred option when it does.[30] Let us call the tremble parameter $K_i \in [0; 0.5]$. It is constrained not to exceed 0.5 as an estimate which would have an individual make mistakes more than half of the time probably mis-estimates his true preference.

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 for example due to imperfect self-knowledge, given his instantaneous draw of risk aversion, an individual would still be making a calculated expected utility maximizing choice. On the other hand, K_i leads him to choose his less preferred option some percentage of the time. This choice cannot be logically justified unless he made a mistake or was not paying attention. As such it can be seen more as a measure of an individual's rationality.

Incorporating the tremble parameter, we obtain 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 if 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.

[29]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 assuming it is hit with a sufficiently large draw of the error term.

[30]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 expend his mental energy and instead choose randomly.

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 4.b.

4.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.

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.[31] Under exponential discounting, the utility of individual i from a proposed payoff of a \$ received in τ years is:

If $\Theta_i \neq 1$

$$U_i = \beta_i^\tau \frac{a_1^{(1-\Theta_i)}}{1 - \Theta_i} \tag{10}$$

If $\Theta_i = 1$

$$U_i = \beta_i^\tau * ln(a_1) \tag{11}$$

where β_i is the discount factor. It can be expressed as $\beta_i = \frac{1}{1+R_i}$ where $R_i \in [0;1]$ is the discount rate.[32]

[31] As with risk preferences, the obtained mapping between time preferences on the one hand and cognitive ability and personality on the other hand is robust to an alternative assumption of CARA utility.

[32] 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 earlier 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 earlier

While the assumption of exponential discounting has been challenged (e.g. Frederick, Loewenstein, and O'Donoghue, 2002), it remains standard and evidence suggests that it may hold well in simple experimental tasks such as the ones used here (see Andersen et al., 2014). In the context of this experiment, the lack of variation of the tendency to choose the later option with varying front-end delay is evidence against hyperbolic discounting. Depending on whether or not one believes that the "passion for the present" lasts longer than the 24-hour minimal front end delay, the fact that it has no effect on observed choices is also either evidence against quasi-hyperbolic discounting (present bias) or suggests that I lack the data necessary to test for it. Nevertheless, as a robustness check I estimate my model under hyperbolic discounting as individuals in this experiment do exhibit greater patience with increasing time horizon.[33]

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 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.

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

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 earlier 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 allow $\Theta_i > 1$ as these are still reasonable levels of risk aversion, I only estimate indifference thresholds for the discount rate up to logarithmic risk aversion. Individuals with an estimated risk aversion beyond this level will be assigned the limit indifference threshold. At these levels of risk aversion, indifference thresholds for the discount rate already approach zero.

[33] I use a simple discounting formula which is adapted to the indifference threshold framework used in this paper and which Andersen et al. (2014) find fits as well as a more general hyperbolic model. The utility of individual i from a proposed payoff of a \$ received in τ years then becomes: $U_i = \frac{1}{1+R_i*\tau} * \frac{a_1^{(1-\Theta_i)}}{1-\Theta_i}$ if $\Theta_i \neq 1$ and $U_i = \frac{1}{1+R_i*\tau} * ln(a_1)$ if $\Theta_i = 1$. Results are robust to this alternative assumption.

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 $\sigma_{R,i} \in [0;1]$. 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. It is restricted to the unit interval as values above one make little economic sense.

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:

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

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:

$$\epsilon_{i,t} \sim \mathcal{N}(0,1) < \frac{ln(R_{12,i,t}) - ln\left(\frac{R_i^2}{\sqrt{(\sigma_{R,i})^2 + R_i^2}}\right)}{\sqrt{ln\left(1 + \frac{(\sigma_{R,i})^2}{R_i^2}\right)}} \tag{13}$$

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

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

$$P(LP_{i,t} = 1) = \Phi\left[\frac{ln(R_{12,i,t}) - ln\left(\frac{R_i^2}{\sqrt{(\sigma_{R,i})^2 + R_i^2}}\right)}{\sqrt{ln\left(1 + \frac{(\sigma_{R,i})^2}{R_i^2}\right)}}\right] \tag{14}$$

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:

$$P(LP_{i,t} = 0) = 1 - P(LP_{i,t} = 1) \tag{15}$$

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 propensity to make mistakes.

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.

$$P(LC_{i,t}=1)=P(LP_{i,t}=1)*(1-K_i)+[1-P(LP_{i,t}=1)]*K_i \tag{16}$$

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:

$$P(LC_{i,t}=LC_{i,t})=P(LC_{i,t}=1)^{LC_{i,t}}*P(LC_{i,t}=0)^{1-LC_{i,t}} \tag{17}$$

or, in full:

$$\begin{aligned}
&P(LC_{i,t}=LC_{i,t})=\\
&=\left\{\Phi\left[\frac{ln(R_{12,i,t})-ln\left(\frac{R_i^2}{\sqrt{(\sigma_{R,i})^2+R_i^2}}\right)}{\sqrt{ln\left(1+\frac{(\sigma_{R,i})^2}{R_i^2}\right)}}\right]*(1-K_i)+\left\langle 1-\Phi\left[\frac{ln(R_{12,i,t})-ln\left(\frac{R_i^2}{\sqrt{(\sigma_{R,i})^2+R_i^2}}\right)}{\sqrt{ln\left(1+\frac{(\sigma_{R,i})^2}{R_i^2}\right)}}\right]\right\rangle*K_i\right\}^{LC_{i,t}}*\\
&*\left\{\left\langle 1-\Phi\frac{ln(R_{12,i,t})-ln\left(\frac{R_i^2}{\sqrt{(\sigma_{R,i})^2+R_i^2}}\right)}{\sqrt{ln\left(1+\frac{(\sigma_{R,i})^2}{R_i^2}\right)}}\right\rangle*(1-K_i)+\Phi\left[\frac{ln(R_{12,i,t})-ln\left(\frac{R_i^2}{\sqrt{(\sigma_{R,i})^2+R_i^2}}\right)}{\sqrt{ln\left(1+\frac{(\sigma_{R,i})^2}{R_i^2}\right)}}\right]*K_i\right\}^{1-LC_{i,t}}
\end{aligned} \tag{18}$$

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

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:

$$L_i=\prod_{l=1}^{55}P(RC_{i,l}=rc_{i,l})*\prod_{t=1}^{48}P(LC_{i,t}=LC_{i,t}) \tag{19}$$

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.

4.b Observed Heterogeneity

A major contribution of this paper is to allow the coefficient of risk aversion and the discount rate, 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 proxied for 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 consistency parameters. Thus:

$$\Theta_i = \theta_0 + \theta_1{}'X_i + \theta_2{}'F_i \tag{20}$$

$$\sigma_{\Theta,i} = \Phi(s_{\theta,0} + s_{\theta,1}{}'X_i + s_{\theta,2}{}'F_i) \tag{21}$$

$$R_i = \Phi(r_0 + r_1{}'X_i + r_2{}'F_i) \tag{22}$$

$$\sigma_{R,i} = \Phi(s_{r,0} + s_{r,1}{}'X_i + s_{r,2}{}'F_i) \tag{23}$$

$$K_i = 0.5 * \Phi(\kappa_0 + \kappa_1{}'X_i + \kappa_2{}'F_i) \tag{24}$$

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 cognitive ability and three factors related to emotional stability, extraversion, and conscientiousness.

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). Each measure is assumed to be a noisy reflection of the underlying factor of interest. The noise to signal ratio of each measure is presented in Section 10.b of the Appendix. This approach allows for a more efficient extraction of information on cognitive ability and personality from available measures 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:

$$M_{i,j,f} = \gamma_{0,j,f} + \gamma_{1,j,f} * F_{i,f} + \epsilon_{i,j,f} \tag{25}$$

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)[34] and of an orthogonal random part:

$$F_{i,f} = \alpha_0 + \alpha_f{}' X_i + \widetilde{F}_{i,f} \tag{26}$$

where $\alpha_f{}'$ is a set of coefficients on the individual's observed characteristics which enter into factor f. The exogenous term $\widetilde{F}_{i,f}$ follows a Normal distribution with mean 0 and variance $\sigma_f^2 \in [0; +\infty)$, 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 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:

$$P(M_{i,j,f} = m_{i,j,f}) = [1 - \Phi(-\gamma_{0,j,f} - \gamma_{1,j,f} * F_{i,f})]^{M_{i,j,f}} * \Phi(-\gamma_{0,j,f} - \gamma_{1,j,f} * F_{i,f})^{1-M_{i,j,f}} \tag{27}$$

The corresponding probabilities for multi-valued and continuous measures can be found in Section 1.b of the Online Appendix.

4.c Unobserved Heterogeneity

Unobserved heterogeneity is incorporated through unobserved types which differ in the intercepts of their preference and consistency 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. Types reflect pure unobserved heterogeneity: they are assumed to be orthogonal to all other variables in the model. Each person is thus as likely to be any of the unobserved types as every other person. The resulting likelihood contribution will thus be a weighted average of the individual type likelihoods, where the weights correspond to each

[34]These characteristics were chosen due to their intuitive importance in explaining personality and cognitive ability and to their availability for the full sample.

type's prevalence in the overall sample. These are parameters to be estimated. The use of unobserved types to represent unobserved heterogeneity is well established since Keane and Wolpin's (1997) seminal paper.

5 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. The probabilities from the previous section cannot be calculated directly, as the factors are unobserved. The factors are modeled as random effects.

Take the example of a binary measure. Combining equations 25 and 26, the probability of observing value 1 on binary measure $M_{i,j,f}$ using factor $F_{i,f}$ as a random effect is:

$$P(M_{i,j,f}=1\Big|\widetilde{F}_{i,f})=P\Big(\epsilon_{i,j,f}<\gamma_{0,j,f}+\gamma_{1,j,f}*(\alpha_0+\alpha_f{}'X_i)+\gamma_{1,j,f}*\widetilde{F}_{i,f}\Big|\widetilde{F}_{i,f})\Big)= \\ =\Phi\Big(\gamma_{0,j,f}+\gamma_{1,j,f}*(\alpha_0+\alpha_f{}'X_i)+\gamma_{1,j,f}*\widetilde{F}_{i,f}\Big|\widetilde{F}_{i,f})\Big) \quad (28)$$

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

$$P(M_{i,j,f}=1)=\int_{-\infty}^{+\infty}\Phi\Big(\gamma_{0,j,f}+\gamma_{1,j,f}*(\alpha_0+\alpha_f{}'X_i)+\gamma_{1,j,f}*\widetilde{F}_{i,f}\Big)*\frac{1}{\sigma_{F_f}}\phi\Big(\frac{\widetilde{F}_{i,f}}{\sigma_{F_f}}\Big)d\widetilde{F}_{i,f} \quad (29)$$

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:

$$L_i\Big|(\widetilde{F}_i=\widetilde{F}_{i,1},\widetilde{F}_{i,2},...,\widetilde{F}_{i,F};UT_i=ut_i)=\prod_{f=1}^{F}\prod_{j=1}^{J}P(M_{i,j,f}=m_{i,j,f}\Big|\widetilde{F}_{i,f})*\prod_{l=1}^{55}P(RC_{i,l}=rc_{i,l}\Big|\widetilde{F}_i,UT_i)*$$
$$*\prod_{t=1}^{48}P(LC_{i,t}=lc_{i,t}\Big|\widetilde{F}_i,UT_i) \quad (30)$$

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 given a particular value of his unobserved type UT_i. The relevant probabilities for observing each of the aforementioned are given in equation 27 for binary measures, equations 34-36 for multi-valued measures, equation 37 for continuous measures, equation 9 for lottery choice tasks, and in equation 18 for temporal choice tasks[35]. 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 consistency parameters and is assumed orthogonal to both unobserved factors and to the observed measures which proxy for the factors.

One now has to choose whether to first integrate out the unobserved factors or the unobserved types.[36] I proceed by integrating out the former:

$$L_i\Big|(UT_i=ut_i)=\int\cdots\int_{\widetilde{F}_i}\prod_{f=1}^{F}\prod_{j=1}^{J}P(M_{i,j,f}=m_{i,j,f}\Big|\widetilde{F}_{i,f})*\prod_{l=1}^{55}P(RC_{i,l}=rc_{i,l}\Big|\widetilde{F}_i,UT_i)*$$
$$*\prod_{t=1}^{48}P(LC_{i,t}=LC_{i,t}\Big|\widetilde{F}_i,UT_i)*f(F_1,...,F_F)d\widetilde{F}_i \quad (31)$$

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:

$$L_i\Big|(UT_i=ut_i)=\int\cdots\int_{\widetilde{F}_i}\prod_{f=1}^{F}\prod_{j=1}^{J}P(M_{i,j,f}=m_{i,j,f}\Big|\widetilde{F}_{i,f})*\prod_{l=1}^{55}P(RC_{i,l}=rc_{i,l}\Big|\widetilde{F}_i,UT_i)*$$
$$*\prod_{t=1}^{48}P(LC_{i,t}=LC_{i,t}\Big|\widetilde{F}_i,UT_i)*\frac{1}{\sigma_{F_1}}\phi\Big(\frac{\widetilde{F}_{i,1}}{\sigma_{F_1}}\Big)*...*\frac{1}{\sigma_{F_F}}\phi\Big(\frac{\widetilde{F}_{i,F}}{\sigma_{F_F}}\Big)d\widetilde{F}_i \quad (32)$$

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

[35]The formulas for multi-valued and continuous measures are in Section 1.a of the Online Appendix.

[36]The latter will actually correspond to a finite sum as there is a finite number of discrete unobserved types. It is set to 5. Results are robust to estimation with 3 unobserved types.

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

$$L_i = \sum_{ut=1}^{UT} (L_i \Big| ut) * p_{ut} \tag{33}$$

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.

6 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 choice model**. It is estimated by maximizing the likelihood, described in equation 19, 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 consistency 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 which measure cognitive ability and personality (see equation 33). Results are obtained using simulated maximum likelihood. This specification includes observed and unobserved heterogeneity and allows me to structurally map economists' preference parameters onto psychologists' personality traits.

The two specifications are complementary. The fixed effects choice model provides individual point estimates of the preference and consistency parameters. 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 consistency 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 consistency parameters (those governing the stability of preferences and the propensity to make mistakes).

6.a Preference Parameters

Results from the full model summarized in Figure 4 reveal that an average individual[37] in the population has a slightly higher than logarithmic risk aversion and a 24% discount rate. The risk aversion estimate is relatively high for the experimental literature but closer to values standardly assumed by macroeconomists. It may be in part due to the inclusion of the OLS tasks in this experiment which cover a wider range of risk aversion than the standard HL design and thus allow for the detection of highly risk-averse individuals. Apesteguia and Ballester (2018) obtain a risk aversion estimate of 0.75 and a 27% discount rate using Danish data in a representative agent framework. Andersen et al. (2018) obtain an even lower estimate for the coefficient of risk aversion, 0.25, using a similar econometric methodology but applied to MPLs which would have trouble distinguishing individuals with higher than logarithmic risk aversion.

Interestingly, the average woman is more risk averse and more patient than the average man. The latter is true, despite the positive sign on the structural female coefficient in the discount factor which implies that being a woman is in and of itself associated with increased impatience. This seeming anomaly is explained by the fact that being a woman is also associated with higher conscientiousness and lower extraversion (see Figure 11) both of which push discount rates downward.

Figure 4: Parameter Values for the Average Person

	Prevalence	Risk Aversion	Risk Aversion SD	Discount Rate	Discount Rate SD	% Hand Trembles
Simulated Average		1.33	0.60	0.24	0.35	0.04
Female Average		1.39	0.58	0.18	0.28	0.05
Male Average		1.26	0.61	0.31	0.45	0.04
Type 1 Average	0.31	1.00	0.65	0.03	0.03	0.04
Type 2 Average	0.24	0.19	0.39	0.56	0.42	0.14
Type 3 Average	0.24	0.41	0.41	0.39	0.33	0.02
Type 4 Average	0.12	-0.22	0.32	0.87	1.00	0.02
Type 5 Average	0.08	5.00	1.00	0.01	0.00	0.08

One of the advantages of the structural model is that it allows us to move beyond simple observed heterogeneity. The impact of unobserved types turns out to be important. The most

[37]An average person is defined as having average values of cognitive ability, personality, and each of the attributes i.e. 46% male, speaking 68% English, etc.

prevalent type (type 1) which represents one third of the population has logarithmic risk aversion and is very patient. There is also one risk seeking type (type 4) who is at the same time the most impatient. These "daredevils" represent 12% of the population which falls within the range of approximately 10-20% of individuals who choose the riskier lottery even when it has a lower expected payoff than the safer one. Their polar opposite (type 5) is similarly frequent but very risk averse and very patient. The remaining types exhibit intermediate values of risk aversion and discount rates.

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 choice model. With the full model, the task is more challenging: we need to use its estimated structural parameters to construct a simulated dataset.[38]

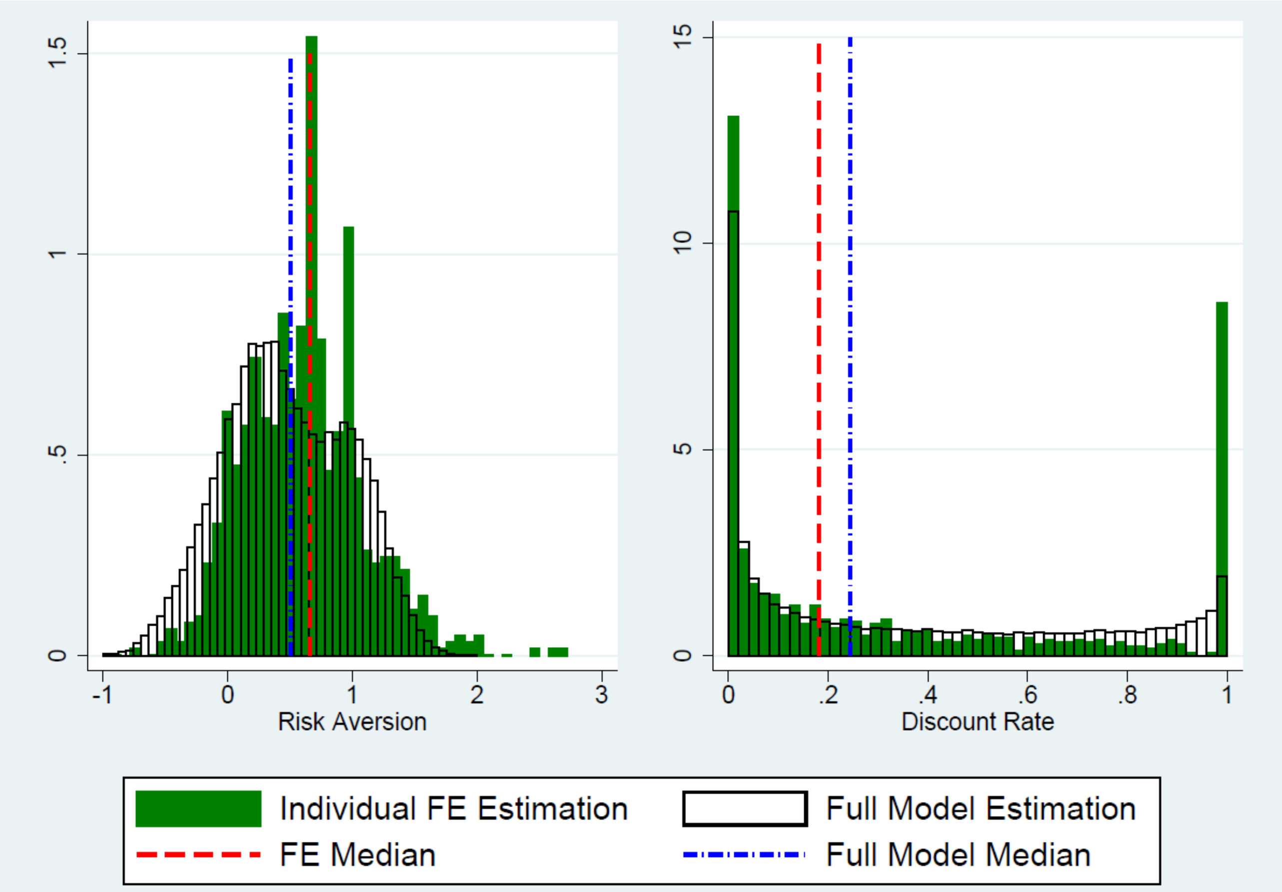
Figure 5 superposes the distributions of preference parameters estimated using alternatively the fixed effects choice model and the full model.[39] They are remarkably similar. The medians (marked by the dashed lines) of the two distributions for each parameter are close. The median value of risk aversion is 0.66 using the fixed effects choice model and .51 using the full model while the median value of the discount rate is 0.18 and 0.24 respectively. The distribution of the risk aversion parameter in the population resembles normality. 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.[40] It reflects the fact that a non-negligible portion of individuals chooses either all earlier or all later payments as described in the Data Section 3.

[38]The simulation is performed exactly according to the model presented in Section 4. It uses observed characteristics of individuals in the data with each individual being drawn 100 times. The unobserved orthogonal components of factors are simulated based on each factor's estimated distribution in the population. Unobserved types are assigned randomly using their respective estimated prevalences in the population.

[39]In both the fixed effects estimation and the full model simulation, extreme values of risk aversion are assigned -1 on the low end and +5 at the high end. Values of θ outside of these bounds represent limit values of risk-seeking and risk-averse behavior respectively given the choice tasks contained in this experiment and concern a negligible part of the population. The displayed chart 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".

[40]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.

Figure 5: Sample Distributions of Risk and Time Preferences



6.a.i Link with Personality Traits

Results from the structural model quantify the supposed relationship between preferences, cognitive ability, and personality. The a priori expectations on the signs of the coefficients are confirmed - risk aversion decreases with extraversion (related to self-reported excitement-seeking and active behavior), discount rates decrease with conscientiousness (related to self-reported discipline and ability to delay gratification), and the propensity to make mistakes decreases with cognitive ability. Furthermore, personality traits and cognitive ability explain a non-negligible part of the variation in preference and consistency 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.[41]

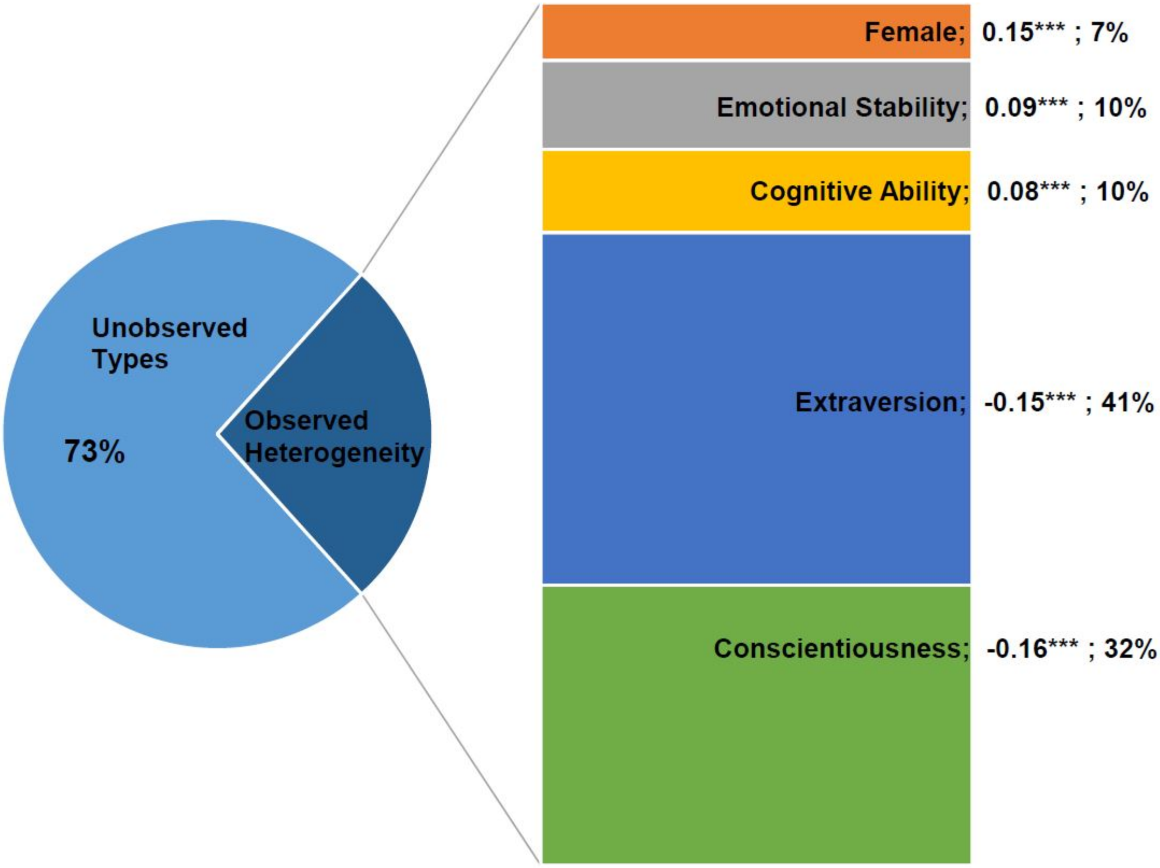
Figure 6 illustrates the contribution of observed and unobserved heterogeneity to the overall cross-sectional variation in risk aversion. It includes both the estimated marginal effects[42] of

[41]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.

[42]Marginal effects represent the effect of increasing each factor by 1 standard deviation (or as the effect of

sex, ability, and personality traits; and the percentage of variation in risk aversion attributed to observed heterogeneity that each of them explains.[43]

Figure 6: 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.[44] The conscientiousness and extraversion personality traits have the highest explanatory power. The coefficient on extraversion is negative. This confirms the intuitive link between risk aversion and extraversion. The marginal effect of changing extraversion by 1 standard deviation is

moving sex from 0 to 1 (male to female) in case of gender). They are calculated as the difference between the estimated value of each structural parameter when the factor of interest is 1 standard deviation above its average value and all other factors are at their average and the estimated value of the structural parameter when *all* factors are at their average.

[43]The explained percentage variation is obtained from the simulated dataset as the R2 of an appropriate regression of structural parameters on unobserved factors and unobserved types derived from equations 20-24.

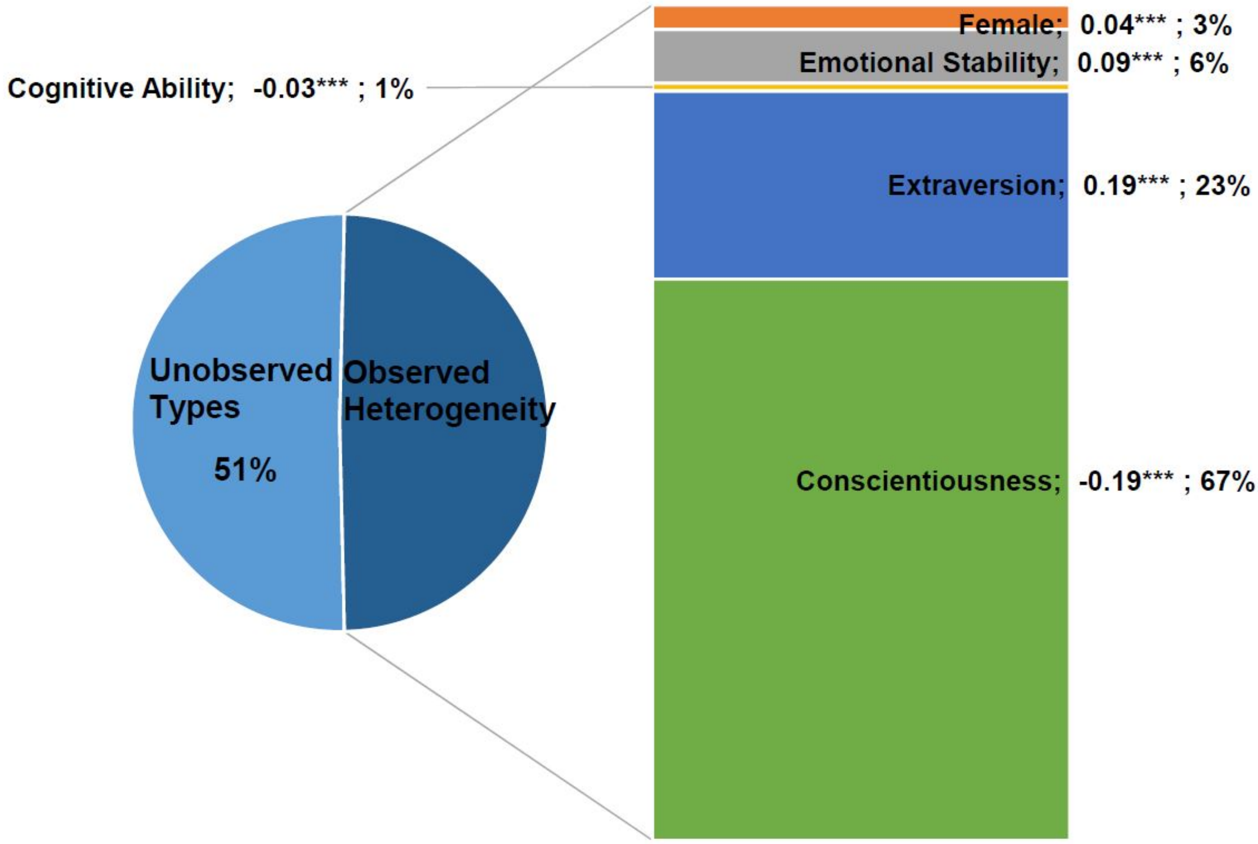
[44]Again, values of risk aversion above 3 are excluded from the analysis. These extreme values can be entirely attributed to unobserved type 1 which represents 8% of the population with limit values of risk aversion. It is a result of the fact that some individuals always choose the less risky alternative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

a 0.15 decrease in the coefficient of risk aversion. This represents a roughly 25% decrease from its estimated median value and a 10% decrease from the average value. The marginal effect of conscientiousness is also negative and of comparable magnitude. It may be understood in terms of 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, emotional stability, and being female increase risk aversion.

The reversal of the sign on cognitive ability compared to the simple correlations presented in Figure 3 is one of the more interesting results of the application of the full structural model. It corrects for the bias hypothesized by Anderson et al. (2016) resulting from random errors which decrease with cognitive ability combined with an MPL design skewed towards choices of the riskier option. The correction is consistent with, but stronger than, that reported by Andersson et al. (2018) even though they use a balanced MPL design *combined with* a basic RPM framework (they find that the correction nullifies the estimated relationship between cognitive ability and risk aversion whereas I find that it actually reverses its sign). I achieve the correction without using a balanced set of MPLs. This suggests that a more elaborate RPM with unobserved heterogeneity and a factor structure may in itself be sufficient to de-bias estimates.

Observed heterogeneity explains half of the cross-sectional variation in discount rates. This can be seen in Figure 7.

Figure 7: 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.

This time conscientiousness possesses the highest explanatory power confirming its intuitive link with discount rates. It explains a third of the total cross-sectional variation in time preference. It also has a high estimated marginal effect. Conscientious individuals have lower discount rates and are thus more patient. Extraversion is the second most important predictor of impatience. However, its impact goes in the opposite direction, unlike in risk aversion. Extraverted individuals are *less patient* and less risk averse whereas conscientious individuals are *more patient* and less risk averse.

On the one hand fully risk averse individuals 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 2 of the Appendix shows the estimated raw structural coefficients for equations 20-24 along with their associated standard errors.[45]

6.b Consistency Parameters

This section presents results on the consistency parameters. The first two parameters govern the stability of an individual's preferences. They represent the standard deviation of an individual's risk and time preference respectively. The third 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.

Individuals' preferences vary between choice tasks. As can be seen in Figure 4, an average individual has a standard deviation of approximately 0.6 on his coefficient of risk aversion and of 0.35 on his discount rate.[46] For comparison purposes, Apesteguia and Ballester (2018) obtain 0.4 and 0.11 respectively using a representative agent framework applied to a representative sample of the adult Danish population. If preference instability is related to imperfect self-knowledge, the fact that they obtain lower values for an older population is not surprising.

Once more, the impact of unobserved heterogeneity is important. Approximately 60% of the population (types 2, 3, and 4) has a low level of instability in their risk preference with a standard deviation of around 0.4, a 31% (type 1) has a moderate level of instability, and the remaining 8% (type 5) has a standard deviation of 1.[47] The dispersion is even wider with discount rates: 40% of the population (types 1 and 5) exhibit completely stable time preference, half (types 2 and 3) have moderate levels of instability, and 13% (type 4) have very unstable time preferences.

The trembling hand parameter varies less in the population. An average person chooses his less preferred option 4% of the time which is consistent with the estimates in Apesteguia and Ballester (2018). Men make fewer mistakes than women. About two thirds of the population behave "rationally" (they make choices in line with their underlying preferences) over 95% of the time while one quarter (type 2) choose their less preferred option in over 10% of the choice tasks.

Figure 8 plots full population distributions of the consistency 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

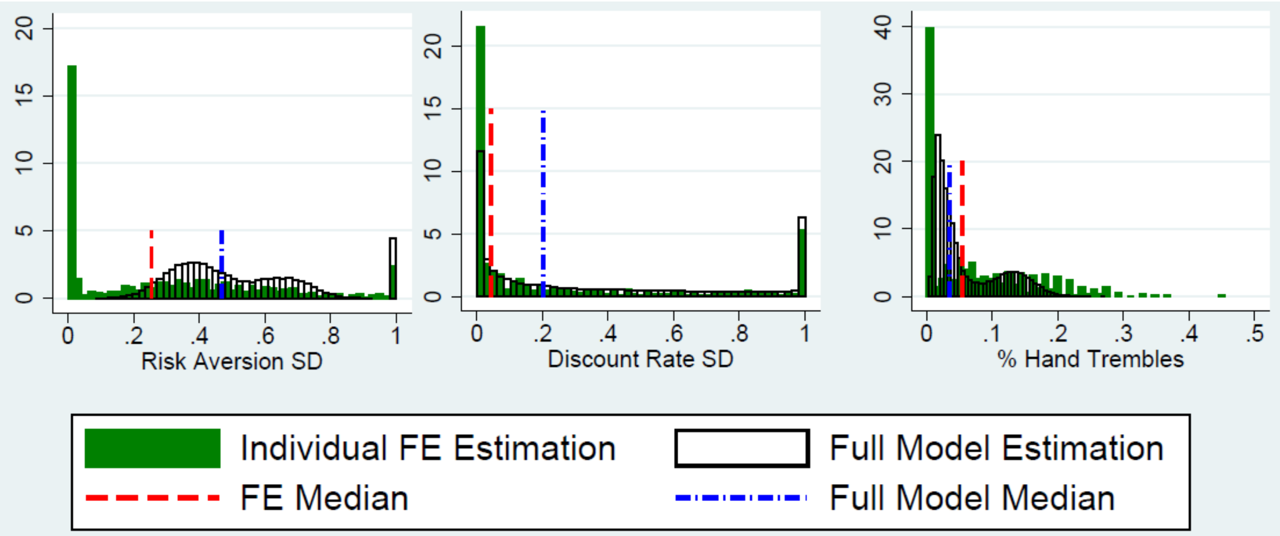
[45] Standard errors are estimated through bootstrap with 200 redraws.

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

[47] 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.

of individuals' risk aversion. On the one hand, using the fixed effects choice model the estimated distribution has mass points at the extremes and otherwise 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 is heavily skewed towards 0 but has a fat tail using estimates both from the fixed effects choice model and from the full model. Finally, the distribution of the trembling hand parameter is also heavily skewed towards zero but has little mass beyond 0.2.

Figure 8: Sample Distributions of consistency parameters



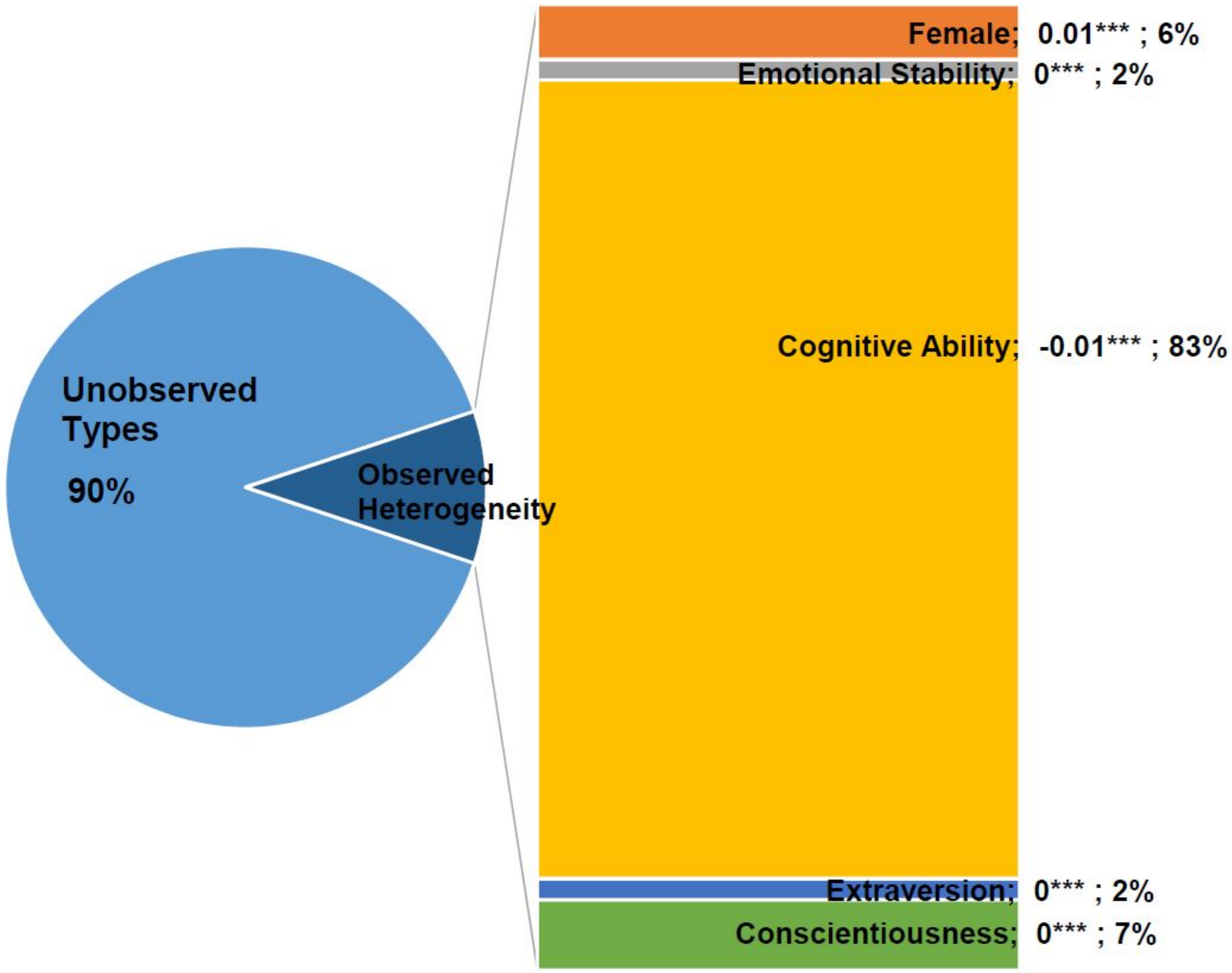
It is not surprising that distributions obtained using the two models diverge more than in the case of preference parameters. Consistency parameters are identified from the *inconsistencies* in individual behavior. In the context of the present experiment, they manifest themselves either through choice reversals within a choice set or, more subtly, through inconsistent switching points between choice sets. While both exist (as documented in Section 3 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 consistency parameters using individual fixed effects should be viewed with some caution.[48] This should be less of an issue in the full model which parametrizes the consistency parameters as a function of observed and unobserved heterogeneity and thus pools information from all individuals' choices.

[48]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, the discount rate, and of the trembling hand parameter were qualitatively unchanged.

6.b.i Link with Personality Traits

Propensity to make mistakes seems largely independent of personality, unlike the remaining preference and consistency parameters (see Figure 9 below). This time, cognitive ability is responsible for a majority of the explained variation. It accounts for over 80% of the variation explained by observed heterogeneity and for approximately 10% of the total cross-sectional variation in the parameter. Unsurprisingly, individuals with higher cognitive ability are able to make choices which are more consistent with their underlying preferences i.e. they make decisions of higher quality. A one standard deviation increase in cognitive ability reduces the propensity to make mistakes by one percentage point which corresponds to a 25% of its estimated median value in the population. This suggests that some individuals face cognitive hurdles when evaluating the standard and relatively simple lottery and temporal choice tasks in this experiment. Taken together with the estimated relationship between preferences and personality, one might conclude that differences in desired outcomes are explained by differences in personality whereas the ability to align preferred and actual choices is a function of cognitive skill.

Figure 9: 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.

Factors related to ability and personality explain approximately one third of the cross-sectional variation in preference instability. Conscientiousness is the dominant personality trait here. It explains 19% and 23% respectively of individual heterogeneity.[49] The marginal effect of conscientiousness on the standard deviation of the discount rate is stronger than on the standard deviation of risk aversion. Highly conscientiousness individuals have more stable risk and time preferences. The relationship makes intuitive sense if one considers the hypothesis that revealed preference instability is a reflection of a lack of self-knowledge and thus of uncertainty as to one's true preferences. Conscientious individuals may take more time for introspection and hence know their true preferences better.

Cognitive ability and extraversion have opposite estimated relationships with the stability of

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

risk and time preferences. The positive link between cognitive ability and risk preference instability is puzzling but it is in line with results reported by Andersson et al. (2018). The positive link between extraversion and time preference instability seems more intuitive. Nevertheless, the explanatory power of these (and other) variables in terms of the overall heterogeneity in preference stability pales in comparison to that of conscientiousness. These results are summarised in Figures 4 and 5 of the Appendix.

6.c Robustness to Alternative Functional Form Specifications

In order to test the robustness of my results to the underlying functional form assumptions, I estimate the structural model under alternative assumptions of a) hyperbolic discounting; and b) CARA utility. The conclusions drawn from the CRRA model with exponential discounting hold. All structural coefficients have the same estimated sign with the exception of the coefficient on sex in the stability of risk preference which turns positive under CARA utility but retains negligible explanatory power. Importantly, the correction on the estimated relationship between risk aversion and cognitive ability is robust to alternative functional form assumptions.

The main takeaways from the mappings described in Section 6 also hold: risk aversion exhibits a strong negative relationship with extraversion and conscientiousness; the discount rate exhibits a strong negative relationship with conscientiousness and a positive one with extraversion; mistakes are decreasing in cognitive ability, and preference instability is decreasing in conscientiousness. The percentage of explained variation in the structural parameters remains high. Hyperbolic discounting has a somewhat improved fit and increases the explanatory power of parameters linked to time preference. CARA utility has a somewhat reduced fit, increases the explanatory power of parameters linked to time preference and decreases the explanatory power of parameters linked to risk preference. It magnifies the impact of conscientiousness.

The estimated structural coefficients and calculated mappings are detailed in Sections 1.e and 1.f of the Online Appendix.

6.d Preference vs. consistency parameters in Observed Choices

Having estimated the distributions of preference and consistency parameters and mapped them onto personality traits, an important question remains. Which of the two - preference or consistency 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 consistency parameters from the fixed effects choice 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 variables 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 10 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 consistency 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 by the five estimated structural parameters into parts explained by preference and consistency parameters respectively. This lets us compare their relative explanatory power. It is included in the table below, expressed as a percentage. Finally, consistency 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 consistency parameters estimated using the fixed effects choice model together explain approximately 50% of the overall variation in observed individual choices on both lottery and temporal choice tasks. The fraction of explained variation rises to 90% for lottery choices and 60% for temporal choices once outliers with an estimated coefficient of risk aversion greater than 3 and smaller than -2 are excluded. Both the total (and therefore also average) number of "safe" and "impatient" choices[50] 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 3 of the Appendix.

Consistency parameters also play a role in explaining choices. They account for approximately 5% of the explained variation in choices and for the vast majority of the variation in individual choice inconsistency. Outright choice reversals[51] within a given MPL are best explained by the mistake parameter. More subtle choice inconsistency reflected in varying switching points

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

[51]E.g. 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 strong choice inconsistency, perhaps irrationality.

across comparable MPLs[52] is explained by the respective preference instability parameters (by the estimated individual standard deviation of risk preference for lottery choice tasks and by the estimated individual standard deviation of time preferences for temporal choice tasks).

This pattern is intuitive. On the one hand, the mistake parameter is modeled such that it results in an outright reversal of the preferred choice to a less preferred one. As such its impact is large and it can explain choices of dominated options and strong inconsistency in the form of choice reversals. On the other hand, preference instability will only have a visible impact if a particular draw of the error term is large enough to affect a choice. This will in general be the case if the person only has a slight preference for one of the two options given his true (or average) level of risk and/or time preference. Thus a person who is close to indifference between a particular pair of options on a choice task may pick one option in the first MPL and another option in the second MPL due to preference instability. However, he is unlikely to reverse his choice on a given MPL due to preference instability as the next task in that MPL has a much higher threshold level of indifference (or lower, in the OLS design).

Figure 10: Explanatory Power on Observed Choices of Preference and Consistency Parameters vs. Demographic and Socioeconomic Variables

		# Safe Choices	# Impatient Choices	# Risk Reversals	# Time Reversals	Risk Switch SD	Time Switch SD
Demographic and Socioeconomic Variables	R2	0.04	0.06	0.02	0.02	0.02	0.01
All Parameters	R2	0.53	0.47	0.56	0.04	0.11	0.30
Preference Parameters		97.3%	96.4%	0.2%	11.2%	2.8%	21.8%
Consistency Parameters		2.7%	3.6%	99.8%	88.8%	97.2%	78.2%
- Stability		0.8%	81.6%	1.7%	14.8%	68.6%	97.8%
- Mistakes		99.2%	18.4%	98.3%	85.2%	31.4%	2.2%

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 consistency 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 inclusion of socio-economic and demographic variables restricts the sample size to 952 observations with available information.
The rows below represent the relative explanatory power of the relevant subgroups of parameters, expressed as a percentage.

6.e Factor Determinants

The estimated coefficients from the factor equations are displayed in Figure 11. R2 here never exceeds 5% indicating that the orthogonal component of the factors dominates the one related 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

[52] It is measured as the standard deviation of switching points across comparable lottery and temporal choice tasks.

components predictive of behavior (Goldberg, 1990). The emotional stability 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 and 0.8 respectively. Being female is associated with lower extraversion and with higher conscientiousness. Native English speakers and older individuals score higher on both of these personality traits.[53] The remaining coefficients on observable characteristics are small.

Figure 11: 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	-0.06	0.00	0.05	0.06	0.06	0.01	0.34	-0.11
Cognitive Ability	0.02	0.02	0.09	0.02	-0.02	0.02	0.29	1.61
Extraversion	-0.29	0.10	0.02	0.20	0.12	0.03	0.93	-0.11
Conscientiousness	0.27	0.14	0.18	0.19	0.20	0.04	0.78	0.13

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 10.b of the Appendix, the magnitudes of the loadings vary widely. This suggests that some questions measure the underlying ability and personality traits more closely while others contain more noise. The last column in Section 10.b shows the estimated signal to noise ratio for each measure. Overall, the measures are revealed to be noisy but the importance of measurement error varies.[54] This confirms the usefulness of using a factor model to address measurement error inherent in indicators for cognitive 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.

7 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

[53]What I can say about the impact of age is limited by the small variation of age in the data.

[54]The average signal to noise ratio is 0.49 for the factor measures with a standard deviation of 0.55. For comparison purposes, if each MPL is taken as one "measure" of risk or time preference (with the total number of risky or patient choices taken as the value of the measure) and an analogous statistical factor model is applied, the average calculated signal to noise ratio is 1.47 for the risk measures and 4.92 for time measures. This of course ignores decision errors, etc. but can be used to illustrate the relatively high noise content of the indicators used to measure cognitive ability and personality. The fact that preferences measures obtained from incentivized choice tasks seem less noisy than qualitative hypothetical measures of cognitive skill and personality is not surprising.

personality explains a much larger share of the variation in preferences within and across individuals than previously supposed.

I establish a formal mapping between factors related to 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). While differences in personality explain differences in desired outcomes, cognitive skill is related to the ability to translate these preferences to actual decisions.

I use a factor model to address measurement error in indicators for cognitive ability and personality. This ensures a more efficient extraction of information on the underlying latent variables of interest contained in the numerous measures available in my dataset. One obvious advantage over simply using an additive score of the measures for cognitive ability and each personality 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 heterogeneous estimated loadings and signal to noise ratios of the indicators for 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 the factors.

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 accounted for, can lead to biased estimates of both risk aversion and of its relationship to observed heterogeneity. I show that my model generates a stronger correction of this bias than Andersson et al.'s (2018) framework and does so without requiring the balanced MPL design they propose. 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.

The large number of observed choices per individual allows me to estimate population distributions of the parameters of interest both as fixed effects and through simulation based on estimated coefficients from the full model with observed and unobserved heterogeneity. The fact that both methods produce similar distributions is reassuring. It 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 personality 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 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 shows that in the future researchers may want to consider an experimental design capable of capturing the subtleties of the behavior of highly risk averse and highly impatient individuals. It also highlights the importance of looking at more than just the population average of the preference and consistency parameters. Indeed, if only one population moment were to be chosen, the median seems preferable to the mean due to the non-negligible prevalence of outliers. However, an examination of the full distribution seems warranted and I recommend that it be used in future research aimed at predicting the impact of economic policies and calculating their welfare implications.

I demonstrate that the estimated structural preference and consistency parameters explain well 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 the hypothesis that preferences contain useful information uncaptured by commonly used controls and should be included in reduced form econometric models as appropriate to reduce omitted variable bias.

The estimates of distributions of risk and time preferences look reasonable given the actual distributions of observed choices and all three a 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 which incorporates a factor structure for noisy measures can be used to obtain reasonable estimates of the distributions of preferences and of their relationship with explanatory variables. I thus provide a framework for estimating and explaining the population heterogeneity in preferences and in individuals' capacity to make consistent rational choices.

Unobserved heterogeneity still explains a majority of the population variation in both preference and consistency parameters. Establishing a more complete mapping between economic and psychological measures of personality skills and preferences will require further research on data with an expanded array of economic preferences and the full *Big Five*.

The employed model based on the maximization of discounted expected utility follows from classical economic theory. It is a standard workhorse framework for decision-making augmented for preference instability and decision error. However, it is not the only one possible. Alternatives have been developed both in the domain of choice under risk and under temporal delay. Cumulative prospect theory with loss aversion and probability weighting (Kahneman and Tversky, 1992) is supported by a body of experimental evidence. The same goes for different models of time discounting (see Frederick, Loewenstein, and O'Donoghue, 2002). Testing alternative models of decision-making and mapping their associated behavioral parameters onto measures of cognitive and non-cognitive skills is a worthwhile exercise. Unfortunately, this dataset is not adapted to doing so. Based on the current state of the literature and on the results presented in this paper, my intuition is that behavioral biases will have a strong link with cognitive ability whereas additional preference parameters such as social preferences will map onto personality traits. To paraphrase Frederick, Loewenstein, and O'Donoghue (2002), economics is not only an art but also a science. These intuitions thus need to be confronted with data, using appropriate econometric methods. I see this as a fruitful avenue for future research.

8 Conclusion

This paper is the first piece of structural research mapping economists' preference and consistency parameters onto cognitive ability and psychologists' personality traits incorporated as latent factors. It uses the Random Preference Model (RPM) and factor analysis to address measurement error and to account for the random components of decision-making. I thus correct the potential bias in previous preference 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 0.51, the median discount rate is 24%, 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.

Up to 50% of the variation in risk aversion, discount rates, and in parameters governing individuals' choice consistency 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 power of personality traits on real-world outcomes. It explains 33% of the cross-sectional variation in discount rates, 9% of the variation in risk aversion, and 23% of the variation in their individual-level stability. Furthermore, extraversion explains 10% of the cross-sectional variation in both discount rates and risk aversion while cognitive ability is strongly associated with making fewer mistakes. These results are robust to alternative functional form assumptions.

The a priori expected relationships (between reported risk-seeking tendency and risk aversion, reported capacity to delay gratitude and discount rates, cognitive ability and the propensity to make mistakes) are confirmed and lend the results further credibility. A pattern begins to emerge: differences in personality explain differences in preferred outcomes whereas cognitive ability mediates individuals' capacity to make decisions in line with their underlying preferences.

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) is an initial step towards a unified framework for understanding the number and nature of attributes driving behavior and responsible for the observed heterogeneity in outcomes. It allows us to better understand the mechanism through which preferences, cognitive ability, and personality influence those outcomes. This can in turn lead to policy recommendations. For example, it could yield a list of competencies to target through schooling, while they are still malleable, and thus help reduce inequalities.

Finally, I confirm that preferences have much higher explanatory power in terms of observed choices under risk and delay than a standard set of demographic and socio-economic variables and thus contain separate information. 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 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.

Nevertheless, individuals' preferences, their stability, and people's propensity to make mistakes remain to a large part a function of unobserved heterogeneity. This suggests that economists' preferences and psychologists' personality traits are related but distinct concepts. However, it may also be an artefact of the limitations of the present dataset which only allows for the identification of basic risk and time preferences and has proxies for three of the *Big 5* personality traits. Further research comparing an expanded set of economic preferences and personality traits is necessary before one can draw firm conclusions. Understanding the role of effort in both preference and skill elicitation and standardizing measurements will be essential for the successful completion of this endeavour.

9 Bibliography

Almlund, M., Duckworth, A. L., Heckman, J. J., & Kautz, T. D. (2011). Personality psychology and economics (No. w16822). National Bureau of Economic Research.

Andersen, S., Harrison, G. W., Lau, M. I., & Rutström, E. E. (2008). Eliciting risk and time preferences. Econometrica, 76(3), 583-618.

Andersen, S., Harrison, G. W., Lau, M. I., & Rutström, E. E. (2014). Discounting behavior: A reconsideration. European Economic Review, 71, 15-33.

Andersson, O., Holm, H. J., Tyran, J. R., & Wengström, E. (2016). Risk aversion relates to cognitive ability: preferences or noise?. Journal of the European Economic Association, 14(5), 1129-1154.

Andersson, O., Holm, H. J., Tyran, J. R., & Wengström, E. (2018). Robust inference in risk elicitation tasks. Available at SSRN 3256637.

Apesteguia, J., & Ballester, M. A. (2018). Monotone stochastic choice models: The case of risk and time preferences. Journal of Political Economy, 126(1), 74-106.

Beauchamp, J. P., Cesarini, D., & Johannesson, M. (2017). The psychometric and empirical properties of measures of risk preferences. Journal of Risk and Uncertainty, 54(3), 203-237.

Becker, A., Deckers, T., Dohmen, T., Falk, A., & Kosse, F. (2012). The relationship between economic preferences and psychological personality measures. Annual Review of Economics, 4(1), 453-478.

Becker, G. M., Degroot, M. H., & Marschak, J. (1963). Probabilities of choices among very similar objects: An experiment to decide between two models. Behavioral Science, 8(4), 306-311.

Belzil, C., Maurel, A., & Sidibé, M. (2017). Estimating the Value of Higher Education Financial Aid: Evidence from a Field Experiment, NBER Working Paper no 23641.

Belzil, C., & Sidibé, M. (2016). Internal and External Validity of Experimental Risk and Time Preferences, IZA Discussion Paper 10348

Benjamin, D. J., Brown, S. A., & Shapiro, J. M. (2013). Who is 'behavioral'? Cognitive ability and anomalous preferences. Journal of the European Economic Association, 11(6), 1231-1255.

Bergen, S. E., Gardner, C. O., & Kendler, K. S. (2007). Age-related changes in heritability of behavioral phenotypes over adolescence and young adulthood: a meta-analysis. Twin Research and Human Genetics, 10(3), 423-433.

Bibby, P. A., & Ferguson, E. (2011). The ability to process emotional information predicts loss aversion. Personality and Individual Differences, 51(3), 263-266.

Binswanger, H. P. (1980). Attitudes toward risk: Experimental measurement in rural India. American journal of agricultural economics, 62(3), 395-407.

Bouchard, T. J., & Loehlin, J. C. (2001). Genes, evolution, and personality. Behavior genetics, 31(3), 243-273.

Bruner, D. M. (2017). Does decision error decrease with risk aversion?. Experimental Economics, 20(1), 259-273.

Carneiro, P., Hansen, K. T., & Heckman, J. J. (2003). Estimating Distributions of Treatment Effects with an Application to the Returns to Schooling and Measurement of the Effects of Uncertainty on College (No. w9546). National Bureau of Economic Research.

Chamberlain, G. (1980). Analysis of Covariance with Qualitative Data. The Review of Economic Studies, 47(1), 225-238.

Chapman, J., Dean, M., Ortoleva, P., Snowberg, E., & Camerer, C. (2018). Econographics (No. w24931). National Bureau of Economic Research.

Chetty, R. (2015). Behavioral economics and public policy: A pragmatic perspective. American Economic Review, 105(5), 1-33.

Choi, S., Kariv, S., Müller, W., & Silverman, D. (2014). Who is (more) rational?. American Economic Review, 104(6), 1518-50.

Cohen, J. D., Ericson, K. M., Laibson, D., & White, J. M. (2016). Measuring time preferences (No. w22455). National Bureau of Economic Research.

Coller, M., & Williams, M. B. (1999). Eliciting individual discount rates. Experimental Economics, 2(2), 107-127.

Conti, G., Heckman, J., & Urzua, S. (2010). The education-health gradient. American Economic Review, 100(2), 234-38.

Cunha, F., & Heckman, J. J. (2009). The economics and psychology of inequality and human development. Journal of the European Economic Association, 7(2-3), 320-364.

Cunha, F., Heckman, J. J., & Schennach, S. M. (2010). Estimating the technology of cognitive and noncognitive skill formation. Econometrica, 78(3), 883-931.

Dean, M., & Ortoleva, P. (2019). The empirical relationship between nonstandard economic behaviors. Proceedings of the National Academy of Sciences, 116(33), 16262-16267.

Dohmen, T., Falk, A., Huffman, D., & Sunde, U. (2010). Are risk aversion and impatience related to cognitive ability?. American Economic Review, 100(3), 1238-60.

Eckel, C. C., & Grossman, P. J. (2002). Sex differences and statistical stereotyping in attitudes toward financial risk. Evolution and human behavior, 23(4), 281-295.

Eckel, C. C., & Grossman, P. J. (2008). Forecasting risk attitudes: An experimental study using actual and forecast gamble choices. Journal of Economic Behavior & Organization, 68(1), 1-17.

El-Gamal, M. A., & Grether, D. M. (1995). Are people Bayesian? Uncovering behavioral strategies. Journal of the American statistical Association, 90(432), 1137-1145.

Frederick, S., Loewenstein, G., & O'Donoghue, T. (2002). Time discounting and time preference: A critical review. Journal of economic literature, 40(2), 351-401.

Gabaix, X. (2014). A sparsity-based model of bounded rationality. The Quarterly Journal of Economics, 129(4), 1661-1710.

Gillen, B., Snowberg, E., & Yariv, L. (2019). Experimenting with measurement error: Techniques with applications to the caltech cohort study. Journal of Political Economy, 127(4), 1826-1863.

Goldberg, L. R. (1990). An alternative" description of personality": the big-five factor structure. Journal of personality and social psychology, 59(6), 1216.

Hansen, Lars Peter. "Large sample properties of generalized method of moments estimators." Econometrica (1982): 1029-1054.

Harrison, G. W., & Elisabet Rutström, E. (2008). Risk aversion in the laboratory. In Risk aversion in experiments (pp. 41-196). Emerald Group Publishing Limited.

Heckman, J. J., Stixrud, J., & Urzua, S. (2006). The effects of cognitive and noncognitive abilities on labor market outcomes and social behavior. Journal of Labor economics, 24(3), 411-482.

Heckman, J. J., Jagelka, T., & Kautz, T. D. (2019). Some contributions of economics to the study of personality (No. w26459). National Bureau of Economic Research.

Hey, J. D., & Orme, C. (1994). Investigating generalizations of expected utility theory using experimental data. Econometrica: Journal of the Econometric Society, 1291-1326.

Holt, C. A., & Laury, S. K. (2002). Risk aversion and incentive effects. American economic review, 92(5), 1644-1655.

Judge, T. A., Erez, A., Bono, J. E., & Thoresen, C. J. (2002). Are measures of self-esteem, neuroticism, locus of control, and generalized self-efficacy indicators of a common core construct?.

Journal of personality and social psychology, 83(3), 693.

Keane, M. P., & Wolpin, K. I. (1997). The career decisions of young men. Journal of political Economy, 105(3), 473-522.

Loomes, G., & Sugden, R. (1995). Incorporating a stochastic element into decision theories. European Economic Review, 39(3-4), 641-648.

Mata, R., Frey, R., Richter, D., Schupp, J., & Hertwig, R. (2018). Risk preference: A view from psychology. Journal of Economic Perspectives, 32(2), 155-72.

Miller, L., Meyer, D. E., & Lanzetta, J. T. (1969). Choice among equal expected value alternatives: Sequential effects of winning probability level on risk preferences. Journal of Experimental Psychology, 79(3p1), 419.

Roberts, B. W. (2009). Back to the future: Personality and assessment and personality development. Journal of research in personality, 43(2), 137-145.

Sargan, John D. "The estimation of economic relationships using instrumental variables." Econometrica (1958): 393-415.

Stango, V., & Zinman, J. (2019). We are all behavioral, more or less: Measuring and using consumer-level behavioral sufficient statistics (No. w25540). National Bureau of Economic Research.

Tversky, A., & Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. Journal of Risk and uncertainty, 5(4), 297-323.

Von Gaudecker, H. M., Van Soest, A., & Wengstrom, E. (2011). Heterogeneity in risky choice behavior in a broad population. American Economic Review, 101(2), 664-94.

Wilcox, N. T. (2011). 'Stochastically more risk averse:'A contextual theory of stochastic discrete choice under risk. Journal of Econometrics, 162(1), 89-104.

10 Appendix

10.a Sample Descriptive Statistics

Figure 1: Sample Demographic and Socioeconomic Variables

Test Subjects		Observations	%	Mean	% if Male	% if Female
	Gender	1224				
	Male		46%	NA	NA	NA
	Female		54%	NA	NA	NA
	Age	1224				
	15-16		12%		11%	13%
	17		67%		65%	70%
	18		15%		17%	13%
	19+		6%		7%	5%
	Language					
	English	1224	68%	NA	69%	68%
	Other	1224	32%	NA	31%	32%
	Born in Canada	1087	96%	NA	96%	97%
	Lives with Siblings	1224	75%	NA	76%	74%
Parents						
	Age	1068	NA	46	NA	NA
	Indian	1224	7%	NA	7%	7%
	# Children under 18	1085	NA	2	NA	NA
	Thinks University is Importan	1088	92%	NA	91%	93%
	High School Dropout	1224	12%	NA	11%	12%
	High School	1224	52%	NA	50%	54%
	University	1224	36%	NA	39%	34%
	Annual Income	976				
	<20k		6%	NA	6%	6%
	20-40k		13%	NA	11%	14%
	40-60k		23%	NA	24%	22%
	60-80k		19%	NA	17%	21%
	80-100k		15%	NA	17%	14%
	100k+		24%	NA	25%	24%

10.b Factor Measures

Factor	#	Measure	Type	Sign Reversal	Loading	Signal to Noise ratio
Emotional Stability	1	When I make plans they work out as I expect.	binary		1.00	0.12
	2	Fate (luck) usually determines what happens to me.	binary		1.14	0.15
	3	Hard work is the key to success.	binary		0.71	0.06
	4	You have little control over the things that happen to you.	multi-valued	x	2.65	0.81
	5	There is really no way you can solve some of the problems you have.	multi-valued	x	3.20	1.18
	6	There is little you can do to change many of the important things in your life.	multi-valued	x	4.53	2.37
	7	You often feel helpless in dealing with the problems of life.	multi-valued	x	4.44	2.28
	8	Sometimes you feel that you are being pushed around in life.	multi-valued	x	2.19	0.55
	9	What happens to you in the future mostly depends on you	multi-valued	x	0.84	0.08
	10	You can do just about anything you really set your mind to do	multi-valued		1.38	0.22
Cognitive Ability	1	In your last year of high school, what was your overall grade average, as a percentage?	multi-valued		1.00	0.08
	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		4.03	1.34
	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		3.95	1.28
	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		1.86	0.29
	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		2.14	0.38
	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		1.50	0.18
	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		2.16	0.38
	8	Numeracy Test Score.	continuous		1.30	0.16
Extraversion		Likelihood of ...				
	1	Exploring an unknown city or section of town.	binary		1.00	0.86
	2	Speaking your mind about an unpopular issue at school.	binary		0.35	0.11
	3	I avoid activities where I might be embarrassed.	binary		0.34	0.10
	4	Crossing a frozen lake with a car or a snowmobile.	multi-valued		0.66	0.38
	5	Going camping in the wild.	multi-valued		0.60	0.32
	6	Engaging in unprotected sex.	multi-valued		0.81	0.57
	7	Never wearing a seat belt.	multi-valued		0.36	0.11
	8	Periodically engaging in a dangerous sport (e.g., mountain climbing or sky diving).	multi-valued		0.23	0.05
	9	Regularly riding your bicycle without a helmet.	multi-valued		1.14	1.13
	10	Trying bungee jumping.	multi-valued		0.43	0.16
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	0.61
	2	I do things impulsively, making decisions on the spur of the moment.	binary	x	0.60	0.22
	3	I select activities in terms of how beneficial they are to my future.	binary		0.58	0.21
	4	I do not like to plan ahead.	binary	x	1.02	0.63
	5	I meet obligations to friends and authorities on time.	binary	x	0.59	0.21
	6	I follow through with a course of action if it will get me where I want to be.	multi-valued		0.75	0.34
	7	I am able to resist temptations when I know there is work to be done.	multi-valued		0.65	0.26
	8	Generally, I am more focused on what is going on now than on what will happen in the future.	multi-valued	x	0.52	0.16
	9	I often think about what I will be doing 10 years from now.	multi-valued		0.53	0.17
	10	I try to live one day at a time.	multi-valued	x	0.41	0.11

10.c Structural Results

Figure 2: Estimated Coefficients on Preference and Consistency Parameters Using the Full Structural Model with 5 Unobserved Types

	Risk Aversion		Risk Aversion SD		Discount Rate		Discount Rate SD		% Hand Trembles	
Female	0.15	***	-0.05	***	0.13	***	0.12	***	0.10	***
	(0.02)		(0.00)		(0.01)		(0.00)		(0.01)	
Internal Locus of Control	0.26	***	0.18	***	0.82	***	0.85	***	0.08	***
	(0.01)		(0.00)		(0.00)		(0.00)		(0.00)	
Cognitive Ability	0.26	***	0.38	***	-0.33	***	-0.43	***	-0.52	***
	(0.01)		(0.01)		(0.01)		(0.01)		(0.01)	
Extraversion	-0.16	***	-0.08	***	0.57	***	0.64	***	0.03	***
	(0.01)		(0.00)		(0.01)		(0.01)		(0.00)	
Conscientiousness	-0.20	***	-0.21	***	-1.18	***	-1.19	***	0.05	***
	(0.03)		(0.00)		(0.01)		(0.00)		(0.00)	

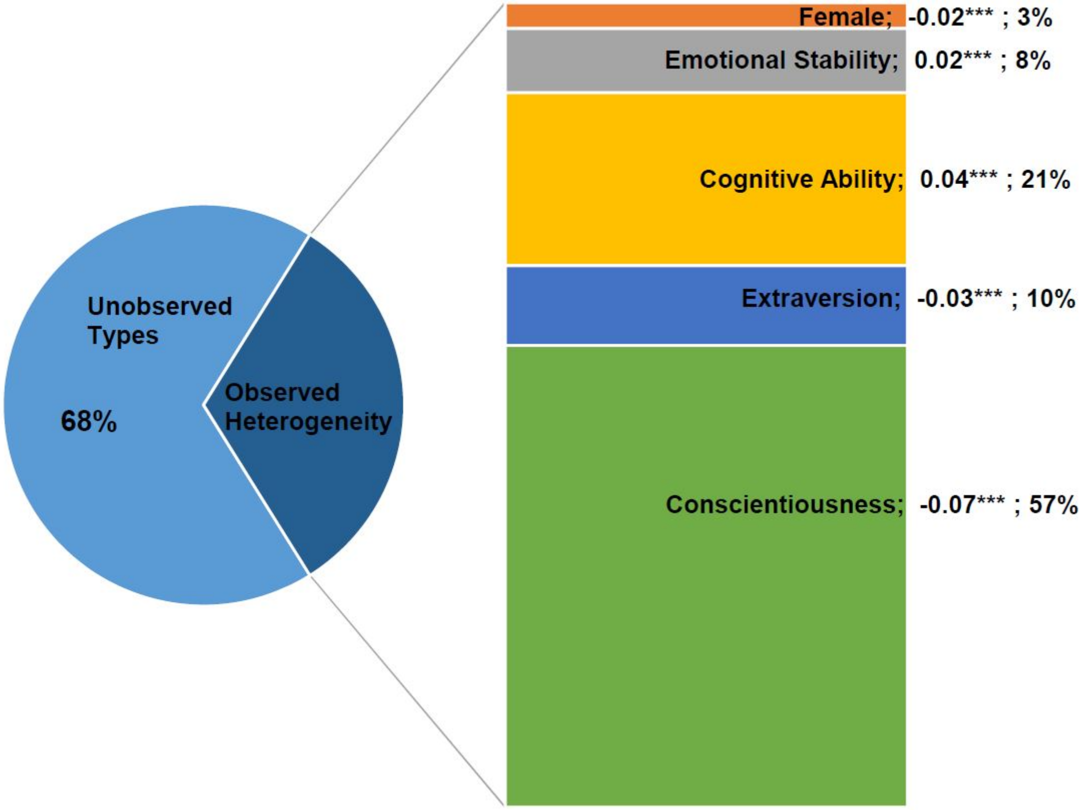
Notes: Bootstrap standard errors with 200 redraws are in parentheses. Significance at the 10% level is denoted by ***, at the 5% level by **, and at the 1% level by *.

Figure 3: Explanatory Power of Individual Parameters with Regards to Individual Choices

		# Safe Choices	# Impatient Choices	# Risk Reversals	# Time Reversals	Risk Switch SD	Time Switch SD
All Parameters	R2	0.53	0.47	0.56	0.04	0.11	0.30
Risk Aversion		98.1%	6.4%	0.3%	8.1%	5.4%	3.4%
Discount Rate			90.5%		10.4%		15.4%
Risk Aversion SD		0.0%	0.0%	1.7%	3.5%	64.9%	0.3%
Discount Rate SD			2.5%		8.1%		79.1%
% Hand Trembles		1.9%	0.6%	98.0%	69.9%	29.7%	1.8%

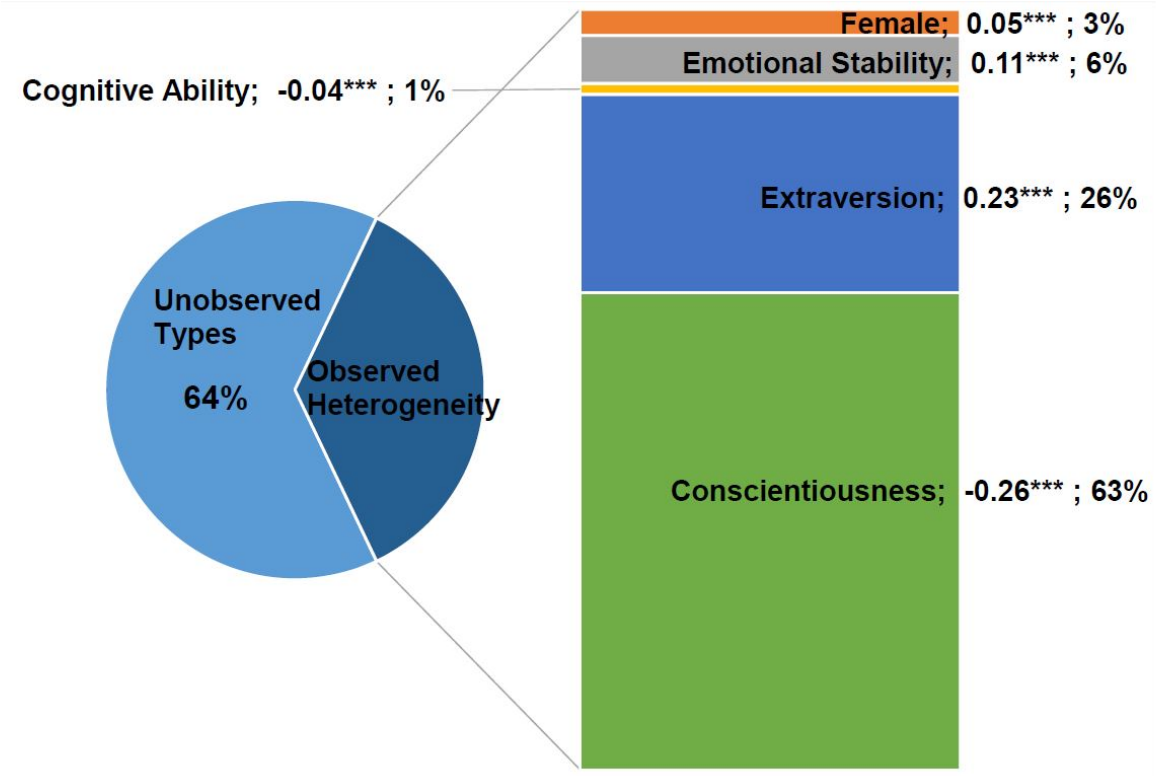
Notes: Row labeled "R2" lists the R2 of the regression of the moment listed in each column title on all five preference and consistency parameters.
The rows below represent the part of explained variation attributable to each parameter.

Figure 4: 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 5: 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.