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

Author:

Tomáš JAGELKA*

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*ECONtribute Cluster of Excellence, IZA, Institute for Applied Microeconomics at the University of Bonn, and CREST. 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 60% 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. Results are robust to a range of alternative assumptions of the structural model.

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, 2021 for a recent summary of the literature). However, the question of whether they work through one another or side by side has 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 measurement and decision 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 risk 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 average risk and time preferences respectively[2]; two parameters which describe the degree of instability of an individual's risk and time preferences; 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 proxies for three of the *Big Five* personality traits validated using a follow-up study.

My main contribution is to show that up to 60% of 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.[3] Overall, the factor related to conscientiousness exhibits the strongest links. It explains a third of the cross-sectional variation in discount rates, 7% of the variation in risk aversion, and a third of the

[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.

[2]Risk aversion also impacts intertemporal choice as it affects the curvature of utility under standardly used utility functions. The discount rate is the parameter which influences intertemporal choice only. I refer to it as "time preference" to simplify notation in this paper.

[3]These factors were chosen to capture both "soft" and "hard" skills given measures available in the data. *Big Five* personality traits are stable characteristics identified by psychologists as particularly important predictors of behavior. 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.d of the Appendix provide proxies for the three studied traits. I validated the proxies in a follow-up study which finds high correlations between measures at my disposal and personality traits obtained using a standard Big 5 questionnaire (see Section 3.e.i for more detail).

variation in their individual-level stability. Furthermore, the factor related to extraversion is strongly related to risk aversion and discount rates while high cognitive ability reduces an individual's propensity to make mistakes.

My results show that heterogeneity in preferences explains most of the variation in observed choices between risky lotteries and between payments occurring at different points in time. Indeed, the five estimated structural parameters have explanatory power which is an order of magnitude larger than that of nearly two dozen demographic and socio-economic variables. While risk and time preferences account for a vast majority of the explained variation in average risky or intertemporal choices, parameters related to randomness in decision making 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 risk 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 latent 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, and five unobserved types.[4] As robustness, I (1) employ different functional forms for utility, (2) allow for time-inconsistent behavior, (3) use alternative methods to select proxy indicators for personality traits, and (4) estimate the model for the full sample and also separately for each sex.

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

[4]Joint estimation 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., 2020).

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 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.[5] 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 rate 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[6] and personality traits[7]. In their 2017 review of the literature, Golsteyn and Schildberg-Hörisch 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."

Despite the "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)[8]

[5] While recent evidence from a replication study somewhat tempers his findings (see Watts et al., 2018), the importance of *stable traits* in predicting *average outcomes* has been confirmed (see e.g. Epstein, 1979 and Heckman, Jagelka, and Kautz, 2021).

[6] 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 rate respectively. More recent economic theory also incorporates social preferences and behavioral biases.

[7] 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.

[8] 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."

This paper is the first attempt to establish such a mapping in a full structural framework of decision-making under risk and delay.

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. Indeed, 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 proxy indicators (see Table 1). My structural approach makes optimal use of available information and addresses *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).

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 (forthcoming) 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.

2.b Modelling Inconsistency in Repeated Choices

Psychologist L.L. Thurstone built the foundations of discrete choice models (Thurstone 1927a,b). He recognized that a decision between two constant options is made based on a psychological "discriminal" process which itself is stochastic. This process concerns "the ambiguity or qualitative variation with which one stimulus is perceived by the same observer on different occasions" (Thustone, 1927b). Mosteller & Nogee (1951) demonstrated that it is feasible to measure decision utility experimentally. They found that subjects "are not so consistent about preference and indifference as postulated by Von Neumann and Morgenstern" and that choice inconsistency was related to differences in expected utility. Based on these insights, economists developed random choice models which reflect the stochastic nature of a decision process by assuming that a decision maker's utility derived from a particular choice is stochastic (for seminal work, see Luce 1959; McFadden, 1974; and Loomes and Sugden, 1995). Random choice models can be divided into two classes based on the placement of the error term.

The first class appends the error term onto utility. Let us call it the Random Utility Model with additive iid errors (aRUM). It includes the often used Fechner and Luce error specifications. The model has a number of attractive features and has been largely favoured by experimentalists doing structural research (e.g. Hey and Orme, 1994; Holt and Laury, 2002; Andersen et al., 2008). The use of an additive utility shock allows the researcher to remain agnostic as to what part of the utility function is subject to randomness (e.g. the perception of attributes, or rather preferences over attributes). The single error shock can explain both small and large choice inconsistencies observed in the laboratory and in the field, including choices of dominated options. Closed form choice probabilities can easily be derived which makes the aRUM very tractable.

However, recent work by Wilcox (2011) and Apesteguia and Ballester (2018) pointed out a serious theoretical shortcoming when the aRUM is applied to the study of risk aversion: choice probabilities under risk derived using the aRUM as traditionally specified exhibit a non-monotonicity which is at odds with a basic theoretical definition of risk preferences.[9] The non-monotonicity arises because under standardly used utility functions such as CRRA and CARA, risk aversion is related to the curvature of utility. Therefore with rising risk aversion, not only does the relative attractiveness of the riskier option fall, but also the attractiveness of all options converges. At some point the additive error shock overwhelms the utility difference between options. This creates a region of non-monotonicity characterized by an upward sloping probability of choosing the riskier option with rising risk aversion. It leads to the nonsensical prediction that the more risk averse of two individuals would choose the riskier option with a higher probability than the less risk averse individual.

The second class of random choice models adds the error term directly to the preference parameters. Let us call it the Random Preference Model (RPM). Aspesteguia and Ballester (2018) prove that the RPM is a monotone stochastic choice model. 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.[10]

In its pure form, the RPM imposes rather strong rationality requirements such as excluding the choice of dominated options. It is therefore naturally paired with a tremble parameter

[9]Apesteguia and Ballester (2018) also prove theoretical non-monotonicity when the aRUM is applied to the estimation of discount rates. However, they note that for standardly used experimental tasks the non-monotonicity occurs at "absurdly high" discount rates.

[10]The predicted general relationship between decision errors and risk aversion under RPM is actually more complex. However, for 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.

which allows for "processing error" on the part of the decision-maker (see e.g. Aspesteguia and Ballester, 2018). While not trivial to estimate,[11] this specification allows the researcher to separate noise in observed decisions into distinct channels, each potentially driven by different cognitive and non-cognitive mechanisms which produce distinct patterns of choice inconsistencies.

By adding a shock onto the preference parameter, the RPM makes a statement as to which component of utility is affected by randomness. It is important to note that the model need not result in unrealistic predictions of individuals experiencing wide swings in fundamental preferences within a short time period. Any discrete choice model implies some randomization when a choice is made. People may simply be unsure of their true preference and randomize within their interval of uncertainty. This interval may depend on familiarity with a particular choice situation and on individual characteristics. Furthermore, while in economics preferences have traditionally been assumed to be stable, this is not a universally shared assumption across social sciences. In the words of Daniel Kahneman, "To a psychologist, it is self-evident that people are neither fully rational nor completely selfish, and that their tastes are anything but stable." (Kahneman, 2011). Indeed, the existence of stochastic preferences is supported by recent evidence in neuroeconomics which finds that decision values are formed from neural activity in the part of the brain called the ventromedial prefrontal cortex. The neural activity itself is stochastic (for a summary of the evidence, see Fehr and Rangel, 2011). Nevertheless, as with any structural model, estimates should pass the proverbial "sniff test". The researcher should check that obtained results make sense and that the degree of choice inconsistency implied by the model is reasonable given the context and the data.

The impact of the placement of the error term on empirical estimates of risk aversion is not yet well understood. Aspesteguia and Ballester (2018) compare the aRUM to the RPM model with decision errors within a *representative agent* framework using Danish data. Their estimates indicate that the degree of relative risk aversion obtained from an aRUM specification is lower than the estimate obtained using an RPM, especially for individuals who are highly risk-averse. However, a structural estimation of the *distributions* of preference (let alone consistency) parameters, had not been performed within the RPM framework previously. The present paper fills this gap.

I consider the RPM specification with trembles the most appropriate for this analysis. On the one hand, the non-monotonicity of the aRUM is empirically relevant in the context of the present dataset as the median individual in my sample is situated in the region of non-monotonicity on over 40% of the binary choices between lotteries which he faces.[12] While choice

[11]The RPM in general does not yield closed form choice probabilities and simulation is needed for estimation. Closed form choice probabilities can nevertheless be obtained under certain conditions (see Aspesteguia and Ballester, 2018).

[12]For more details, see Figure 1 of the Online Appendix.

probabilities derived under the aRUM can be made monotone through appropriate modifications, further research is needed to understand the theoretical and empirical properties of such a monotonicity correction.[13] On the other hand, the RPM is monotone and provides sensible predictions regarding choice probabilities involving risk and temporal delay. As a further advantage, this model incorporates two disparate sources of randomness and thus allows me to separate noise into two psychologically distinct sources which I link to different traits and to distinct types of inconsistency in observed choices.

2.c Separating Signal From Noise in Observed Measures

Empirical evidence on the inherent randomness of choices may seem at odds with the existence of enduring traits and preferences which predict life outcomes. The apparent paradox is resolved once one considers the myriad situational influences which may impact a *given* decision but do not preclude the existence of an *overarching tendency* driven by a person's stable attributes. Coming back to the Marshmallow experiment, a person who is normally able to delay gratification as evidenced by a lifetime pattern of patient behavior may nevertheless succumb to the temptation of a box of chocolates laying in front of him after a sleepless night. Furthermore, one may simply be unsure of what exactly he wants. Indeed, recent research provides evidence that imperfect self-knowledge is an important driver of inconsistent decisions (e.g. Enke and Graeber, 2019; Falk et al., 2021). Such an individual may thus randomize within his interval of uncertainty which would lead to inconsistent choices. Assuming that he has at least some self-knowledge, his choices will nevertheless display a pattern which allows the econometrician to identify his underlying preference. I find evidence consistent with the importance of stable preferences which drive behavior but are obscured by random noise: average observed choices in the analyzed dataset are very well predicted by true (or average) economic preferences, whereas choice inconsistencies are well predicted by imperfect self-knowledge and random mistakes.

My econometric approach offers a comprehensive treatment of random errors in observed choices both on incentivized experimental tasks designed to elicit economic preferences and on self-reported personality questionnaires. While the addition of various types of stochastic components to models of decision-making is not new, my approach is unique in that it combines factor analysis with a model of decision-making under risk and delay which allows both for preference instability and for individuals to make random mistakes which further depend on both observed and unobserved heterogeneity.

I build on a rich literature concerned with separating true preferences from stochastic com-

[13]Preliminary results suggest that my findings are robust to using an alternative version of the aRUM which incorporates a monotonicity correction in the form of a task-specific parametrization of the scale parameter. While such a correction can remove the problematic region of non-monotonicity, the intuition for it is not straightforward to provide. Results are available from the author upon request.

ponents which affect 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 a standard Multiple Price List (MPL) experimental design which relies on groups of choice tasks between lotteries with two potential outcomes ordered such that the attractiveness of the riskier alternative is either increasing or decreasing. He obtains an error propensity from the number of choices of a stochastically dominated option in separate choice tasks. In the absence of a structural model, Bruner (2017) 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, forthcoming and Chapman et al., 2018) refer to Gillen et al. (2019) in using multiple measures of an experimental variable as instruments for one another to reduce *measurement error*. While this approach is valid, it is not as original as claimed. The estimation system follows directly from Hansen (1982) and Sargan (1958). 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.[14]

Insofar as decision errors depend on observed and unobserved heterogeneity, they can also lead to a spurious estimated relationship between preferences and explanatory variables if they are not properly accounted for. Andersson et al. (2018) provide an empirical illustration. They show that by varying the proportion of choices in which a risk-neutral individual would select the riskier option, they are able to generate a spurious negative correlation between risk aversion and cognitive ability. They attempt to correct for this decision error bias through the us of an innovative experimental design and by using an RPM with heterogeneous trembles. Either method applied separately retains the spurious negative correlation between risk aversion and cognitive ability while their joint application results in an insignificant (albeit still negative) estimate. Using my data, I also document a negative relationship between cognitive ability and risk aversion using reduced form methods. My results from a structural model with a rich specification of both observed and unobserved heterogeneity provide further evidence that this negative correlation may be spurious and suggest that the actual relationship is in fact positive.

Von Gaudecker, Van Soest, and Wengstrom (2011) come perhaps the closest to my treatment

[14]As an illustration, take the example of a person whose level of risk aversion would lead him to choose the riskier option on 8 out of 10 tasks in a deterministic framework. Random mistakes will more likely turn his choice to safe than to risky, leading to an overestimation of risk aversion. This bias will not average out in repeat elicitation which some authors use as instruments. Rather it will induce a correlation between errors in the measure and in its instrument, thus invalidating the instrument.

of random errors. They incorporate observed and unobserved heterogeneity and include both a parameter representing the stability of individuals' choices under risk and a "trembling hand" parameter which allows for completely random decision-making some percentage of the time. However, while the authors note 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.

3 Data

The data comes from "The Millenium Foundation Field Experiment on Education Financing" which involved a representative sample of 1,248 Canadian citizens 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. In the present analysis I exclude 24 individuals who are not Canadian citizens.[15]

The experiment was conducted using pen and paper choice booklets as well as simple random sampling devices like bingo balls and dice. The sample is drawn from provinces of Manitoba, Saskatchewan, Ontario and Quebec due to project cost considerations which required that participants have convenient travel connections to Ottawa and Montreal. The implementation team was able to carry out work in urban and rural schools in each of the four provinces.

The dataset includes additional survey questions and experiments regarding attitudes towards education and its financing which are not used in the present paper. There are several recent papers which analyze this dataset using a structural model. Belzil and Sidibe (2016) estimate individual risk and time preferences and investigate their predictive power in explaining the take-up of grants for higher education. Belzil, Maurel and Sidibe (2021) 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.

The experiment contains 103 binary choice tasks designed to elicit risk and time preferences.[16] 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.

[15]These are likely recent immigrants with a different cultural background who may understand (and respond to) the experiment differently than the rest of the sample. Their low prevalence - less than 2% of the sample - precludes a meaningful analysis of these differences.

[16]There are a few additional multiple choice tasks which are not analyzed in this paper.

3.a Holt & Laury's (H&L) 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 intuitive pie chart representation popularized by Hey and Orme (1994). There are 3 groups (MPLs) 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. In a deterministic world, each person's "switching point" should be indicative of his risk aversion. By design, in the absence of a shock to either 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 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 (MPLs) 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

[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.

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.

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 (MPLs) 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 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. 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. 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. There is a 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.

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

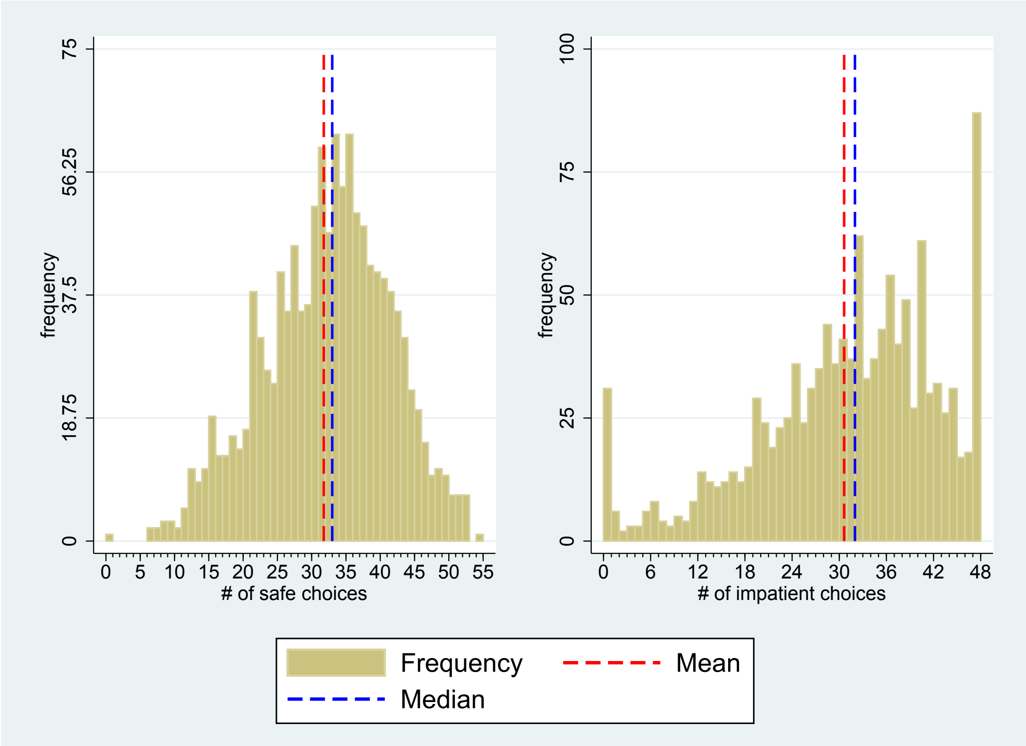
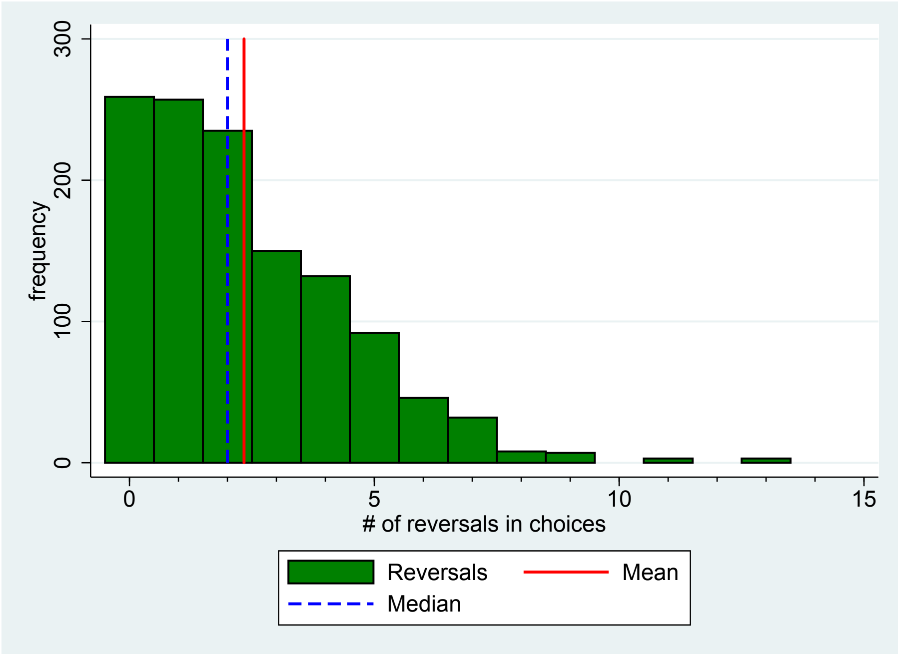


Figure 2 shows that contrary to standard predictions, some individuals exhibit reversals in their choices within a set of choice tasks.[19] This confirms the importance of analyzing data on the full set of tasks as opposed to assuming that each individual will maintain his choice after his "switching point" (as is often done in the literature, see Bruner, 2017 for a recent example).

[19]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, 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.d of the Appendix lists measures selected to approximate cognitive ability and 3 of the *Big Five* personality traits. Cognitive ability is measured by various indicators related to cognitive skill – grades, a numeracy test, and self-reports of skills: oral, written, mathematical, etc. Conscientiousness is measured by questions related to self-reported ambition, ability to delay gratification, and diligence. Extraversion is measured by questions related to self-reported tendencies towards active, sociable behavior and excitement-seeking. Emotional stability is measured by questions related to confidence, self-esteem, and self-efficacy. I restrict my analysis to these 3 personality traits as the data does not contain good proxies for the remaining *Big Five* personality traits: agreeableness and openness to experience.

3.e.i Experimental Validation of Employed Measures

The survey associated with the original dataset does not contain previously validated measures for the *Big Five* personality traits. Appropriate measures were thus selected from available indicators based on the closeness of fit of each question's wording with the respective trait's definition. The chosen indicators were validated through a follow-up study conducted online through the Dynata platform between December 2020 and February 2021 using a comparable sample of individuals to those who participated in the original experiment.[20]

The validation study includes two waves of data-collection with an average delay of 5 weeks between the initial survey and the recontact. Participants provided responses to validated *Big 5* measures from the commonly used BFI-2 questionnaire[21] and to questions regarding personality contained in "The Millenium Foundation Field Experiment on Education Financing".[22] 651 participants aged 18-25 from 4 major English-speaking countries completed both survey waves. 120 of them are Canadians.

Correlations between validated *Big 5* traits and the utilized proxies available in the original experiment are high. They are 0.46 (0.47) for extraversion, 0.63 (0.69) for conscientiousness, and 0.48 (0.57) for emotional stability in the Canadian sub-sample (in the full sample of 4 major English-speaking countries). These correlations are well above a rough cutoff value of 0.3 frequently used for determining whether a proxy is valid in the experimental literature (see e.g. Becker et al., 2012). They thus satisfy the criterion for convergent validity from Campbell and Fiske (1959). In addition, the obtained correlations also meet their criterion for discriminant validity which requires that "[m]easures of the same trait should correlate higher with each other than they do with measures of different traits involving separate methods."

To fully appreciate the magnitude of these correlations, it is helpful to consider test-retest correlations of the examined constructs.[23] Test-retest correlations of measures taken only a few weeks apart for a given individual provide a useful upper bound on a correlation which we could expect from a "perfect proxy" as the underlying constructs of interest (e.g. personality) can reasonably be considered stable within this time frame. The difference between such a test-retest correlation and 1 can thus be attributed to measurement error and even a "perfect" proxy cannot be expected to surpass this upper bound (see Falk et al., 2016).

Test-retest correlations in my validation study are 0.8 for the Big Five traits measured using the BFI-2 questionnaire and 0.7 for the proxy measures which I use. The obtained correlations between the official *Big Five* traits and my proxies which are in the vicinity of 0.5-0.6 are therefore close to the theoretical upper bound for a perfect proxy.

[20]As a robustness check, I select measures from those available in the original experiment solely based on the strength of empirical correlations with each relevant *Big Five* trait in the validation study. Overlap between the two methods for the selection of personality measures is high (80% of the chosen indicators are the same) and results obtained from the structural model are robust.

[21]The BFI-2 questionnaire (Soto & John, 2017) contains 60 items, 12 per each personality trait. One of the advantages of this questionnaire is that the traits can further be subdivided into facets.

[22]The survey also contains additional items which are not relevant to the present study.

[23]A test-retest correlation is the correlation between responses of individuals on identical questions elicited at different points in time.

The proxies also load well on facets of the relevant Big 5 traits.[24] Correlations for the 9 facets range from 0.24 to 0.59 with 8 out of 9 having a correlation of 0.3 or higher. See Figure 3 of the Appendix for details.

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 proxies of cognitive ability and the three personality traits obtained as a simple sum of their respective underlying measures.[25] Table 1 compares correlations obtained in this dataset to those presented in Becker et al. (2012).[26] 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.

Table 1: Correlational Evidence on the Link Between Risky and Impatient Choices and Personality

	Safe Choices			Impatient Choices		
	Becker et al. (2012)		Current Dataset	Becker et al. (2012)		Current Dataset
	Table 2	Table 3		Table 2	Table 3	
Neuroticism	0.12	-0.03	0.02	0.05	0.06	-0.02
Extraversion	-0.08	-0.08	-0.10	0.01	0.07	0.04
Conscientiousness	0.06	0.07	0.02	-0.01	0.07	-0.11
Cognitive Ability	NA	NA	-0.05	NA	NA	-0.17

Source: Becker et al. (2012), Table 2 and 3; author's estimates

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 2 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. Extraversion is associated with picking

[24]Facets of extraversion are: sociability, assertiveness, and energy level. Facets of conscientiousness are: organization, productiveness, and responsibility. Facets of emotional stability are: lack of anxiety, lack of depression, and emotional stability. See Soto & John (2017).

[25]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.

[26]Neuroticism is the inverse of emotional stability. The sign on the correlations presented in Becker et al. (2012) 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.

fewer safe choices, conscientiousness with fewer impatient ones, and emotional stability with more impatient choices. The low R2 would suggest that the link between preferences and personality is at best weak as even the little 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 exposit the general set-up of the model. 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.[27] 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. As described in Section 2, the existence of variable preferences is rooted in recent evidence from neuroscience on the stochastic nature of brain processes involved in establishing decision values. It can reflect imperfect self-knowledge, actual preference instability, 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 proxies for psychological personality traits.[28] I also allow for heterogeneity in self-knowledge and in

[27]Apesteguia, Ballester, and Gutierrez (2020) shows that this experimental elicitation mechanism is empirically sound.

[28]This approach allows me to stay within a standard economic framework for decision-making under risk 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 assuming that

the propensity to make mistakes. This approach allows me to distinguish heterogeneity in the curvature of the utility function and discount rates from 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, latent factors, and pure unobserved heterogeneity. The following sections describe in turn each of the building blocks of the model.

4.a Risk Aversion

Assume that individual i is endowed with a utility function $U_i(.)$ which maps monetary values into utility. $U_i(a)$ then represents the utility which he obtains from a dollars. Define the coefficient of relative risk aversion $\Theta_i = \frac{-a*U''(a)}{U'(a)}$. A constant relative risk aversion (CRRA) utility function can then be written as:

$$U_i(a) = \frac{a^{(1-\Theta_i)}}{1-\Theta_i} = U(a,\theta_i) \tag{1}$$

Assuming no background consumption[29], for a lottery X with two possible outcomes, x_1 dollars with probability p_{x_1} and x_2 dollars with probability $1-p_{x_1}$, an individual's expected utility (EU) is:

If $\Theta_i \neq 1$

$$EU_i(X) = p_{x_1} * \frac{x_1^{(1-\Theta_i)}}{1-\Theta_i} + (1-p_{x_1}) * \frac{x_2^{(1-\Theta_i)}}{1-\Theta_i} \tag{2}$$

If $\Theta_i = 1$

$$EU_i(X) = p_{x_1} * ln(x_1) + (1-p_{x_1}) * ln(x_2) \tag{3}$$

where $\Theta_i \in (-\infty;+\infty)$ is individual i's coefficient of risk aversion.[30]

a suitable model existed.

[29]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. Only one binary choice task - the 45th lottery choice - used in this experiment involves a potential payoff of zero. For the lottery in question, a payment value of \$0.01 is assumed in the model.

[30]The obtained mapping between preferences and traits is robust to an alternative assumption of constant

4.a.i The Random Preference Model

In this experiment, each individual makes 55 binary choices between two lotteries. This is equivalent to observing a panel of 55 decisions for each agent which provides fertile ground to not only estimate individuals' latent true (or average) risk preferences but also to examine the consistency of their choices with respect to them. Observed choices reflect a degree of inconsistency which cannot be justified by variation in task characteristics alone. I introduce shocks to preferences following Loomes and Sugden (1995) and more recently Apesteguia and Ballester (2018) to account for the randomness in individuals' choices from the point of view of the econometrician.

When making a choice between lottery X and lottery Y an individual first receives a realization of the preference shock ε_i. The shock is assumed to affect the individual's true (or average) risk preference embodied by his coefficient of relative risk aversion θ_i which represents the relevant coefficient of risk aversion that would prevail in a purely deterministic choice context. Within a stochastic choice environment, a random shock can reflect imperfect self-knowledge or actual variation in risk preference due to factors unobserved by the econometrician. The individual will then use the shocked (or instantaneous) value of risk preference $\theta_i + \varepsilon_i$ to compare the two alternatives. The expected utility of individual i from lottery X and lottery Y respectively becomes:

$$\begin{aligned} EU_i(X) &= p_{x_1} * \frac{x_1^{1-(\Theta_i+\varepsilon_i)}}{1-(\Theta_i+\varepsilon_i)} + (1-p_{x_1}) * \frac{x_2^{1-(\Theta_i+\varepsilon_i)}}{1-(\Theta_i+\varepsilon_i)} \\ &= EU(X;\theta_i+\varepsilon_i) \end{aligned} \tag{4}$$

and

$$\begin{aligned} EU_i(Y) &= p_{y_1} * \frac{y_1^{1-(\Theta_i+\varepsilon_i)}}{1-(\Theta_i+\varepsilon_i)} + (1-p_{y_1}) * \frac{y_2^{1-(\Theta_i+\varepsilon_i)}}{1-(\Theta_i+\varepsilon_i)} \\ &= EU(Y;\theta_i+\varepsilon_i) \end{aligned} \tag{5}$$

Assume that lottery X is less risky (has a lower variance in potential payouts) than lottery Y in all lottery choice tasks l=1,...,55 that an individual faces. He will prefer the riskier lottery Y to the safer lottery X if

$$EU(Y;\theta_i+\varepsilon_i) > EU(X;\theta_i+\varepsilon_i) \tag{6}$$

absolute risk aversion (CARA) utility or expo-power (E-P) utility of Abdellaoui et al. (2007). The functional form for CARA is $U_i(a) = \frac{1-\exp(-\Theta_i * a)}{\Theta_i}$ if $\Theta_i \neq 0$ and $U_i(a) = a$ if $\Theta_i = 0$. The functional form for E-P is $U_i(a) = -\exp(-\frac{a^{1-\Theta_i}}{1-\Theta_i} + \frac{1}{1-\Theta_i})$ if $\Theta_i \neq 1$ and $U_i(a) = -\frac{1}{a}$ if $\Theta_i = 1$, with a normalized to lie in the interval [0,1].

The probability that Y is preferred is equivalent to the probability that the value of the shock is such that the above inequality is satisfied. As ε_i enters expected utility non-linearly, obtaining a closed form expression for this probability is non-trivial. I use a trick provided by Apesteguia and Ballester (2018) to do so, which relies on the monotonicity of the RPM.

Define $YP_{i,l}$, a binary variable which takes on the value of 1 if individual i derives higher expected utility from the riskier lottery Y than from the safer lottery X in choice task l and 0 otherwise. $P(YP_{1,l} = 1)$ then characterizes the situation in which individual i prefers the riskier lottery Y. Intuitively, a convincing model of choice under risk should predict that when given the choice between a riskier lottery Y and a safer lottery X, an individual who is more risk averse will pick the riskier lottery with a lower probability than an individual who is less risk averse. More formally, take two individuals *1* and *2*: if $\theta_1 > \theta_2$, then $P(YP_{1,l} = 1) < P(YP_{2,l} = 1)$. Let us call monotone a model of decision-making under risk which satisfies the above condition for any such pair θ_1, θ_2. Apesteguia and Ballester (2018) prove that the RPM is monotone.

Given that the RPM is monotone, the predicted probability of choosing the riskier option is monotonically decreasing in risk aversion θ. Therefore, individual i will prefer the riskier lottery if he receives a *sufficiently low* value of the shock $\varepsilon_{i,l}$. Define $\overline{\varepsilon}_{i,l}(\theta_i, X, Y)$, the value of the preference shock at which the individual is indifferent between the safer and the riskier lottery. It is a function of both the individual's true (or average) risk aversion θ_i and of the parameters of the two lotteries that he has to choose between. Following Apesteguia and Ballester (2018) the latter can be succinctly summarized by a threshold level of indifference θ_l^{eq} which reflects the relative attractiveness of the riskier lottery compared to the safer lottery on task l. For a given assumed functional form of utility (here CRRA), the threshold level of indifference is uniquely determined by the characteristics of lottery X: x_1, x_2, p_{x_1} and by the characteristics of lottery Y: y_1, y_2, p_{y_1} between which an individual has to choose on choice task l.

Define the threshold level of indifference for choice task l as the value of θ which satisfies $EU(X, \theta_l^{eq}) = EU(Y, \theta_l^{eq})$. When faced with a choice between lottery X and lottery Y, individuals who have a higher level of risk aversion than the threshold level of indifference will choose the safer alternative X while those who have a lower level of risk aversion will choose the riskier alternative Y. Individual i will prefer the riskier lottery Y on task l if his shocked value of risk aversion is lower than the indifference threshold associated with task l:

$$\Theta_i + \epsilon_{i,l} < \theta_l^{eq} \tag{7}$$

or, rearranging, if the realization of the shock is lower than $\overline{\varepsilon}_{i,l}$, the value of the preference shock at which the individual is indifferent between the safer and the riskier lottery:

$$\epsilon_{i,l} < \bar{\varepsilon}_{i,l} = \theta_l^{eq} - \Theta_i \tag{8}$$

If one assumes a parametric distribution on the random shock, the probability that individual i prefers the riskier option Y on choice task l has a closed form expression. $P(YP_{i,l} = 1)$ is increasing in the difference between the task specific threshold of indifference θ_l^{eq} and the individual's true (or average) risk aversion Θ_i. Assuming that the random shock is normally distributed with $\epsilon_{i,l} \sim N(0, \sigma_{\theta,i}^2)$, we can write:

$$P(YP_{i,l} = 1) = \Phi(\frac{\theta_l^{eq} - \Theta_i}{\sigma_{\theta,i}}) \tag{9}$$

The probability of preferring the safer option is simply:

$$P(YP_{i,l} = 0) = 1 - P(YP_{i,l} = 1) \tag{10}$$

4.a.ii Adding Trembles

While the RPM model preserves monotonicity, it imposes strong rationality requirements and predicts that dominated choices are never chosen. However, in reality individuals choose dominated options with a positive probability.

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.

Incorporating the tremble parameter $K_i \in [0; 0.5]$, 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:

$$P(YC_{i,l} = 1) = P(YP_{i,l} = 1) * (1 - K_i) + [1 - P(YP_{i,l} = 1)] * K_i \tag{11}$$

where $YC_{i,l}$ is a binary variable which takes on the value of 1 if individual i *chooses* the riskier option in lottery choice task l and 0 otherwise.

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

$$P(YC_{i,l} = yc_{i,l}) = P(YC_{i,l} = 1)^{YC_{i,l}} * P(YC_{i,l} = 0)^{1 - YC_{i,l}} \tag{12}$$

where $yc_{i,l}$ is a particular realization of $YC_{i,l}$.

4.a.iii Identification of Consistency Parameters

Both $\sigma_{\Theta,i}$ and K_i measure the consistency of an individual's choice. However, each generates a specific pattern of choice inconsistency.

As previously mentioned in describing the RPM, no value of the preference shock can explain choices of dominated options. Multiple choice tasks in the present experiment involve such options and individuals choose them with non-zero probability. The only part of the employed RPM which can explain such choices is the tremble parameter K_i. K_i is therefore trivially identified from such choices.

K_i is a source of uniform noise which affects all choices equally whereas $\sigma_{\Theta,i}$ represents noise which has a higher chance to reverse a choice closer to an individual's point of indifference. It is identified from residual noise after stripping away the uniform component identified from choices of dominated options.

More generally, K_i and $\sigma_{\Theta,i}$ are parametrically identified from different moments of the noise distribution. Assume a normal distribution on $\sigma_{\Theta,i}$. The probability that this "sigma-noise" reverses a choice relative to an individual's true or average preference falls with rising distance between the individual's true (or average) level of risk aversion θ_i and the indifference threshold θ_l^{eq} associated with a particular choice task. It approaches zero some 2 or 3 standard deviations away from θ_l^{eq}. Now suppose that the distribution of choices inconsistent with the true (or average) level of risk preference has a bell-shaped pattern but that such choices also occur far away from θ_i with a non-negligible probability. To the extent that these inconsistent choices concern non-dominated options, one could explain them by increasing $\sigma_{\Theta,i}$. However, this would come at the cost of increasing the predicted occurrence of inconsistent choices around the indifference point. The two sources of noise in my RPM model can be identified even without the presence of dominated options due to the tension between the occurrence of inconsistent choices close to, or far away from, an individual's true (or average) preference.

To see an illustration of this idea, consider choice reversals *within* an ordered list of choice tasks and inconsistent switching points *between* lists. A reversal within a list represents relatively large choice inconsistency compared to inconsistent switching points. Take two ordered lists of choice tasks with the same theoretical switching point. Assume that on the first one an individual always chooses the option which he prefers given his true (or average) level of risk preference. On the second list, one inconsistent choice just before (or after) the individual's "regular" switching point is enough to make him switch early (or late) and results in inconsistent switching points between the lists. A reversal within the list would require an inconsistent choice further away from the individual's "regular" switching point (or an additional inconsistent choice).

I simulated choices for a sample of the size of my experimental dataset (1,224 individuals) to illustrate the relevance of the above-mentioned points for tasks which I use. In order to focus on the tradeoff between σ and K noise, I use a representative agent model with the values of the structural parameters set at estimated values for the median individual.[31] A simulation which turns off the tremble parameter yields a total of 1,025 inconsistent switching points compared to 1,031 observed in the experimental data[32]. However, it severely *under-predicts* the number of choice reversals (198 simulated vs. 2,779 actual). If $\sigma_{\Theta,i}$ is tripled to 0.45, the simulated number of reversals approaches the actual one (2,628 vs. 2,779); however, this comes at the cost of severely *over-predicting* the number of inconsistent switch points (1,657 simulated vs. 1,031 actual). This illustrates the tension between predicting choice inconsistency around points of indifference and far from them while relying solely on normally distributed shocks with standard deviation $\sigma_{\Theta,i}$.

Even if dominated options are removed from the simulation, the Hessian is invertible and yields reasonable standard errors providing further evidence that both consistency parameters are identified also in the absence of dominated choices.

4.b Time Preference

Time preference under RPM is treated analogously to risk aversion. In case of time preference (delay-aversion) the parameter of interest will be the individual's discount rate R_i.

Assume that an individual is faced with two choices which differ in the payment they offer and in the time at which the payment takes place. One can define a threshold level of the discount rate $R_{i,t}^{eq}$ at which the discounted utilities of the two options will be equal for individual i on temporal choice task t. As with lotteries described in the previous section, the threshold will vary by choice task. However, with delay aversion, the threshold of a particular choice task is no longer common to all individuals, which is why it has the subscript i. It depends on each individual's level of risk aversion, Θ_i, which affects the curvature of his utility function.

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

If $\Theta_i < 1$

$$DU_i(a) = \beta_i^{\tau} \frac{a^{(1-\Theta_i)}}{1-\Theta_i} \tag{13}$$

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.

[31]The values of consistency parameters for the median individual are calculated from individual-specific estimates as follows: Individuals are first sorted by estimated risk aversion. The employed values of $\sigma_{\Theta,i}$ and K_i are averages for a window of four observations above and below the median individual.

[32]Inconsistent switching points are calculated for the 3 sets of 10 lottery tasks which have the same predicted theoretical switch points under CRRA utility.

Discount rates between 0 and 100% allow the researcher to capture a wide range of time preferences. Negative discount rates make little sense. Estimates based on well-known experimental datasets suggest that a 100% upper bound is generous (see e.g. Andersen et al., 2008; Andersen et al., 2014; Apesteguia, Ballester and Gutierrez, 2020). As robustness I test a specification which includes 200% annual discount rates, the highest rate of interest offered in this experimental dataset. The correlation in estimated discount rates using either upper bound is 0.92. Both fixed effect and full model results are robust.

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.[33] I assign individuals with an estimated $\Theta_i > 1$ a value of $\Theta_i = 0.99$ for the purposes of calculation of indifference thresholds for the discount rate.[34] At these levels of risk aversion, indifference thresholds for the discount rate already approach zero. Nevertheless, as robustness I also employ a slightly modified version of CRRA utility which keeps utility positive for payments greater than \$1 and thus allows the calculation of indifference thresholds for the discount rate also using $\Theta_i > 1$. In this case discounted utility can be written as: $DU_i(a) = \beta_i^\tau \frac{a^{(1-\Theta_i)}-1}{1-\Theta_i}$. Results are robust to this alternative specification of CRRA utility.

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 this dataset, the lack of variation in 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 featured in this experiment, the fact that it has no effect on observed choices is either also 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. To this end, 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 discounted utility of individual i from a proposed payoff of a \$ received in τ years then becomes: $DU_i(a) = \frac{1}{1+R_i*\tau} * \frac{a^{(1-\Theta_i)}}{1-\Theta_i}$ if $\Theta_i < 1$. Results are robust to this alternative assumption.

[33] 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 larger later payment until it reaches, at the threshold level of discount rate, the value of the smaller earlier payment. When ordinal utility is negative, this mechanism no longer works with a traditionally defined discount factor. Applying a standard discount factor (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. Standard discounting lowers the absolute value of utility, which in the case of negative utilities makes it less negative and thus in fact higher.

[34] Similarly, I assign individuals with an estimated $\Theta_i < -0.3$ a $\Theta_i = -0.3$ in estimation of indifference thresholds for the discount rate. This simplifies numerical optimization and such high values of risk-seeking concern only approximately 1% of the sample. Results are robust to extending this lower limit to $\Theta_i = -2$.

4.b.i Choice Probabilities

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 making R_i a random variable. I assume a lognormal distribution for time preferences as the discount rate has to always stay positive. The discount rate is thus 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.

As the log of a lognormally distributed random variable is normally distributed, the log of the discount rate is a normally distributed random variable with mean $ln\left(\frac{R_i^2}{\sqrt{(\sigma_{R,i})^2+R_i^2}}\right)$ and standard deviation $\sqrt{ln\left(1+\frac{(\sigma_{R,i})^2}{R_i^2}\right)}$. Individual i will prefer the later option in temporal choice task t if his realization of the discount rate is below his threshold of indifference between the earlier and later option, $R_{i,t}^{eq}$. Alternatively, he will prefer the later option if the *log* of his realization of the discount rate is below the *log* threshold of indifference between the earlier and later option $ln(R_{i,t}^{eq})$. With this insight we obtain the temporal equivalent of Equation 9, the probability of preferring the later option:

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

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 and 0 otherwise. In the case of choice under risk, the probability of preferring the riskier of two options was increasing in the difference between the task specific threshold of indifference and the individual's true (or average) risk aversion. In temporal choice, the probability of preferring the later option is increasing in the difference between (the log of) the task specific threshold of indifference, evaluated at the individual's level of risk aversion, and (the log of) the individual's true (or average) discount rate.

The probability of preferring 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. As robustness, I allow K_i to vary between temporal and lottery choices. Estimated mappings are preserved.

After incorporating the tremble parameter, I obtain 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 and 0 otherwise.

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

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

where $lc_{i,t}$ is a particular realization of $LC_{i,t}$.

4.c Individual Likelihood Contribution

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:

$$L_i = \prod_{l=1}^{55} P(YC_{i,l} = yc_{i,l}) * \prod_{t=1}^{48} P(LC_{i,t} = lc_{i,t}) \tag{18}$$

4.d 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. Observed heterogeneity consists of directly observable individual characteristics, and of unobserved factors related to ability and personality noisily proxied for by observed measures. Unobserved heterogeneity 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.

In Equations 19 through 23, I write each preference and consistency parameter as a function of a) pure unobserved heterogeneity captured by the parameter's respective population intercept θ_0 through κ_0; b) a vector of directly observed characteristics X_i; and c) a vector of latent factors F_i which have observed proxy indicators in the data. Each structural parameter is assumed to depend on the same set of observed characteristics and latent factors.[35] Differences in the impact of unobserved heterogeneity are captured by the population intercepts. The differential importance of each component of observed heterogeneity in explaining a particular preference or consistency parameter is captured by the coefficients θ_1 through κ_1 for directly observed characteristics, and by the coefficients θ_2 through κ_2 for the latent factors.

$$\Theta_i = \theta_0 + \theta_1{}'X_i + \theta_2{}'F_i \tag{19}$$

$$\sigma_{\Theta,i} = \Phi(s_{\theta,0} + s_{\theta,1}{}'X_i + s_{\theta,2}{}'F_i) \tag{20}$$

$$R_i = \Phi(r_0 + r_1{}'X_i + r_2{}'F_i) \tag{21}$$

$$\sigma_{R,i} = \Phi(s_{R,0} + s_{R,1}{}'X_i + s_{R,2}{}'F_i) \tag{22}$$

$$K_i = 0.5 * \Phi(\kappa_0 + \kappa_1{}'X_i + \kappa_2{}'F_i) \tag{23}$$

4.d.i Latent Factors with Observed Noisy Proxies

The unobserved factors are estimated from multiple observed proxy measures (for seminal work on using factor analysis to estimate cognitive and non-cognitive skills see Cunha, Heckman, and Schennach, 2010). Each measure is assumed to be a noisy reflection of the underlying factor of interest. This approach allows for a more efficient extraction of information on cognitive ability and personality from available measures than the often used alternative approach of simply summing up the observed indicators for each latent characteristic.

A measure's contribution to the overall likelihood depends on whether the proxy 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:

$$M_{i,j,f} = \gamma_{0,j,f} + \gamma_{1,j,f} * F_{i,f} + \epsilon_{i,j,f} \tag{24}$$

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.

[35] In order to keep the model tractable, sex was chosen as the observed characteristic for the main specification because its influence on economic preferences is hotly debated. The latent factors are cognitive ability and three factors related to emotional stability, extraversion, and conscientiousness.

The factor itself is composed of a deterministic part which contains an individual's characteristics and of an orthogonal random part:

$$F_{i,f} = \alpha_0 + \alpha_f{}' X_i + \widetilde{F}_{i,f} \tag{25}$$

where $\alpha_f{}'$ is a set of coefficients on the individual's observed characteristics which enter into factor f.[36] 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 of 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:

$$P(M_{i,j,f} = m_{i,j,f}) = [1 - \Phi(-\gamma_{0,j,f} - \gamma_{1,j,f} * F_{i,f})]^{M_{i,j,f}} * \Phi(-\gamma_{0,j,f} - \gamma_{1,j,f} * F_{i,f})^{1-M_{i,j,f}} \tag{26}$$

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

4.e Unobserved Heterogeneity

Unobserved heterogeneity is incorporated through unobserved types which differ in the intercepts of preference and consistency parameters as seen in Equations 19 through 23.[37] Each type is thus characterized by a vector of 5 intercepts, one for each parameter of interest. 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. 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. The resulting likelihood contribution will thus be a weighted average of the individual type likelihoods, where the weights correspond to each type's prevalence in the overall sample. These are parameters to be estimated.

[36] Sex, native language, and age were chosen for the main specification due to their intuitive importance in explaining personality and cognitive ability and to their availability for the full sample. Sex figures both in the structural parameter Equations 19 through 23, estimated from choices on incentivized tasks, and in the factor Equation 25, estimated from observed factor proxy measures. This allows for a separate identification of the direct impact of sex on each preference and consistency parameter, and of its indirect impact through its effect on the latent factors. Results are robust to excluding sex from the factor equation.

[37] 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 proxy measures and individual choices in the lottery and temporal choice tasks given unobserved factors and types which drive the observed measures and choices. The factors are modeled as random effects.

Take the example of a binary measure. Combining equations 24 and 25, the probability of observing value 1 on binary measure $M_{i,j,f}$ using factor $F_{i,f}$ as a random effect is:

$$P(M_{i,j,f}=1\Big|\widetilde{F}_{i,f})=P\Big(\epsilon_{i,j,f}<\gamma_{0,j,f}+\gamma_{1,j,f}*(\alpha_0+\alpha_f{}'X_i)+\gamma_{1,j,f}*\widetilde{F}_{i,f}\Big|\widetilde{F}_{i,f})\Big)= \\ =\Phi\Big(\gamma_{0,j,f}+\gamma_{1,j,f}*(\alpha_0+\alpha_f{}'X_i)+\gamma_{1,j,f}*\widetilde{F}_{i,f}\Big|\widetilde{F}_{i,f})\Big) \quad (27)$$

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

$$P(M_{i,j,f}=1)=\int_{-\infty}^{+\infty}\Phi\Big(\gamma_{0,j,f}+\gamma_{1,j,f}*(\alpha_0+\alpha_f{}'X_i)+\gamma_{1,j,f}*\widetilde{F}_{i,f}\Big)*\frac{1}{\sigma_{F_f}}\phi\Big(\frac{\widetilde{F}_{i,f}}{\sigma_{F_f}}\Big)d\widetilde{F}_{i,f} \quad (28)$$

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 latent factors. 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:

$$L_i\Big|(\widetilde{F}_i=\widetilde{F}_{i,1},\widetilde{F}_{i,2},...,\widetilde{F}_{i,F};UT_i=ut_i)=\prod_{f=1}^{F}\prod_{j=1}^{J}P(M_{i,j,f}=m_{i,j,f}\Big|\widetilde{F}_{i,f})*\prod_{l=1}^{55}P(YC_{i,l}=yc_{i,l}\Big|\widetilde{F}_i,UT_i)* \\ *\prod_{t=1}^{48}P(LC_{i,t}=lc_{i,t}\Big|\widetilde{F}_i,UT_i) \quad (29)$$

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 the individual's 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 26 for binary measures, equations 33-35 for multi-valued measures, equation 36 for continuous measures, equation 12 for lottery choice tasks, and in equation 17 for temporal choice tasks.[38] Note that unobserved types only affect choice probabilities on lottery and temporal choice tasks as each unobserved type is a vector of intercepts on the preference and consistency parameters and is assumed to be orthogonal to both unobserved factors and to the observed measures which proxy for the factors.

I next integrate out the unobserved factors:

$$L_i\Big|(UT_i = ut_i) = \int_{\widetilde{F}_i} \cdots \int \prod_{f=1}^{F}\prod_{j=1}^{J} P(M_{i,j,f} = m_{i,j,f}\Big|\widetilde{F}_{i,f}) * \prod_{l=1}^{55} P(YC_{i,l} = yc_{i,l}\Big|\widetilde{F}_i, UT_i) * \\ * \prod_{t=1}^{48} P(LC_{i,t} = lc_{i,t}\Big|\widetilde{F}_i, UT_i) * f(F_1,...,F_F) d\widetilde{F}_i \quad (30)$$

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

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

The above is implemented through simulation by averaging over the 200 factor draws for each individual. The unconditional individual likelihood is obtained by integrating out the unobserved types:

$$L_i = \sum_{ut=1}^{UT} (L_i\Big|ut) * p_{ut} \quad (32)$$

where p_{ut} is the prevalence of unobserved type ut in the overall population. Since this is pure unobserved heterogeneity, a person is as likely to be any of the unobserved types as another person and thus p_{ut} is not indexed by i. The resulting likelihood contribution is a weighted average of the likelihoods calculated for each type where weights correspond to the prevalence of each type in the overall population.[39]

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

[39]With 5 unobserved types, the estimated prevalence of the least frequent type is already less than 10%. Results are robust to estimation with 3 unobserved types.

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 18, 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 as summarized in Figure 3 below.

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 32). Results are obtained using simulated maximum likelihood. This specification includes observed and unobserved heterogeneity.

The two specifications are complementary. The fixed effects choice model provides individual point estimates of the preference and consistency parameters. The full model enables me to structurally map economists' preference parameters onto psychologists' personality traits. 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 governing the stability of preferences and the propensity to make mistakes.

Figure 3: Summary: Structural Parameters of Interest

	Risk	**Time**
Preference Parameters	Coefficient of Relative Risk Aversion (**Θ**)	Discount Rate (**R**)
Consistency Parameters		
- Stability	Standard Deviation of the Coefficient of Relative Risk Aversion (σ_Θ)	Standard Deviation of the Discount Rate (σ_R)
- Mistakes	Trembling Hand Parameter (**K**)	

6.a Preference Parameters

Results from the full model summarized in Figure 4 reveal that the average individual[40] in the population has logarithmic risk aversion and a 23% 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. (2020) obtain an even lower estimate for the coefficient of risk aversion, 0.25, using a similar econometric methodology but applied to risk elicitation tasks 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 rate, which implies that the direct effect of being a woman increases impatience. This seeming anomaly is explained by indirect effects. Being a woman is also associated with higher conscientiousness and lower extraversion (see Figure 13), both of which push discount rates downward.

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 prevalent type (type 1) which represents one third of the population has higher than logarithmic risk aversion and is very patient. There is one risk seeking type (type 4) who is at the same time very 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 but relatively high discount rates. These results suggest that the inclusion of unobserved types is warranted and necessary to explain heterogeneity in observed choices.

[40]The 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.

Figure 4: Parameter Values for the Average Person

	Prevalence	Risk Aversion	Discount Rate	Risk Aversion SD	Discount Rate SD	% Hand Trembles
Simulated Average		0.99	0.23	0.41	0.20	0.06
Female Average		1.04	0.17	0.40	0.13	0.07
Male Average		0.93	0.32	0.43	0.30	0.06
Type 1 Average	0.31	1.15	0.01	0.62	0.01	0.05
Type 2 Average	0.23	0.33	0.67	0.36	0.55	0.17
Type 3 Average	0.25	0.60	0.49	0.37	0.46	0.03
Type 4 Average	0.12	-0.05	0.62	0.30	0.73	0.02
Type 5 Average	0.08	5.16	0.02	0.14	0.01	0.10

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 estimated structural parameters to construct a simulated dataset.[41]

Figure 5 superposes the distributions of preference parameters estimated using alternatively the fixed effects choice model and the full model.[42] They are remarkably similar and show that using only the coefficients from my structural model, information on observed heterogeneity, and my estimates regarding unobserved types, I am able to simulate as rich a distribution of preferences as can be obtained from estimates based on the full set of observed individual choices. The median value of risk aversion is 0.66 using the fixed effects choice model and 0.7 using the full model while the median value of the discount rate is 0.2 and 0.24 respectively.[43] Not only are the medians of the two distributions virtually identical for each preference parameter, but so is the 25th percentile, the 75th percentile, the mean, and the standard deviation.[44] In contrast, using observed and unobserved heterogeneity, Von Gaudecker, Van Soest, and Wengstrom (2011) are able to cover only about one third of the distribution of risk preferences which they obtain using information on individual choices on incentivized tasks designed to

[41]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 prevalence in the population.

[42]The displayed chart goes through risk aversion of +3 as the overwhelming majority of observations fall within this range. There is a small spike again at +5 as a result of the existence of individuals choosing all or almost all safe options. These are the "type 5".

[43]For comparison purposes, Apesteguia, Ballester, and Gutierrez (2020) use three experimental datasets to obtain estimates for the median value of risk aversion between 0.03 and 0.72. The large dispersion in reported estimates by these authors is not surprising as the analyzed datasets involve relatively few observations.

[44]More precisely, for the coefficient of risk aversion these are 1.01 vs 0.99 (mean); 1.31 vs 1.34 (standard deviation); 0.33 vs 0.29 (25th percentile); 0.70 vs 0.66 (median); 1.12 vs 1.00 (75th percentile) respectively for the full model and for the fixed effects model. For the discount are these are 0.37 vs 0.36 (mean); 0.36 vs 0.37 (standard deviation); 0.02 vs 0.02 (25th percentile); 0.24 vs 0.20 (median); 0.71 vs 0.68 (75th percentile) respectively for the full model and for the fixed effects model.

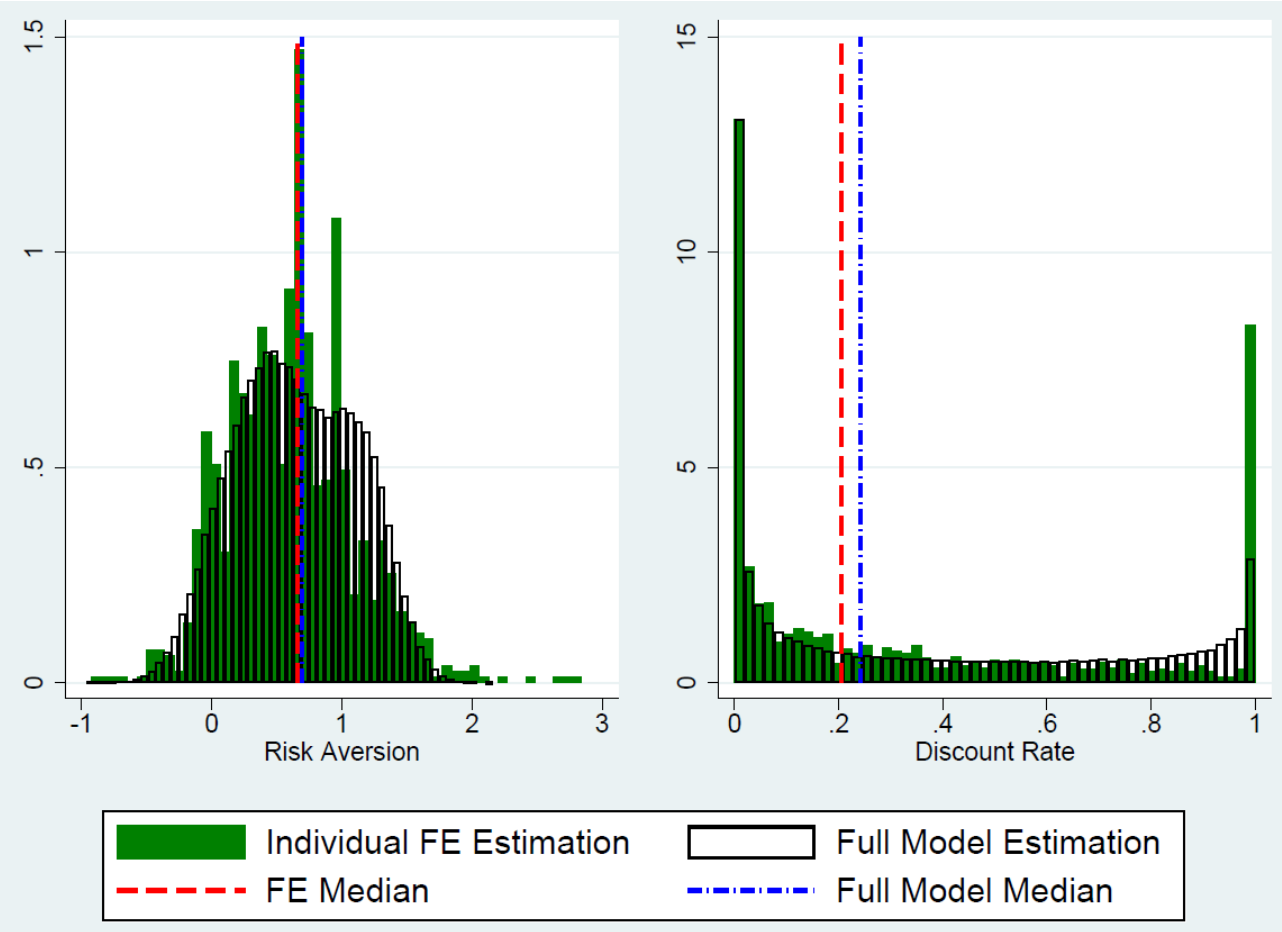
elicit risk preferences.

Due to the presence of unobserved factors and types in the full model it is not trivial to obtain a direct measures of goodness of fit with observed individual choices. However, this is straightforward to do using the fixed effects model. The coefficient of risk aversion alone explains almost 90% of the variation across individuals in the number of safe choices selected on lottery choice tasks. The discount rate parameter explains close to 65% of the variation across individuals in the number of impatient choices selected on intertemporal choice tasks. The fixed effects model thus fits the observed choice data very well (see Section 6.d for an in depth analysis). Given that distributions of preference parameters obtained using the full model are very similar to the ones obtained using the fixed effects model, one can conclude that both models constitute a reasonable approximation of the data generating process.

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.[45] 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.

[45] The spike at the upper bound does not disappear if the upper bound on discount rates is relaxed to +2 in the fixed effects estimation. This is indicative of the existence of individuals exhibiting limit values of impatience in the context of this experiment, visible also in raw choice data displayed in Figure 1. A similar finding is replicated in other experimental datasets (see e.g. Apesteguia, Ballester, and Gutierrez, 2020).

Figure 5: Sample Distributions of Risk and Time Preferences



6.a.i Link with Personality Traits

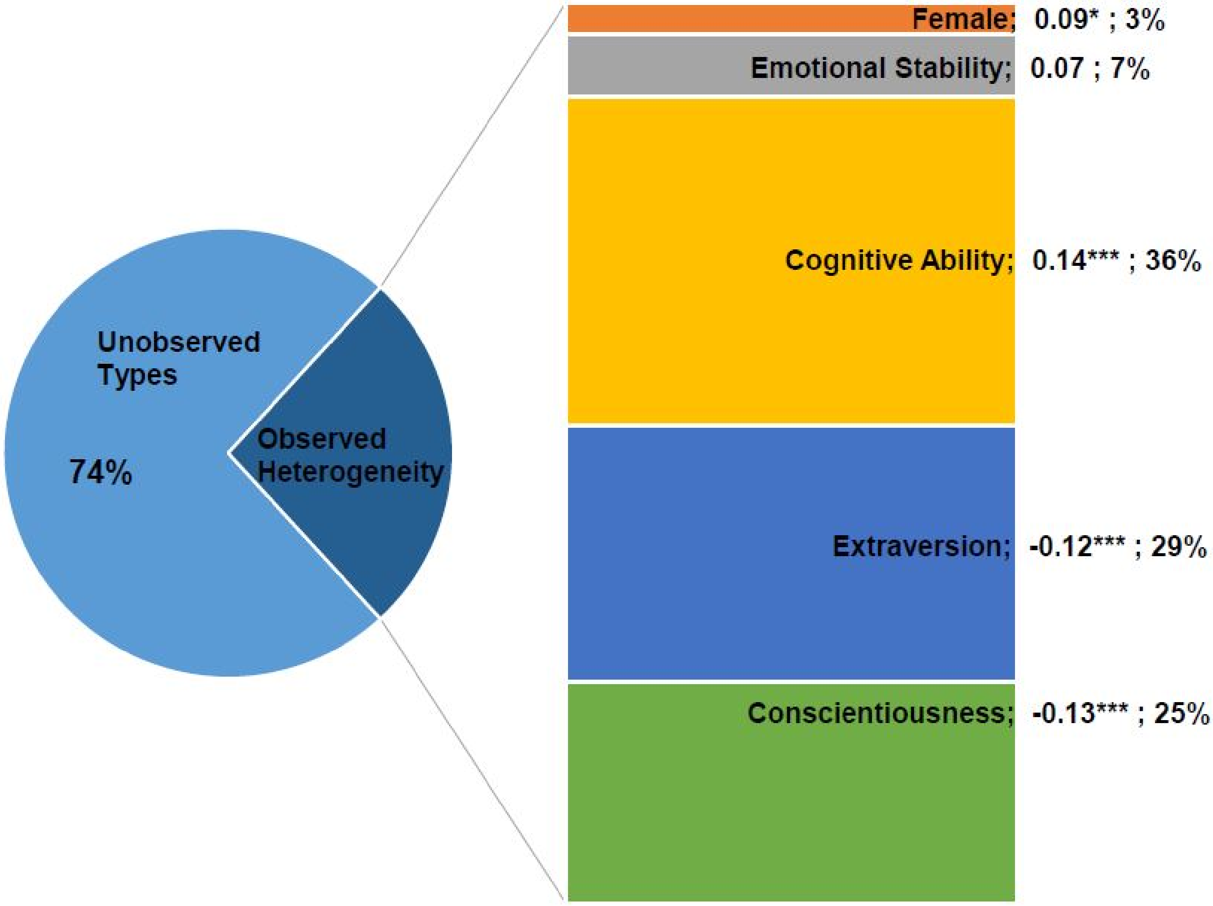
Results from the structural model quantify the long-supposed relationship between preferences, cognitive ability, and personality. The a priori expectations on the signs of the coefficients are confirmed: risk aversion decreases with the factor related to extraversion (a measure of self-reported excitement-seeking and active behavior), discount rates decrease with the factor related to conscientiousness (a measure of self-reported discipline and ability to delay gratification), and the propensity to make mistakes decreases with cognitive ability. Furthermore, factors related to 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 personality and preferences.[46]

Figure 6 illustrates the contribution of observed and unobserved heterogeneity to the overall

[46]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.

cross-sectional variation in risk aversion. It includes both the estimated marginal effects[47] of sex and factors related to ability and personality traits; and the percentage of variation in risk aversion attributed to observed heterogeneity that each of them explains.[48]

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.[49]

[47]Magnitudes of the marginal effects represent the average effect of increasing and decreasing each factor by 1 standard deviation (or the effect of moving sex from 0 to 1, male to female, in case of sex). They are calculated as the difference between the estimated value of each structural parameter when the factor of interest is 1 standard deviation above/below 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. The sign of the marginal effect corresponds to the case of *increasing* each factor by 1 standard deviation (or moving sex from 0 to 1, male to female, in case of sex).

[48]The explained percentage variation is obtained from the simulated dataset as the R2 of the relevant regression of structural parameters on unobserved factors and unobserved types derived from equations 19-23.

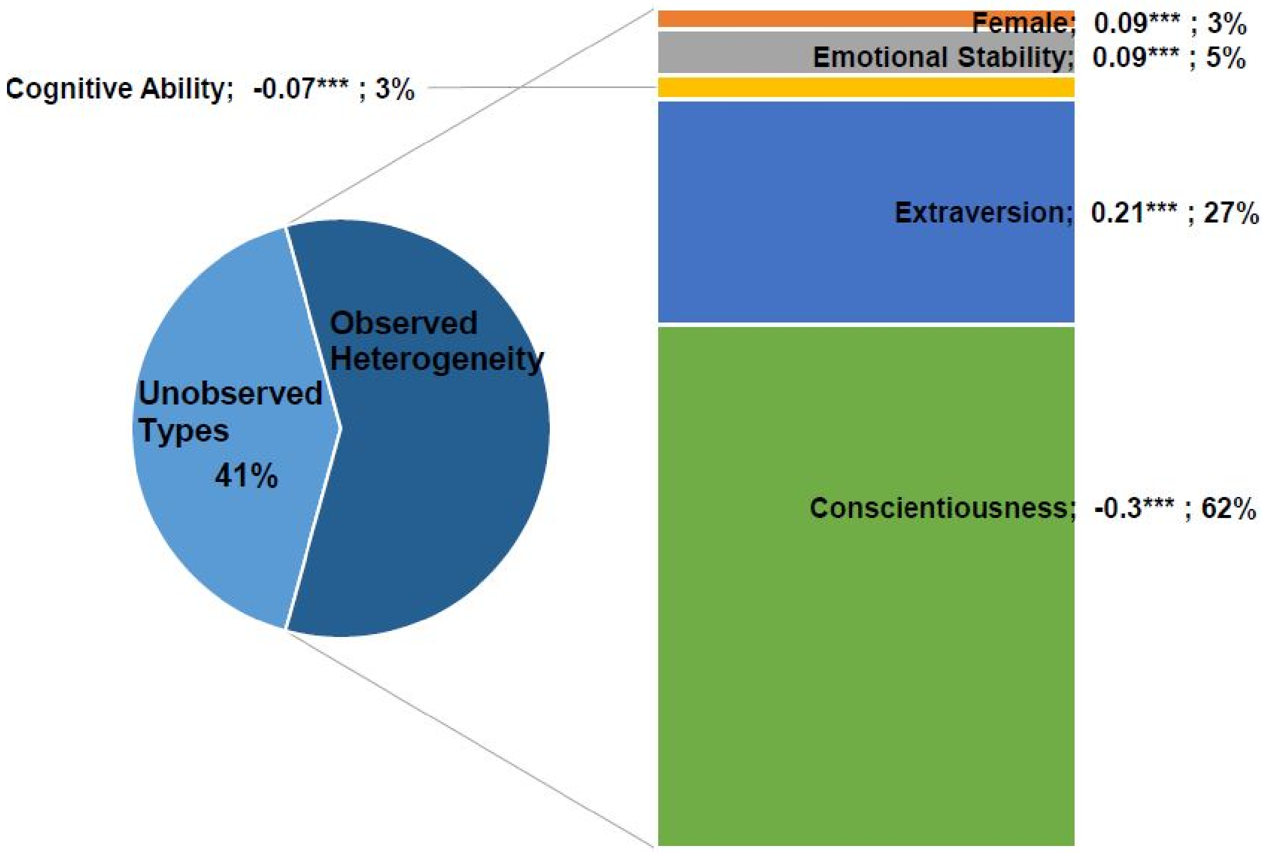
[49]Values of risk aversion above 3 are excluded from the analysis. These extreme values are due to unobserved type 1 which represents 8% of the population with limit values of risk aversion. It is a result of the fact that some individuals always choose the less risky alternative on the 55 lottery choice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

Amongst factors related to personality, conscientiousness and extraversion have the highest explanatory power. The coefficient on the factor related to extraversion is negative. This confirms the intuitive link between risk aversion and extraversion. The marginal effect of increasing the factor related to extraversion by 1 standard deviation is a 0.12 decrease in the coefficient of risk aversion. This represents a roughly 20% decrease from its estimated median value and a 10% decrease from the average value. The marginal effect of the factor related to conscientiousness is also negative and of comparable magnitude. It may be understood in terms of conscientious individuals taking a disciplined big picture view and thus being able to look through short term fluctuations which reflect risk. In contrast, higher cognitive ability, emotional stability, and being female are associated with increased risk aversion.

The reversal of the sign on cognitive ability (compared to the simple correlations presented in Figure 1) is another interesting result of the application of the full structural model. The full model is capable of correcting for the *decision bias* identified by Anderson et al. (2016) which can result from random errors correlated with cognitive ability combined with an experimental design skewed towards choices of one of the options (risky or safe). The correction is consistent with, but stronger than, that reported by Andersson et al. (2018). They find that using a combination of experimental design and structural techniques nullifies the estimated relationship between cognitive ability and risk aversion. I find that the estimated coefficient actually reverses sign compared to reduced form techniques which do not properly account for decision error (see Table 1 of the main paper and Figure 2 of the Online Appendix). I achieve the correction without needing to adapt the experimental design. This suggests that a more elaborate RPM with unobserved heterogeneity and a factor structure applied to rich data is in itself sufficient to de-bias estimates.

Observed heterogeneity explains 60% 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.

The factor related to Conscientiousness possesses by far the highest explanatory power, confirming its intuitive link with discount rates. It explains a third of the total cross-sectional variation in discount rates. It also has a high estimated marginal effect. Conscientious individuals have lower discount rates which indicate greater patience. The factor related to extraversion is the second most important predictor of impatience. Its impact goes in the opposite direction which is in contrast to the case of risk aversion. Extraverted individuals are *less patient* and less risk averse whereas conscientious individuals are *more patient* and less risk averse.

Figure 4 of the Appendix shows the estimated raw structural coefficients for equations 19-23 along with their associated standard errors.

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.

Estimates indicate a degree of apparent instability in individuals' preferences which means that individuals are either not fully self-aware or that their preferences fluctuate. 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."

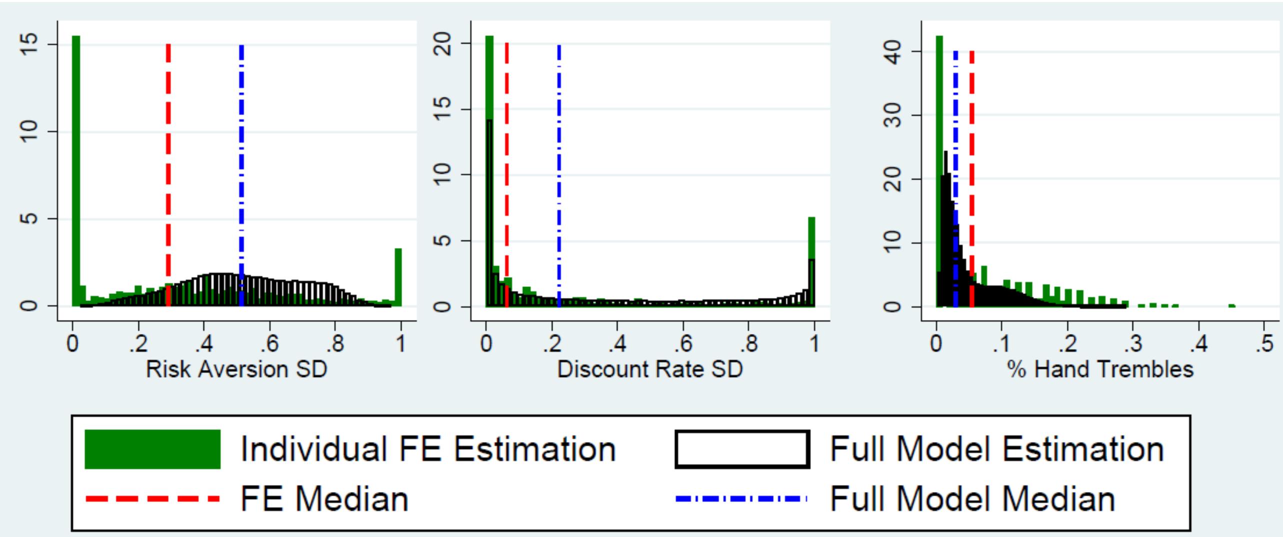
As can be seen in Figure 4, the average individual has a standard deviation of 0.41 on his coefficient of risk aversion and of 0.20 on his discount rate. For comparison purposes, Apesteguia and Ballester (2018) obtain 0.4 and 0.11 respectively using a representative agent framework applied to a representative sample of the adult Danish population. If preference instability is related to imperfect self-knowledge, the fact that they obtain slightly 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) exhibits a low level of instability in their risk preference with a standard deviation of around 0.3, 31% (type 1) exhibits an elevated level of instability, while the remaining 8% (type 5) exhibit very stable risk preferences. The dispersion is even wider with discount rates: 40% of the population (types 1 and 5) exhibit stable time preference, a half (types 2 and 3) exhibit moderate levels of instability, and 12% (type 4) exhibit very unstable time preferences.

The trembling hand parameter varies less in the population. An average person chooses his less preferred option 6% 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 make choices in line with their underlying preferences at least 95% of the time while one quarter (type 2) choose their less preferred option in over 15% 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. In general, the fixed effects choice model implies lower preference instability. This may be compared to the results of Apesteguia, Ballester, and Gutierrez (2020) who find that preference instability is lower in individual estimation than when using a representative agent model. The two models yield somewhat different distributions of the standard deviation 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 0.3.

Figure 8: Sample Distributions of consistency parameters



It is not surprising that distributions of consistency parameters obtained using the two models differ 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 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.[50] 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.

6.b.i Plausibility of Implied Preference Instability

In order to judge the plausibility of preference instability estimates in the context of this experiment, it may be instructive to consider the degree of choice inconsistency implied by the

[50]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. Distributions of risk aversion, the discount rate, and of the trembling hand parameter were qualitatively unchanged. Results are available from the author upon request.

estimated preference shocks. Consider the median individual who has an estimated true (or average) coefficient of relative risk aversion of 0.66. Given the respective value of the estimated scale parameter $\sigma_{\Theta,i}$, this individual will behave 68% of the time as if his coefficient of relative risk aversion lay between 0.51 and 0.81 and 95% of the time as if it were between 0.36 and 0.96. Similarly, the median individual who has an estimated true (or average) discount rate of 0.2 will behave 68% of the time as if his discount rate lay between 0.1 and 0.3 and 95% of the time as if it were between 0.06 and 0.52.[51]

Figure 9 illustrates what this implies in terms of choices on the employed experimental tasks. The thick vertical line represents the theoretical switching point on each group of choice tasks under CRRA utility for the median individual in the absence of noise. Cells highlighted in yellow represent inconsistent choices which the individual might make given draws from his risk aversion (or discount rate) distribution in the 68% interval while red cells represent additional choice inconsistency which would result from draws within the 95% interval. Upon examination of Figure 9, it is clear that for the median individual, choice inconsistency generated by the estimated preference shocks is in general concentrated within one cell from the switch point implied by constant preferences set at their average value.

Figure 9: Implied Choice Inconsistency due to Preference Shocks for Median Individual

Holt & Laury Type MPL Indifference Thresholds

	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10
MPL 1-3	-1.71	-0.95	-0.49	-0.14	0.15	0.41	0.68	0.97	1.37	Inf

Binswanger Type Binarized MPL Indifference Thresholds

MPL 4	2.97	1.00	0.60	0.42	0.00
MPL 5	4.73	1.69	1.06	0.78	0.00
MPL 6	1.37	0.45	0.26	0.17	0.00
MPL 7	4.46	1.50	0.94	0.68	0.00
MPL 8	1.54	0.51	0.30	0.20	0.00

Temporal MPL Indifference Thresholds at Median Risk Aversion

	Q1	Q2	Q3	Q4	Q5	Q6
MPL 1-4	0.02	0.03	0.07	0.18	0.39	0.88
MPL 5-8	0.02	0.03	0.06	0.15	0.27	0.45

6.b.ii Link with Personality Traits

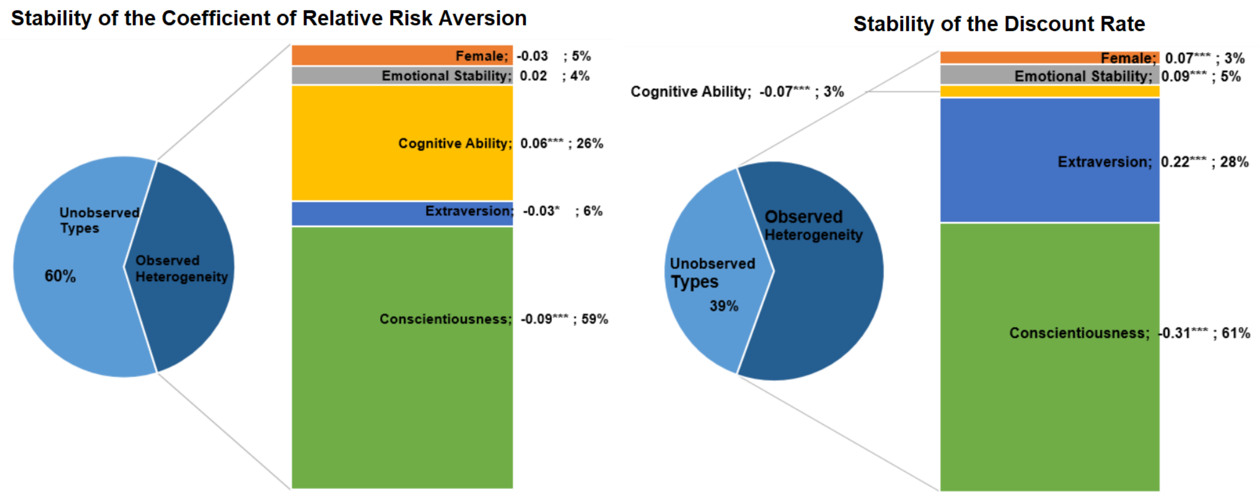
Factors related to ability and personality explain approximately half of the cross-sectional variation in preference instability as shown in Figure 10. The factor related to conscientiousness is

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

dominant and explains 60% of individual heterogeneity for both preferences.[52] The marginal effect of conscientiousness is stronger for the standard deviation of the discount rate and accordingly the percentage of explained variation is higher than for the standard deviation of risk aversion. Highly conscientiousness individuals have more stable risk and time preferences. The relationship is coherent with the hypothesis that revealed preference instability is a reflection of a lack of self-knowledge. Conscientious individuals may take more time for introspection and hence know their true preferences better.

Factors related to cognitive ability and extraversion have opposite estimated relationships with the stability of 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 the factor related to conscientiousness.

Figure 10: Heterogeneity in Individuals' Stability Parameters



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.

Propensity to make mistakes seems largely independent of personality, unlike the other preference and consistency parameters (see Figure 11 below). This time, cognitive ability is responsible for a majority of the explained variation. It accounts for almost three quarters of the variation explained by observed heterogeneity and for approximately 15% of the total cross-sectional variation in the parameter. Unsurprisingly, individuals with higher cognitive ability

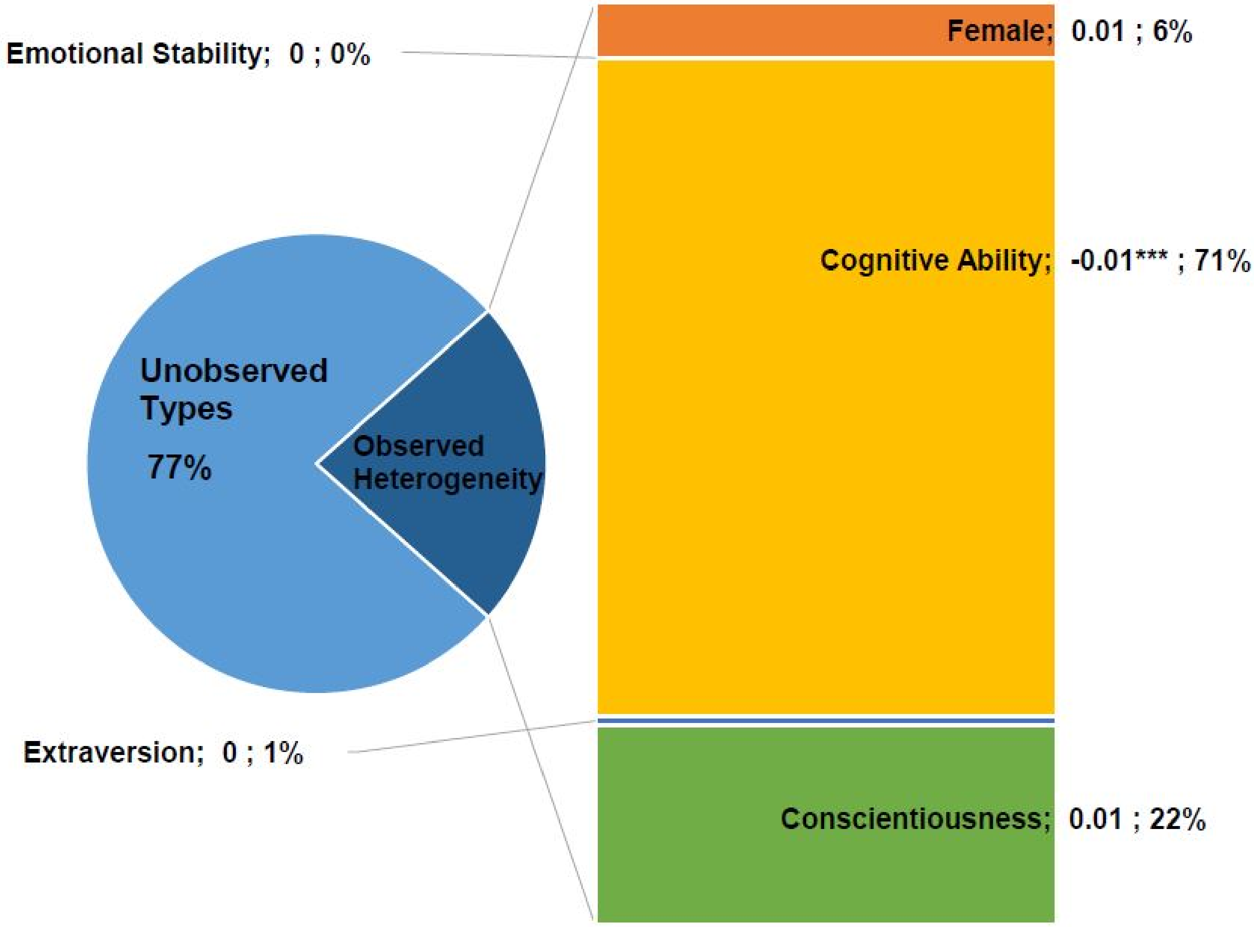
[52] As with the coefficient of risk aversion, the analysis of its standard deviation excludes observations attributed to unobserved type 1 which represents the 8% of the population which exhibits limit values of risk aversion.

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 33% decrease from its estimated median value in the population and a 15% decrease from the average value. This suggests that some individuals face cognitive hurdles when evaluating the standard and relatively simple lottery and temporal choice tasks in this experiment.[53]

The obtained mappings suggest that the separation of noise into preference instability and decision mistakes yields valuable insights. Given a preference shock, a person is still choosing the alternative which he prefers at that point in time. This type of choice inconsistency is linked to personality, specifically to low conscientiousness. A decision error results in not choosing the preferred alternative and is linked to low cognitive ability. Taken together with the estimated relationship between preferences and personality, one might conclude that differences in desired outcomes are predominantly explained by differences in personality whereas the ability to align preferred and actual choices is a largely a matter of cognitive skill.

[53] In one of the robustness checks I allow for a separate mistake coefficient on risk and time tasks. This exercise reveals that mistakes are predominantly concentrated on lottery tasks. A possible explanation is that these impose a higher cognitive load as they involve calculations of expected values.

Figure 11: 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.

6.c Robustness of Mappings

In order to test the robustness of the mappings, I estimate the structural RPM model alternatively a) using a set of proxy measures for the *Big Five* personality traits selected solely based on the strength of the correlation with each respective personality trait in the validation sample; b) using the sample of men only; c) using the sample of women only; d) allowing for a separate coefficient on the tremble parameter in temporal tasks; e) allowing for discount rates of up to 200%; f) assuming hyperbolic discounting; g) assuming CARA utility; h) assuming an alternative form of CRRA utility which allows for the use of a coefficient of risk aversion greater than 1 in discount rate calculation; and i) assuming expo-power utility. Conclusions drawn from the main specification (RPM model with CRRA utility and exponential discounting using the full sample and the preferred set of proxy measures for personality) hold.

All structural coefficients maintain the same estimated sign for the preference parameters.

The factor related to extraversion has a robust negative mapping with risk aversion and a positive one with discount rates. The factor related to conscientiousness has a robust negative mapping with both risk aversion and the discount rate. It is by far the dominant factor for the latter with explanatory power hovering around 60% of explained cross-sectional variation (and 40% of total variation). The factor related to cognitive ability maps positively onto risk aversion and negatively onto discount rates. The correction on the estimated relationship between risk aversion and cognitive ability is thus robust to alternative assumptions.

The main insights on mappings hold also for the stability parameters. Conscientiousness is the dominant correlate of stability for both risk and time preferences in approximately 80% of estimates. More conscientious individuals tend to have more stable preferences, possibly because they are more self-aware. The factor related to conscientiousness accounts for around 50% of the explained cross-sectional variation in apparent preference instability, with approximately 40% for risk preference and 60% for time preference (roughly 15% and 40% respectively in terms of total variation). Variation in the propensity to make mistakes is in all cases best explained by the factor related to cognitive ability which is associated with making fewer mistakes. It accounts for approximately 75% of the total explained cross-sectional variation.

The estimated structural coefficients and calculated mappings are detailed in Section 10.c of the paper and in Sections 1.d.ii through 1.d.ix of the Online Appendix.

6.d Preference and consistency parameters in Observed Choices

It is useful to verify that estimated structural parameters explain raw observed choice patterns in expected ways.

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. I add a regression of the choice moments on 18 demographic and socioeconomic variables as a point of comparison.[54]

Figure 12 presents first the R2 of regressions with 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 variation in choices due to the five estimated structural parameters into parts explained by preference and consistency parameters respectively. This lets us compare their relative explanatory power, expressed as a percentage. Consistency parameters are further broken down into *stability parameters* - the standard deviation of risk

[54]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.

aversion and of the discount rate - and the *trembling hand parameter* related to people's tendency to make mistakes. This allows me to provide empirical evidence on the identification of the two types of consistency parameters based on different moments of choice inconsistency as outlined in Section 4.a.iii.

Preference and consistency parameters estimated using the fixed effects choice model together explain almost 90% of the overall variation in observed individual choices on lottery tasks and 65% of variation on temporal choice tasks. The total number of both "safe" and "impatient" choices is 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 7 of the Appendix.

These results reveal that the fixed effects model has excellent predictive power with regards to observed choices on both lottery and temporal choice tasks.

Consistency parameters account for the vast majority of the explained variation in individual choice inconsistency on all tasks. As expected, strong choice inconsistency in the form of outright choice reversals within a given MPL is best explained by the mistake parameter. More subtle choice inconsistency reflected in varying switching points across comparable risk and time MPLs is explained by the respective preference instability parameters. See Figure 7 of the Appendix for a breakdown by R2 for each structural parameter.

Figure 12: 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	0.06	0.07	0.02	0.02	0.03	0.02
All Parameters	R2	0.86	0.64	0.59	0.05	0.11	0.15
Preference Parameters		91.7%	98.7%	0.2%	12.9%	2.0%	34.5%
Consistency Parameters		8.3%	1.3%	99.8%	87.1%	98.0%	65.5%
- Stability		82.8%	74.2%	2.3%	16.4%	80.7%	95.7%
- Mistakes		17.2%	25.8%	97.7%	83.6%	19.3%	4.3%

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 relevant structural parameters of the model.
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. These variables are available for 869 individuals.
Socioeconomic variables include parents' level of education and income.
The rows below represent the relative explanatory power of the relevant subgroups of parameters, expressed as a percentage.
Outliers representing extreme values of risk aversion (ϴ>3 and ϴ<-1) are excluded. This leaves 1,109 observations.

6.e Factor Determinants

The estimated coefficients from the factor equations are displayed in Figure 13. The percentage of explained variation 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 constructed as to be a parsimonious representation of personality through five orthogonal components predictive of behavior (Goldberg, 1990). The first three factors have estimated standard deviations of around 0.3 while the factor related to conscientiousness has an estimated standard deviation of 0.81. Being female is associated with lower values on the factor related to extraversion and with higher values on the factor related to conscientiousness. Native English speakers and older individuals score higher on both of these personality traits.[55] The remaining coefficients are small.

Figure 13: 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	-0.07	-0.01	0.06	0.06	0.01	0.01	0.35	-0.10
Cognitive Ability	0.02	0.01	0.08	0.00	-0.05	0.03	0.28	1.60
Extraversion	-0.13	0.03	0.12	0.16	0.14	0.05	0.35	0.13
Conscientiousness	0.30	0.14	0.19	0.21	0.26	0.05	0.81	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.[56] As can be seen in Section 10.d of the Appendix, the magnitudes of the loadings vary widely. This suggests that some questions are much better measures of cognitive ability and personality than others. The last column in Figure 2 of the Appendix 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. The average signal to noise ratio is 0.52 for the factor measures, with a standard deviation of 0.55.[57] 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 the literature, appears insufficient.

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

[56] A factor loading is the structural coefficient on the relevant factor in the measurement Equation 24. It reflects the importance of the latent factor for a given proxy measure.

[57] 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 are less noisy than self-reported measures of cognitive skill and personality is not surprising.

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 embedded within a stochastic economic model of discrete choice under risk and delay allows me to better account for measurement and decision error. I am thus able to show that personality explains a much larger share of the variation in preferences within and across individuals than previously supposed.

Establishing this link not only connects but also *enriches* the economic and psychological systems for characterizing human differences. Psychologists gain formal insights into how personality may impact financial decisions studied by economists. Economists learn how individuals with a particular set of preferences may behave in a range of situations studied more closely by psychologists. Because preferences and traits, as well as the quality of decision making, have been shown to predict outcomes and to be highly heritable, these findings also have ramifications for understanding inequality and the mechanisms underlying the inter-generational transmission of socio-economic status.[58] Nevertheless, this is just the beginning of a larger effort to bring together competing classifications of human differences in order to determine the number and nature of skills required to explain heterogeneity in observed behavior and outcomes. The framework developed in this paper is waiting to be applied to datasets containing a broader range of economic preferences, the full set of *Big Five* personality traits along with their facets measured using a dedicated questionnaire, and other influential measures of personality such as self-control.

Since El-Gamal and Grether's (1995) 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; Choi et al., 2014; and Stango and Zinman, forthcoming). While making mistakes can clearly be costly in many situations, the point is slightly more subtle when it comes to preference instability. Individuals who are less sure of their preferences, and thus behave in a somewhat erratic manner, may be penalized in environments like the stock market which tend to reward stable, long-term decisions. 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

[58]Heritability estimates are about 50% for cognitive skill and personality (see for example Bouchard and Loehlin, 2001; and Bergen, Gardner, and Kendler, 2007). Evidence is more mixed regarding the heritability of preferences although recent research has shown that they may be as heritable as cognitive and non-cognitive traits (see for example Beauchamp, 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, they suggest that all of the above may be heritable to a large degree.

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 and higher stability of preferences, which will induce him to make better savings and investment decisions.

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 calls into question the adequacy of using a simple population average of risk and time preferences in the calibration of structural models. 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 results confirm that the Random Preference Model is well suited for estimating economic preferences with observed and unobserved heterogeneity. In addition to satisfying monotonicity, it enables the separation of noise in observed choices into two psychologically distinct components which explain different moments of choice inconsistency and map onto separate traits. Nevertheless, given the prevalence of the Random Utility Model with additive shocks in the literature and its multiple attractive features, further research into developing a monotone version with respect to risk (and time) preferences appears justified. One of the goals of this research should to establish which random choice model is most appropriate under what circumstances.

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. If one population moment were to be chosen to characterize the preference distribution, the median may be preferable to the mean. Future research may want to consider an experimental design capable of capturing the subtleties of the behavior of highly risk averse and highly impatient individuals.

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 demonstrates that accounting for measurement and decision error in a structural framework can help us establish the hypothesized but empirically long elusive mapping between economists' preferences and psychologists' personality traits. It provides a blueprint for mapping parameters of economic models onto other systems for measuring human differences.

Up to 60% of the variation in risk aversion, discount rates, and in parameters governing individuals' choice consistency can be explained by factors related to cognitive ability and personality. 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. The a priori expected relationships (between reported risk-seeking tendency and the factor related to risk aversion, reported capacity to delay gratitude and the factor related to discount rates, propensity to make mistakes and the factor related to cognitive ability) 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 heterogeneity in observed 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.

I confirm that preferences have much higher explanatory power in terms of observed choices under risk and temporal 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 may be an artefact of the limitations of the present dataset which only allows for the identification of basic risk and time preferences and contains rough proxy measures for three of the *Big 5* personality traits. Further research comparing an expanded set of both standard and non-standard economic preferences and personality traits is necessary before one can draw firm conclusions. Competing models for random choice should be estimated and compared. The viability of an aRUM with a monotonicity correction in risk estimation should be explored. Understanding the role of effort and self-knowledge in both preference and skill elicitation, and standardizing measurements, will be essential for the successful completion of this endeavour.

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10 Appendix

10.a Sample Descriptive Statistics

Figure 1: Sample Demographic and Socioeconomic Variables

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

10.b Experimental Measures of Cognitive Ability and Personality

Figure 2: Factor Loadings

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	My School was a place where I felt like an outsider or like I was left out of things.	binary	x	1.10	0.15
	3	I have a good idea of what I will be doing for an extended period of time.	binary		0.87	0.10
	4	I worry I might be taken advantage of by a sales person.	binary	x	0.91	0.10
	5	You have little control over the things that happen to you.	multi-valued	x	2.48	0.76
	6	There is really no way you can solve some of the problems you have.	multi-valued	x	3.08	1.18
	7	There is little you can do to change many of the important things in your life.	multi-valued	x	4.28	2.27
	8	You often feel helpless in dealing with the problems of life.	multi-valued	x	4.41	2.42
	9	Sometimes you feel that you are being pushed around in life.	multi-valued	x	2.22	0.61
	10	You can do just about anything you really set your mind to do.	multi-valued		1.23	0.19
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		3.90	1.18
	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		3.69	1.06
	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	0.27
	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		2.26	0.40
	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		1.71	0.23
	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		2.36	0.43
	8	Numeracy test score.	continuous		1.46	0.19
Extraversion	1	I am stronger than most people I know.	binary		1.00	0.12
	2	I believe I could defend myself if someone attacked me.	binary		1.18	0.17
	3	I am not very good at sports.	binary	x	1.08	0.14
	4	Likelihood of trying bungee jumping.	binary		3.38	1.39
	5	Likelihood of speaking your mind about an unpopular issue at school.	binary		1.00	0.12
	6	I avoid activities where I might be embarrassed.	binary	x	1.06	0.14
	7	Likelihood of going camping in the wild.	multi-valued		1.95	0.46
	8	Likelihood of exploring an unknown city or section of town.	multi-valued		1.48	0.27
	9	Likelihood of periodically engaging in a dangerous sport (e.g., mountain climbing or sky diving).	multi-valued		2.94	1.05
	10	You can do just about anything you really set your mind to do.	multi-valued		0.93	0.11
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	0.65
	2	I do things impulsively, making decisions on the spur of the moment.	binary	x	0.51	0.17
	3	I select activities in terms of how beneficial they are to my future.	binary		0.67	0.30
	4	I do not like to plan ahead.	binary	x	0.90	0.53
	5	I meet obligations to friends and authorities on time.	binary		0.68	0.30
	6	I follow through with a course of action if it will get me where I want to be.	multi-valued		0.93	0.56
	7	I am able to resist temptations when I know there is work to be done.	multi-valued		0.85	0.47
	8	During my last year of high school, I did as little work as possible; I just wanted to get by.	multi-valued	x	0.67	0.29
	9	I set sub-goals and consider specific means for reaching them.	multi-valued		0.90	0.53
	10	I often think about what I will be doing 10 years from now.	multi-valued		0.52	0.18

Figure 3: Correlations Between Available Proxy Measures and the Official BFI-2 Questionnaire, Canadian Sample

	Proxy Extraversion
BFI-2 Extraversion and Facets	**0.46**
Sociability	0.34
Assertiveness	0.41
Energy	0.30

	Proxy Conscientiousness
BFI-2 Conscientiousness and Facets	**0.63**
Organization	0.53
Productiveness	0.57
Responsibility	0.51

	Proxy Emotional Stability
BFI-2 Emotional Stability and Facets	**0.48**
Anxiety	0.24
Depression	0.59
Emotional Volatility	0.36

10.c Structural Results

Figure 4: Estimated Coefficients on Preference and Consistency Parameters Using the Full Structural Model

	Risk Aversion		Discount Rate		Risk Aversion SD		Discount Rate SD		% Hand Trembles	
Female	0.09	*	0.30	***	-0.09		0.27	***	0.12	
	(0.05)		(0.06)		(0.06)		(0.05)		(0.10)	
Emotional Stability	0.19		0.90	***	0.16		0.92	***	0.03	
	(0.16)		(0.21)		(0.12)		(0.08)		(0.17)	
Cognitive Ability	0.50	***	-0.82	***	0.56	***	-0.91	***	-0.71	***
	(0.19)		(0.19)		(0.17)		(0.07)		(0.14)	
Extraversion	-0.34	***	2.07	***	-0.23	*	2.34	***	0.09	
	(0.12)		(0.15)		(0.12)		(0.08)		(0.18)	
Conscientiousness	-0.16	***	-1.36	***	-0.27	***	-1.48	***	0.12	
	(0.06)		(0.07)		(0.08)		(0.06)		(0.17)	

Notes: Clustered robust standard errors are in parentheses. Significance at the 10% level is denoted by ***, at the 5% level by **, and at the 1% level by *.

Figure 5: Estimated Coefficients on Preference and Consistency Parameters Using the Full Structural Model: Personality Measures Selected Based on Strength of Correlations in Validation Study

	Risk Aversion		Discount Rate		Risk Aversion SD		Discount Rate SD		% Hand Trembles	
Female	0.09	**	0.28	***	-0.09		0.35	***	0.11	
	(0.05)		(0.06)		(0.07)		(0.05)		(0.09)	
Emotional Stability	0.27	***	1.71	***	0.19		2.06	***	-0.23	
	(0.04)		(0.11)		(0.16)		(0.14)		(0.23)	
Cognitive Ability	0.52	***	-1.11	***	0.64	***	-1.08	***	-0.64	***
	(0.11)		(0.16)		(0.15)		(0.09)		(0.20)	
Extraversion	-0.51	***	1.99	***	-0.28	**	2.37	***	0.18	
	(0.05)		(0.11)		(0.12)		(0.09)		(0.20)	
Conscientiousness	-0.09	**	-1.36	***	-0.16	***	-1.64	***	0.05	
	(0.04)		(0.06)		(0.06)		(0.10)		(0.16)	

Notes: Clustered robust standard errors are in parentheses. Significance at the 10% level is denoted by ***, at the 5% level by **, and at the 1% level by *.

Figure 6: Cross-sectional variation in Preference and Consistency Parameters Explained by Observed and Unobserved Heterogeneity using Personality Measures Selected Based on Strength of Correlations in Validation Study

		Risk Aversion	Discount Rate	Risk Aversion SD	Discount Rate SD	% Hand Trembles
Unobserved Types	R2	0.56	0.26	0.64	0.26	0.76
Observed Heterogeneity	R2	0.44	0.74	0.36	0.74	0.24
Emotional Stability		19%	23%	11%	23%	22%
Cognitive Ability		25%	3%	44%	2%	59%
Extraversion		47%	22%	17%	21%	9%
Conscientiousness		7%	52%	27%	53%	4%

Notes: The rows labeled "R2" list the R2 of a regression of the structural parameter listed in each column title on alternatively the 5 unobserved types or on 4 unobserved factors in simulated data.
The rows below represent the fraction of the explained cross-sectional variation in each structural parameter attributable to the four factors related to cognitive ability and personality.

Figure 7: 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	0.86	0.64	0.59	0.05	0.11	0.15
Risk Aversion		95.4%	4.4%	0.2%	0.0%	3.7%	7.9%
Discount Rate			94.6%		15.1%		15.8%
Risk Aversion SD		3.8%	0.6%	2.3%	0.3%	77.7%	0.8%
Discount Rate SD			0.1%		13.6%		72.2%
% Hand Trembles		0.8%	0.3%	97.5%	70.9%	18.6%	3.3%

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.
Outliers representing extreme values of risk aversion (ϴ>3 and ϴ<-1) are excluded. This leaves 1,109 observations.

10.d Robustness Measures of Cognitive Ability and Personality Selected Solely Based on Correlations with Corresponding Traits from BFI-2 Questionnaire

Figure 8: Robustness Factor Loadings

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	0.25
	2	There is really no way you can solve some of the problems you have.	binary	x	1.72	0.74
	3	You often feel helpless in dealing with the problems of life.	binary	x	2.30	1.32
	4	Sometimes you feel that you are being pushed around in life.	binary	x	1.59	0.63
	5	You can do just about anything you really set your mind to do.	binary		0.75	0.14
	6	My school was a place where I felt like an outsider or like I was left out of things.	binary	x	1.11	0.31
	7	I have a good idea about what I will be doing for an extended period of time.	binary		0.62	0.10
	8	Likelihood of disagreeing with your father on a major issue.	multi-valued	x	0.25	0.02
	9	Most people can be trusted.	multi-valued		0.42	0.04
	10	Most people would try to take advantage if they got a chance.	multi-valued	x	0.56	0.08
Cognitive Ability	1	In your last year of high school, what was your overall grade average, as a percentage?	multi-valued		1.00	0.09
	2	How would you rate your ability to use a computer? For example, using software applications, programming, or using a computer to find or process information.	multi-valued		3.97	1.36
	3	How would you rate your writing abilities? For example, writing to get across information or ideas to others, or editing writing to improve it.	multi-valued		4.22	1.54
	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		1.95	0.33
	5	How would you rate your oral communication abilities? For example, explaining ideas to others, speaking to an audience, or participating in discussions.	multi-valued		2.13	0.39
	6	How would you rate your ability to solve new problems? For example, identifying problems and possible causes, planning strategies to solve problems, or thinking of new ways to solve problems.	multi-valued		1.42	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		2.00	0.35
	8	Numeracy test score.	continuous		1.17	0.14
Extraversion	1	I avoid activities where I might be embarrassed.	binary	x	1.00	0.18
	2	Likelihood of speaking your mind about an unpopular issue at school.	binary		0.68	0.08
	3	Likelihood of trying bungee jumping.	binary		2.77	1.35
	4	I am stronger than most people I know.	binary		0.94	0.15
	5	I worry I might be taken advatage of by a sales person	binary	x	0.31	0.02
	6	I am not very good at sports.	binary	x	1.08	0.20
	7	I believe I could defend myself if someone attacked me.	binary		1.08	0.21
	8	I often think about what I will be doing 10 years from now.	multi-valued		-0.07	0.00
	9	Likelihood of exploring an unknown city or section of town.	multi-valued		0.94	0.15
	10	Likelihood of periodically engaging in a dangerous sport (e.g., mountain climbing or sky diving).	multi-valued		2.40	1.01
Conscientiousness	1	I am not good about preparing in advance for things, even if they have direct bearing upon my futur	binary	x	1.00	0.87
	2	I do things impulsively, making decisions on the spur of the moment.	binary	x	0.54	0.25
	3	I do not like to plan ahead.	binary	x	0.91	0.72
	4	I meet obligations to friends and authorities on time.	binary		0.66	0.38
	5	I think that it is useless to plan too far ahead because things hardly ever come out the way you planr	binary	x	0.71	0.43
	6	I follow through with a course of action if it will get me where I want to be.	multi-valued		0.81	0.57
	7	I am able to resist temptations when I know there is work to be done.	multi-valued		0.74	0.48
	8	Likelihood of never wearing a seat belt.	multi-valued	x	0.47	0.20
	9	I set sub-goals and consider specific means for reaching them.	multi-valued		0.51	0.23
	10	I did as little work as possible; I just wanted to get by.	multi-valued	x	0.86	0.64

Figure 9: Correlations Between Robustness Proxy Measures for Personality and the Official BFI-2 Questionnaire

	Proxy Extraversion
BFI-2 Extraversion and Facets	0.56
Sociability	0.46
Assertiveness	0.45
Energy	0.36

	Proxy Conscientiousness
BFI-2 Conscientiousness and Facets	0.71
Organization	0.59
Productiveness	0.63
Responsibility	0.62

	Proxy Emotional Stability
BFI-2 Emotional Stability and Facets	0.64
Lack of Anxiety	0.48
Lack of Depression	0.67
Emotional Stability	0.53