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

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I propose a method for mapping psychological personality traits to economic preferences. 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 and parameters related to choice inconsistency. I explain up to 60% of variation in average risk and time preferences and individuals' capacity to make consistent choices using factors related to cognitive ability and three of the Big Five personality traits. Differences in preferred outcomes are related to personality, whereas mistakes in decisions are related to cognitive skill.

I. Introduction

There is extensive evidence that economic preferences, cognitive ability, and personality predict a wide range of economic outcomes (for a recent

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summary of the literature, see Heckman, Jagelka, and Kautz 2021). 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 to determine the number and nature of attributes that constitute human capital and explain differences in life outcomes.[1] I demonstrate that careful modeling of measurement and decision errors allows one to establish the long supposed but empirically elusive link (see Almlund et al. 2011; 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 five estimated structural parameters of interest: the coefficient of risk aversion and the discount rate, which measure true (or average) risk and time preferences, respectively;[2] two parameters that describe the degree of apparent instability of an individual's risk and time preferences; and a "mistake" parameter that 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]

Pennsylvania, Universitat Pompeu Fabra, Williams College, the International Association of Agricultural Economists (IAAE) annual conference, the International Association for Research in Economic Psychology 2022 conference, the Foundations of Utility and Risk 2022 conference, the North American Winter Meeting of the Econometric Society, the Royal Economic Society (RES) annual conference, the RES PhD meetings, the RES junior symposium, the annual conference of the Slovak Economic Association, and the World Congress of the Econometric Society for their feedback. I gratefully acknowledge the receipt of the Student Travel Grant for the IAAE 2019 conference and the prize for "Best paper presented by a graduate student" at the conference. This research is funded by the Deutsche Forschungsgemeinschaft (German Research Foundation) under Germany's Excellence Strategy (EXC 2126/1-390838866). This paper was edited by James J. Heckman.

[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 that 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

Overall, the factor related to conscientiousness exhibits the strongest links. It explains one-third of the cross-sectional variation in discount rates, 7% of the variation in risk aversion, and one-third of the 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 payments occurring at different points in time. Indeed, the five estimated structural parameters have explanatory power that is an order of magnitude larger than that of nearly two dozen demographic and socioeconomic 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 (EU)–maximizing behavior, which itself depends on an individual's risk and time preferences but is subject to random errors. I allow preferences and individual consistency to depend on both observed heterogeneity and 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 Millennium 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*) 38 questions designed to measure cognitive ability and personality, all given his observed characteristics, the four unobserved latent factors, and five unobserved types.[4] For robustness,

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 app. sec. A2 provide proxies for the three studied traits. I validated the proxies in a follow-up study that finds high correlations between measures at my disposal and personality traits obtained using a standard Big Five questionnaire (for more detail, see sec. III.E).

[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, 2014; Cohen et al. 2020).

I (1) employ different functional forms for utility and the structural parameters, (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 as well as 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 that accounts for errors in both decision-making and measurement and thus allows one to separate signal from noise in observed choices.

The rest of the paper is organized as follows: section II situates my contribution within the broader economic and psychological literature, section III describes the data, section IV presents the theoretical underpinnings of the structural model, section V details the empirical methodology, section VI presents the empirical results, section VII provides a general discussion of the broader implications of the findings presented in this article, and section VIII concludes.

II. Background

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, and so on later in life. Their choice to defer immediate gratification thus seemed to reflect some characteristic—preference or skill—that 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 and personality traits.[6] In their 2017 review of the literature, Golsteyn and

[5] For a recent discussion of this study, see Mischel and Shoda (2011). While recent evidence from a replication study somewhat tempers his findings (see Watts, Duncan, and Quan 2018), the importance of *stable traits* in predicting *average outcomes* has been confirmed (see, e.g., Epstein 1979; 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 the discount rate, respectively. More recent economic theory also incorporates social preferences and behavioral biases. Roberts (2009, 140) 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

Schildberg-Hörisch (2017, 1) 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, 70).[7] 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 results—low correlations between preferences and personality—similar to those reported in previous research (e.g., Becker et al. 2012) when relying on reduced-form measures used in that research—that is, 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 sec. III.F). My structural approach makes optimal use of available information and addresses *attenuation bias* resulting from measurement error (see, e.g., Carneiro, Hansen, and Heckman 2003; Cunha and Heckman 2009; 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 an underlying structure of more comprehensive theories of behavioral decision-making" by correlating various behavioral measures and sorting them into clusters (e.g., Dean

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.

[7] The question is as valid now as it was 13 years ago. In a 2018 *Journal of Economic Perspectives* symposium on "Risk in Economics and Psychology," Mata et al. (2018, 167) mention the need "to make conceptual progress by addressing the psychological primitives or traits underlying individual differences in the appetite for risk."

and Ortoleva 2019; Chapman et al. 2023, 154). A second strand concerns itself with summarizing the various documented behavioral tendencies in a simplified measure, such as a sufficient statistic (e.g., Chetty 2015) or a sparsity model (e.g., Gabaix 2014). Stango and Zinman (2023) 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.

B. Modeling Inconsistency in Repeated Choices

Psychologist L. L. Thurstone built the foundations of discrete choice models (Thurstone 1927a, 1927b). He recognized that a decision between two constant options is made based on a psychological "discriminal" process that is itself stochastic. This process concerns "the ambiguity or qualitative variation with which one stimulus is perceived by the same observer on different occasions" (Thurstone 1927a, 269–70). Mosteller and Nogee (1951, 404) 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 EU. Based on these insights, economists developed random choice models that 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; 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 independent and identically distributed errors (aRUM). It includes the often-used Fechner and Luce error specifications. The model has a number of attractive features and has been largely favored 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 nonmonotonicity that is at odds with a basic theoretical definition of risk preferences.[8] The nonmonotonicity arises because under standardly used utility functions such as constant relative risk aversion (CRRA) and constant absolute risk aversion (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 nonmonotonicity 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). Apesteguia 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.[9]

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, which allows for "processing error" on the part of the decision maker (see, e.g., Apesteguia and Ballester 2018). While not trivial to estimate,[10] this specification allows the researcher to separate noise in observed decisions into distinct channels, each potentially driven by different cognitive and noncognitive mechanisms that produce distinct patterns of choice inconsistency.

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 actually have a preference for randomization (Agranov and Ortoleva 2017), or they may simply be unsure of their true preference and randomize within their interval of

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

[9] The predicted general relationship between decision errors and risk aversion under the 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.

[10] 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 Apesteguia and Ballester 2018).

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, 269). Indeed, the existence of stochastic preferences is supported by recent evidence in neuroeconomics that 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. Apesteguia 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 nonmonotonicity 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 nonmonotonicity on over 40% of the binary choices between lotteries that he faces.[11] While choice 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.[12] 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

[11] For more details, see online table 1.

[12] Preliminary results suggest that my findings are robust to using an alternative version of the aRUM that 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 nonmonotonicity, the intuition for it is not straightforward to provide. Results are available from the author upon request.

two psychologically distinct sources that I link to different traits and distinct types of inconsistency in observed choices.

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 that predict life outcomes. The apparent paradox is resolved once one considers the myriad situational influences that 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., Falk, Neuber, and Strack 2021; Enke and Graeber 2023; Dohmen and Jagelka, forthcoming). 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 that allows the econometrician to identify his underlying preferences. I find evidence consistent with the importance of stable preferences that 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 (apparent preference instability) and random mistakes.

My econometric approach offers a comprehensive treatment of random errors in observed choices on both incentivized experimental tasks designed to elicit economic preferences and 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 imperfect self-knowledge (apparent preference instability) and for individuals to make random mistakes that further depend on both observed and unobserved heterogeneity.

I build on a rich literature concerned with separating true preferences from stochastic components that 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 MPLs to reduce measurement error, a commonly used but imperfect solution. Several recent papers (e.g., Chapman et al. 2023; Stango and Zinman 2023) refer to Gillen, Snowberg, and Yariv (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 Sargan (1958) and Hansen (1982). Moreover, it does not deal with *decision error* mentioned by Andersson et al. (2016), who suggest that random mistakes, if not properly accounted for, may bias preference estimates.[13] Finally, Dohmen and Jagelka (forthcoming) find that self-reported reliability of answers is highly predictive of revealed answer reliability and can be used to reduce attenuation bias in estimates involving latent traits.

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. (2020) 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 use 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.[14]

[13] As an illustration, take the example of a person whose level of risk aversion would lead him to choose the riskier option on eight 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.

[14] There is some evidence that the relationship between cognitive ability and risk preferences may be nonlinear. For example, Burks et al. (2009) find that cognitive ability best predicts risk neutrality.

Gaudecker, Soest, and Wengstrom (2011, 677) come perhaps the closest to my treatment 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 that 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.

III. Data

The data come from the Millennium 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. 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, such as 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 toward education and its financing that are not used in the present paper. There are several recent papers that analyze this dataset using a structural model. Belzil and Sidibé (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 Sidibé (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.

[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 that are not analyzed in this paper.

The full experimental setup is included in appendix C (apps. B and C are available online).

A. *Holt and Laury's 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 three 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 three sets of H&L questions.[18]

B. *Binswanger's Ordered Lottery Selection 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, 2008). They consist of five groups (MPLs) of five 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

[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 CRRA utility function but not for alternatives, such as CARA utility.

certain amount in the first row and all other alternatives increase in expected payoff but also in 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 five sets of OLS-type questions for a given individual, unlike in the H&L design. However, a risk-neutral individual should always at least weakly prefer the riskier alternative. In the absence of stochastic shocks to utilities of preferences, the H&L tasks should allow for the identification of an interval for an individual's risk aversion, while the OLS tasks should permit the refinement of this interval. Furthermore, while the H&L tasks focus on the most common range of risk preferences (up to a coefficient of risk aversion of 1.37 under CRRA utility), OLS tasks let us identify highly risk-averse individuals.

Harrison and Rutström (2008, 82) compare estimates based on H&L-type tasks and OLS-type tasks for the same sample of individuals. They conclude that "the 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.

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 eight groups (MPLs) of six questions with variations on front-end delay (1 day to 3 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.

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 nonzero 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

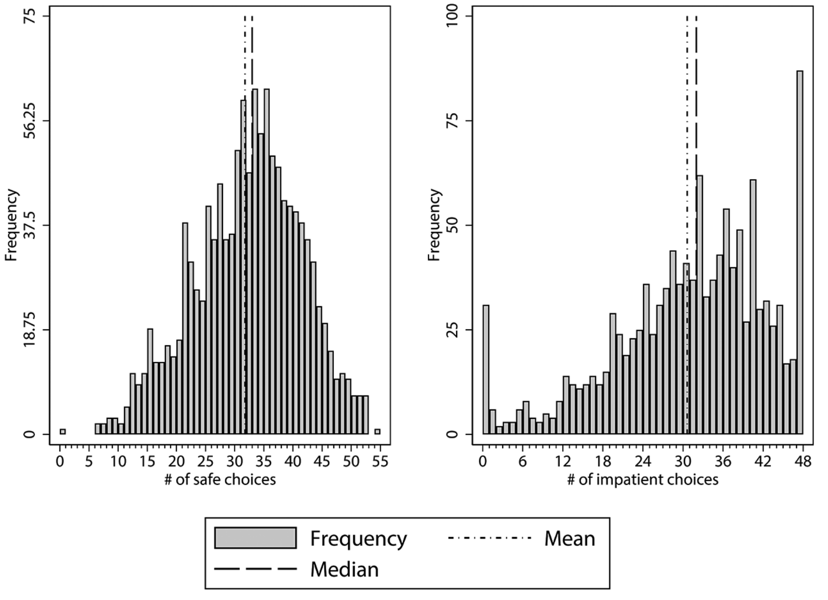

FIG. 1.—Distribution of individual choices on lottery and temporal tasks.

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 to be able to draw conclusions about their discount rates.

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; for a recent example, see Bruner 2017).

E. Background Information

The experiment also solicits a large amount of background information collected from both students and their parents. The collected information

[19] A reversal is defined as follows. Take, e.g., 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 temporal choice tasks.

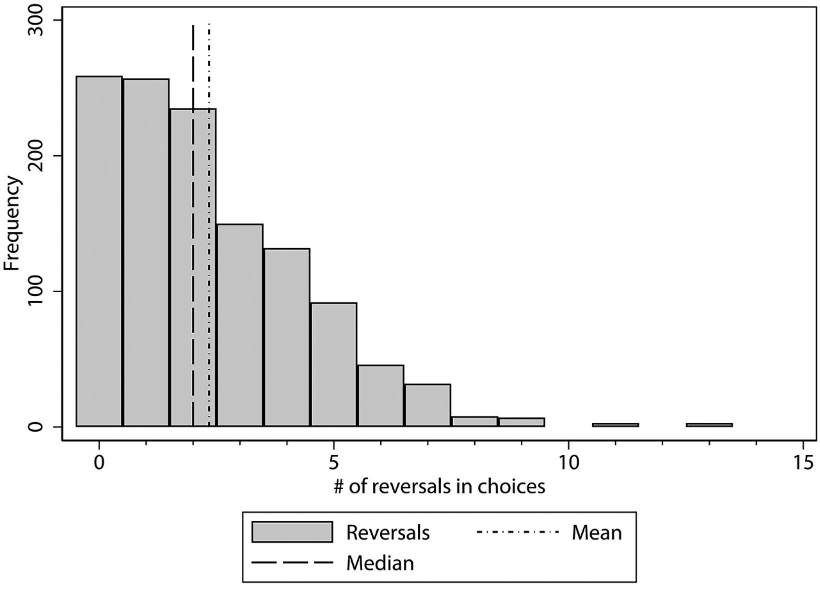

FIG. 2.—Observed reversals per individual on lottery and temporal choice tasks.

includes grades, a measure of numeracy, measures of nonverbal ability, personality, finances, and so on. Detailed descriptive statistics including demographic and socioeconomic variables for test subjects and their families are in table A1.

Table A2 lists measures selected to approximate cognitive ability and three 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, and so on. 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 toward 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 three personality traits as the data do not contain good proxies for the remaining Big Five personality traits (agreeableness and openness to experience).

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 sample of individuals comparable with 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 Five measures from the commonly used Big Five Inventory–2 (BFI-2) questionnaire,[21] as well as responses to questions regarding personality contained in the Millennium Foundation Field Experiment on Education Financing.[22] Six hundred and fifty-one participants aged 18–25 from four major English-speaking countries completed both survey waves; 121 of them are Canadians.

Correlations between validated Big Five 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 subsample (in the full sample of four 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 "measures of the same trait should correlate higher with each other than they do with measures of different traits involving separate methods" (Campbell and Fiske 1959, 104).

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 that 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. 2023).

[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. For details, see tables A5 and A6 and online tables 2 and 3.

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

[22] The survey also contains additional items that are not relevant to the present study. For more information, see Dohmen and Jagelka (forthcoming).

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

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 that I use. The obtained correlations between the official Big Five traits and my proxies that are in the vicinity of 0.5–0.6 are therefore close to the theoretical upper bound for a perfect proxy.

The proxies also load well on facets of the relevant Big Five traits.[24] Correlations for the nine facets range from 0.24 to 0.59, with eight out of nine having a correlation of 0.3 or higher. For details, see table A3.

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 variables for each individual: 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 with 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.

One can go a step further and conduct a linear regression of observed choices on gender and simple score indexes of cognitive ability and personality traits. These results are summarized in online table 4. 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 fewer safe choices, conscientiousness with fewer impatient ones, and emotional stability with more impatient choices. The low R^2 would suggest that the link between preferences

[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 and John (2017).

[25] Categorical measures are normalized to lie on the 0–1 interval; continuous measures are normalized to have zero mean and a standard deviation of one.

[26] Neuroticism is the inverse of emotional stability. The signs on the correlations presented in Becker et al. (2012) are reversed in accord with the direction of the risk and time measures as used in my paper: higher values reflect higher risk aversion and discount rates, respectively.

TABLE 1
Correlational Evidence on the Link between Risky and Impatient Choices and Personality

	Safe Choices			Impatient Choices		
	Becker et al. (2012)		Current	Becker et al. (2012)		Current
	Table 2	Table 3	Dataset	Table 2	Table 3	Dataset
Neuroticism	.12	−.03	.02	.05	.06	−.02
Extraversion	−.08	−.08	−.10	.01	.07	.04
Conscientiousness	.06	.07	.02	−.01	.07	−.11
Cognitive ability	NA	NA	−.05	NA	NA	−.17

Source.—Becker et al. (2012), tables 2 and 3; author's estimates.
Note.—NA = not applicable.

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 artifact 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.

IV. Model

Before providing technical details, let us exposit the general setup 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 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

[27] Apesteguia, Ballester, and Gutierrez (2019) show that this experimental elicitation mechanism is empirically sound.

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 II, 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 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 will 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.

A. Risk Aversion

Assume that individual i is endowed with a utility function $U_i(.)$ that maps monetary values into utility; $U_i(a)$ then represents the utility that he obtains from a dollars. Define the coefficient of relative risk aversion $\Theta_i = -a \times U_i''(a)/U_i'(a)$. A CRRA utility function can then be written as

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

or

[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 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 a suitable model existed.

$$U_i(a) = \frac{a^{(1-\Theta_i)} - 1}{1 - \Theta_i} = U(a, \Theta_i). \tag{2}$$

Equations (1) and (2) are equivalent in terms of all analyses related to risk preferences presented in this paper, as they result in the same indifference thresholds between lottery pairs, which are used in estimation (see sec. IV.A.1). Slight differences arise in the estimation of time preferences. I rely on equation (1) to facilitate comparability with previous structural results in the literature (e.g., Andersen et al. 2008; Apesteguia and Ballester 2018) and use equation (2) as a robustness check in time preference estimation (see sec. IV.B).[29] Results are robust.

Starting with equation (1) and assuming no background consumption,[30] 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 EU is as follows:

If $\Theta_i \neq 1$,

$$\mathrm{EU}_i(X) = p_{x_1} \times \frac{x_1^{(1-\Theta_i)}}{1 - \Theta_i} + (1 - p_{x_1}) \times \frac{x_2^{(1-\Theta_i)}}{1 - \Theta_i}. \tag{3}$$

If $\Theta_i = 1$,

$$\mathrm{EU}_i(X) = p_{x_1} \times \ln(x_1) + (1 - p_{x_1}) \times \ln(x_2), \tag{4}$$

where $\Theta_i \in (-\infty; +\infty)$ gives individual i's coefficient of risk aversion.[31]

1. The RPM

In this experiment, each individual makes 55 binary choices between two lotteries. This is equivalent to observing a panel of 55 decisions for each

[29] Equation (2) has better behavior in the immediate vicinity of $\Theta = 1$ and keeps utility positive for payments greater than \$1 even if $\Theta > 1$, which is advantageous for time preference estimation.

[30] Using the same experimental dataset, Belzil and Sidibé (2016) compared an "alternative model" with a similar assumption with 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" (Belzil and Sidibé 2016, 25). When they estimate individual coefficients on the parameter, they discover that "a vast majority" of the subjects in the sample use a background consumption reference point that approaches zero. The CRRA utility function is undefined for zero payoffs when the coefficient of risk aversion is greater than one. 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.

[31] The obtained mapping between preferences and traits is robust to an alternative assumption of CARA utility or expo-power (E-P) utility of Abdellaoui, Barrios, and Wakker (2007). The functional form for CARA is $U_i(a) = (1 - \exp(-\Theta_i \times a))/\Theta_i$ if $\Theta_i \neq 0$ and $U_i(a) = a$ if $\Theta_i = 0$. The functional form for E-P is $U_i(a) = -\exp(-(a^{1-\Theta_i}/(1 - \Theta_i)) + (1/(1 - \Theta_i)))$ if $\Theta_i \neq 1$ and $U_i(a) = -(1/a)$ if $\Theta_i = 1$, with a normalized to lie in the interval [0, 1].

agent and provides fertile ground to not only estimate individuals' latent true (or average) risk preferences but also examine the consistency of their choices with respect to them. Observed choices reflect a degree of inconsistency that 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 EU of individual i from lottery X and lottery Y respectively becomes

$$\begin{aligned} \mathrm{EU}_i(X) &= p_{x_1} \times \frac{x_1^{1-(\Theta_i+\varepsilon_i)}}{1-(\Theta_i+\varepsilon_i)} + (1-p_{x_1}) \times \frac{x_2^{1-(\Theta_i+\varepsilon_i)}}{1-(\Theta_i+\varepsilon_i)} \\ &= \mathrm{EU}(X;\Theta_i+\varepsilon_i) \end{aligned} \tag{5}$$

and

$$\begin{aligned} \mathrm{EU}_i(Y) &= p_{y_1} \times \frac{y_1^{1-(\Theta_i+\varepsilon_i)}}{1-(\Theta_i+\varepsilon_i)} + (1-p_{y_1}) \times \frac{y_2^{1-(\Theta_i+\varepsilon_i)}}{1-(\Theta_i+\varepsilon_i)} \\ &= \mathrm{EU}(Y;\Theta_i+\varepsilon_i). \end{aligned} \tag{6}$$

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

$$\mathrm{EU}(Y;\Theta_i+\varepsilon_i) > \mathrm{EU}(X;\Theta_i+\varepsilon_i). \tag{7}$$

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 EU nonlinearly, obtaining a closed-form expression for this probability is nontrivial. I use a method provided by Apesteguia and Ballester (2018) to do so, which relies on the monotonicity of the RPM.

Define $\mathrm{YP}_{i,l}$, a binary variable that takes on a value of 1 if individual i derives higher EU from the riskier lottery Y than from the safer lottery X in choice task l and 0 otherwise; $P(\mathrm{YP}_{i,l} = 1)$ 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 a 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 $P(\mathrm{YP}_{1,l} = 1) < P(\mathrm{YP}_{2,l} = 1)$. Let us call monotone a model of decision-making under risk that 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 $\bar{\varepsilon}_{i,l}(\Theta_i, X, Y)$, 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 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} that reflects the relative attractiveness of the riskier lottery compared with 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 that satisfies $\mathrm{EU}(X, \Theta_l^{\mathrm{eq}}) = \mathrm{EU}(Y, \Theta_l^{\mathrm{eq}})$. 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:

$$\Theta_i + \epsilon_{i,l} < \Theta_l^{\mathrm{eq}}, \tag{8}$$

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

$$\epsilon_{i,l} < \bar{\varepsilon}_{i,l} = \Theta_l^{\mathrm{eq}} - \Theta_i. \tag{9}$$

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; $P(\mathrm{YP}_{i,l} = 1)$ 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 $\epsilon_{i,l} \sim N(0, \sigma^2_{\Theta,i})$, we can write

$$P(\mathrm{YP}_{i,l} = 1) = \Phi\left(\frac{\Theta_l^{\mathrm{eq}} - \Theta_i}{\sigma_{\Theta,i}}\right). \tag{10}$$

The probability of preferring the safer option is simply

$$P(\mathrm{YP}_{i,l} = 0) = 1 - P(\mathrm{YP}_{i,l} = 1). \tag{11}$$

2. 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:

$$P(\mathrm{YC}_{i,l} = 1) = P(\mathrm{YP}_{i,l} = 1) \times (1 - K_i) + [1 - P(\mathrm{YP}_{i,l} = 1)] \times K_i, \tag{12}$$

where $\mathrm{YC}_{i,l}$ is a binary variable that takes on a 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

$$P(\mathrm{YC}_{i,l} = \mathrm{yc}_{i,l}) = P(\mathrm{YC}_{i,l} = 1)^{\mathrm{YC}_{i,l}} \times P(\mathrm{YC}_{i,l} = 0)^{1-\mathrm{YC}_{i,l}}, \tag{13}$$

where $\mathrm{yc}_{i,l}$ is a particular realization of $\mathrm{YC}_{i,l}$.

3. 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 nonzero probability. The only part of the employed RPM that can explain such choices is the tremble parameter K_i, which is therefore trivially identified from such choices.

The parameter K_i is a source of uniform noise that affects all choices equally, whereas $\sigma_{\Theta,i}$ represents noise that 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 nonnegligible probability. To the extent that these inconsistent choices concern nondominated 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 when a person is close to being indifferent given his true (or average) level of risk aversion. 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 with inconsistent switching points between lists. 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 that 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 abovementioned points for tasks that I use. To focus on the trade-off 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.[32] A simulation that

[32] 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.

turns off the tremble parameter yields a total of 1,025 inconsistent switching points compared with 1,031 observed in the experimental data.[33] However, it severely *underpredicts* the number of choice reversals (198 simulated vs. 2,779 actual). If $\sigma_{\Theta,i}$ is tripled, the simulated number of reversals approaches the actual one (2,628 vs. 2,779); however, this comes at the cost of severely *overpredicting* 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.

B. *Time Preference*

Time preference under RPM is treated analogously to risk aversion. In the 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 that 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 $R_{i,t}^{\mathrm{eq}}$ 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 above 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 (DU) of individual i from a proposed payoff of a dollars received in τ years is as follows:

If $\Theta_i < 1$,

$$\mathrm{DU}_i(a) = \beta_i^{\tau} \frac{a^{(1-\Theta_i)}}{1-\Theta_i}, \tag{14}$$

where β_i represents the discount factor. It can be expressed as $\beta_i = 1/(1 + R_i)$, where $R_i \in [0; 1]$ represents the discount rate.

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

[33] Inconsistent switching points are calculated for the three sets of 10 lottery tasks that have the same predicted theoretical switch points under CRRA utility.

a 100% upper bound is generous (see, e.g., Andersen et al. 2008, 2014; Apesteguia, Ballester, and Gutierrez 2019). For robustness, I test a specification that 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 $1/(1 + R_i)$ holds only for $\Theta_i \leq 1$, as otherwise ordinal utility is negative under the standard CRRA specification seen in equation (1).[34] 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.[35] At these levels of risk aversion, indifference thresholds for the discount rate already approach zero. Nevertheless, for robustness I also employ a slightly modified version of CRRA utility, seen in equation (2), that keeps utility positive for payments greater than \$1 and thus allows for the calculation of indifference thresholds for the discount rate also using $\Theta_i > 1$. In this case, discounted utility can be written as $\mathrm{DU}_i(a) = \beta_i^{\tau}((a^{(1-\Theta_i)} - 1)/(1 - \Theta_i))$. 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 in the literature, 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 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 either is 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

[34] 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, at the threshold level of discount rate, it reaches 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 zero and one) 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.

[35] 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. Estimation is robust to extending this lower limit to $\Theta_i = -2$. Results are available from the author upon request.

end, I use a simple discounting formula that is adapted to the indifference threshold framework used in this paper and that 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 dollars received in τ years then becomes $\mathrm{DU}_i(a) = (1/(1 + R_i \times \tau)) \times (a^{(1-\Theta_i)}/(1 - \Theta_i))$ if $\Theta_i < 1$. Results are robust to this alternative assumption.

Choice probabilities.—As with risk aversion in the above 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 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 $\ln(R_i^2/(\sqrt{(\sigma_{R,i})^2 + R_i^2}))$ and standard deviation $\sqrt{\ln(1 + ((\sigma_{R,i})^2/R_i^2))}$. 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, $R_{i,t}^{\mathrm{eq}}$. 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 $\ln(R_{i,t}^{\mathrm{eq}})$. With this insight, we obtain the temporal equivalent of equation (10), the probability of preferring the later option:

$$P(\mathrm{LP}_{i,t} = 1) = \Phi\left[\frac{\ln(R_{i,t}^{\mathrm{eq}}) - \ln\left(R_i^2\Big/\left(\sqrt{(\sigma_{R,i})^2 + R_i^2}\right)\right)}{\sqrt{\ln(1 + (\sigma_{R,i})^2/R_i^2)}}\right], \quad (15)$$

where $\mathrm{LP}_{i,t}$ is a binary variable that takes on a 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

$$P(\mathrm{LP}_{i,t} = 0) = 1 - P(\mathrm{LP}_{i,t} = 1). \quad (16)$$

As in the above 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 will assume that the tremble parameter K_i applies to all choice tasks individual i faces—whether they be lottery based or temporal in nature. For robustness, I allow K_i to vary between temporal and lottery choices. Estimated mappings are preserved.

After incorporating the tremble parameter, I obtain an expression for the probability that individual i chooses the later option in choice task t:

$$P(\mathrm{LC}_{i,t} = 1) = P(\mathrm{LP}_{i,t} = 1) \times (1 - K_i) + [1 - P(\mathrm{LP}_{i,t} = 1)] \times K_i, \quad (17)$$

where $\mathrm{LC}_{i,t}$ is a binary variable that takes on a value of one if individual i chooses the later option in temporal choice task t and zero otherwise.

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

$$P(\mathrm{LC}_{i,t} = \mathrm{lc}_{i,t}) = P(\mathrm{LC}_{i,t} = 1)^{\mathrm{LC}_{i,t}} \times P(\mathrm{LC}_{i,t} = 0)^{1-\mathrm{LC}_{i,t}}, \quad (18)$$

where $\mathrm{lc}_{i,t}$ is a particular realization of $\mathrm{LC}_{i,t}$.

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:

$$L_i = \prod_{l=1}^{55} P(\mathrm{YC}_{i,l} = \mathrm{yc}_{i,l}) \times \prod_{t=1}^{48} P(\mathrm{LC}_{i,t} = \mathrm{lc}_{i,t}). \quad (19)$$

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 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 (20)–(24), 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 that have observed proxy indicators in the data. Each structural parameter is assumed to depend on the same set of observed characteristics and latent factors.[36] 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:

$$\Theta_i = \Theta_0 + \Theta_1' X_i + \Theta_2' F_i, \tag{20}$$

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

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

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

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

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 noncognitive 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:

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

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

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

[36] 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.

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

where α_f' is a set of coefficients on the individual's observed characteristics that enter into factor f.[37] The exogenous term $\tilde{F}_{i,f}$ follows a normal distribution with mean zero and variance $\sigma_f^2 \in [0; +\infty)$, specific to each factor. The assumption that a random effect, here the unobserved factor, is composed of a deterministic part related to individual characteristics and a residual normally distributed orthogonal term was first made by Chamberlain (1980). It allows for a potential correlation between the various factors based on observed characteristics.

A binary measure's contribution to the likelihood function is

$$\begin{aligned} P(M_{i,j,f} = m_{i,j,f}) = {} & [1 - \Phi(-\gamma_{0,j,f} - \gamma_{1,j,f} \times F_{i,f})]^{M_{i,j,f}} \\ & \times \Phi(-\gamma_{0,j,f} - \gamma_{1,j,f} \times F_{i,f})^{1-M_{i,j,f}}. \end{aligned} \tag{27}$$

The corresponding probabilities for multivalued and continuous measures can be found in online appendix section B.b.

E. *Unobserved Heterogeneity*

Unobserved heterogeneity is incorporated through unobserved types that differ in the intercepts of preference and consistency parameters, as seen in equations (20)–(24).[38] Each type is thus characterized by a vector of five 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.

V. Empirical Methodology

Estimation is done through maximum likelihood. The estimator maximizes the joint likelihood of observing the factor proxy measures and

[37] Sex, native language, and age were chosen for the main specification due to their intuitive importance in explaining personality and cognitive ability and their availability for the full sample. Sex figures in both the structural parameter eqq. (20)–(24), estimated from choices on incentivized tasks, and the factor eq. (26), 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 its indirect impact through its effect on the latent factors. Obtained mappings are robust to excluding sex from the factor eq. (26).

[38] The use of unobserved types to represent unobserved heterogeneity is well established since Wolpin's (1997) seminal paper.

individual choices in the lottery and temporal choice tasks given unobserved factors and types that drive the observed measures and choices. The factors are modeled as random effects.

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

$$\begin{aligned} P(M_{i,j,f} = 1|\tilde{F}_{i,f}) &= P(\epsilon_{i,j,f} < \gamma_{0,j,f} + \gamma_{1,j,f} \times (\alpha_0 + \alpha_f' X_i) + \gamma_{1,j,f} \times \tilde{F}_{i,f}|\tilde{F}_{i,f})) \\ &= \Phi(\gamma_{0,j,f} + \gamma_{1,j,f} \times (\alpha_0 + \alpha_f' X_i) + \gamma_{1,j,f} \times \tilde{F}_{i,f}|\tilde{F}_{i,f})). \end{aligned} \tag{28}$$

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

$$\begin{aligned} P(M_{i,j,f} = 1) = \int_{-\infty}^{+\infty} & \Phi(\gamma_{0,j,f} + \gamma_{1,j,f} \times (\alpha_0 + \alpha_f' X_i) + \gamma_{1,j,f} \times \tilde{F}_{i,f}) \\ & \times \frac{1}{\sigma_{F_f}} \phi\left(\frac{\tilde{F}_{i,f}}{\sigma_{F_f}}\right) d\tilde{F}_{i,f}. \end{aligned} \tag{29}$$

Empirically, the above integral is approximated using 200 independent draws of the orthogonal random part of the factor $\tilde{F}_{i,f}$ per individual from a normal distribution with mean zero and variance $\sigma^2_{F_f}$ that 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 $\tilde{F}_i$ of individual i's orthogonal components of his latent factors. The loading of the first measure of each factor is normalized to one 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

$$\begin{aligned} L_i|(\tilde{F}_i = \tilde{F}_{i,1}, \tilde{F}_{i,2}, \ldots, \tilde{F}_{i,F}; \mathrm{UT}_i = \mathrm{ut}_i) = & \prod_{f=1}^{F}\prod_{j=1}^{J} P(M_{i,j,f} = m_{i,j,f}|\tilde{F}_{i,f}) \\ & \times \prod_{l=1}^{55} P(\mathrm{YC}_{i,l} = \mathrm{yc}_{i,l}|\tilde{F}_i, \mathrm{UT}_i) \\ & \times \prod_{t=1}^{48} P(\mathrm{LC}_{i,t} = \mathrm{lc}_{i,t}|\tilde{F}_i, \mathrm{UT}_i), \end{aligned} \tag{30}$$

where $L_i|(\tilde{F}_i, \mathrm{UT}_i)$ represents the individual likelihood of jointly observing $j = 1, \ldots, J$ measures of each factor $f = 1, \ldots, 4$, $l = 1, \ldots, 55$ lottery choice task decisions, and $t = 1, \ldots, 48$ temporal choice task decisions for individual i given a particular draw $\tilde{F}_i$ of the orthogonal components of the individual's factors $f = 1, \ldots, F$ and given a particular value of his unobserved type UT_i. The relevant probabilities for observing each of the aforementioned are given in equation (27) for binary measures, equations (34)–(36) for multivalued measures, equation (37) for continuous measures, equation (13) for lottery choice tasks, and equation (18) for temporal choice tasks.[39] Note that unobserved types affect only 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 the observed measures that proxy for the factors.

I next integrate out the unobserved factors:

$$\begin{aligned} L_i|(\mathrm{UT}_i = \mathrm{ut}_i) = \int_{\tilde{F}_i} \cdots \int \prod_{f=1}^{F} \prod_{j=1}^{J} P(M_{i,j,f} = m_{i,j,f}|\tilde{F}_{i,f}) \times \prod_{l=1}^{55} P(\mathrm{YC}_{i,l} = \mathrm{yc}_{i,l}|\tilde{F}_i, \mathrm{UT}_i) \\ \times \prod_{t=1}^{48} P(\mathrm{LC}_{i,t} = \mathrm{lc}_{i,t}|\tilde{F}_i, \mathrm{UT}_i) \times f(F_1, \ldots, F_F)\, d\tilde{F}_i, \end{aligned} \tag{31}$$

where $f(F_1, \ldots, F_F)$ represents the joint probability of observing the full set of simulated factor values $\tilde{F}_i$ for individual i. Because the factor draws are assumed to be independent, I can write

$$\begin{aligned} L_i|(\mathrm{UT}_i = \mathrm{ut}_i) = \int_{\tilde{F}_i} \cdots \int \prod_{f=1}^{F} \prod_{j=1}^{J} P(M_{i,j,f} = m_{i,j,f}|\tilde{F}_{i,f}) \times \prod_{l=1}^{55} P(\mathrm{YC}_{i,l} = \mathrm{yc}_{i,l}|\tilde{F}_i, \mathrm{UT}_i) \\ \times \prod_{t=1}^{48} P(\mathrm{LC}_{i,t} = \mathrm{lc}_{i,t}|\tilde{F}_i, \mathrm{UT}_i) \times \frac{1}{\sigma_{F_1}} \phi\left(\frac{\tilde{F}_{i,1}}{\sigma_{F_1}}\right) \times \cdots \times \frac{1}{\sigma_{F_F}} \phi\left(\frac{\tilde{F}_{i,F}}{\sigma_{F_F}}\right) d\tilde{F}_i. \end{aligned} \tag{32}$$

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:

$$L_i = \sum_{\mathrm{ut}=1}^{\mathrm{UT}} (L_i|\mathrm{ut}) \times p_{\mathrm{ut}}, \tag{33}$$

where p_{ut} represents 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.[40] Finally,

[39] The formulas for multivalued and continuous measures are in online app. sec. B.b.

[40] With five unobserved types, the estimated prevalence of the least frequent type is already less than 10% (see table 3). Obtained mappings are robust to estimation with three unobserved types. Results are available from the author upon request.

the log of the average individual likelihoods is summed across all individuals to yield the objective function to be maximized.

VI. Empirical Results

The empirical results presented below come from two distinct structural specifications of the model presented in the above section. The first specification will be referred to as the *fixed effects choice model*. It is estimated by maximizing the likelihood, described in equation (19), of observing each individual's choices on the lottery and temporal choice tasks. Estimation is performed individual by individual. This means that each of the 1,224 test subjects will have an estimated vector of five preference and consistency parameters as summarized in table 2.

The second specification will 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 that measure cognitive ability and personality (see eq. [33]). 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 through direct estimation and the second through simulation based on estimated values of the structural parameters. These are 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.

TABLE 2
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)	

TABLE 3
PARAMETER VALUES FOR THE AVERAGE PERSON

	Prevalence	Risk Aversion	Discount Rate	Risk Aversion Standard Deviation	Discount Rate Standard Deviation	% Hand Trembles
Simulated average		1.01	.22	.52	.21	.04
Female average		1.05	.16	.50	.14	.04
Male average		.96	.30	.55	.30	.03
Type 1 average	.31	1.14	.01	.73	.01	.03
Type 2 average	.25	.64	.50	.48	.46	.01
Type 3 average	.23	.33	.45	.65	.57	.11
Type 4 average	.12	.03	.60	.36	.75	.02
Type 5 average	.08	5.17	.02	.20	.01	.06

A. *Preference Parameters*

Results from the full model summarized in table 3 reveal that the average individual in the population has logarithmic risk aversion and a 22% discount rate.[41] The risk aversion estimate is relatively high for the experimental literature but closer to values standardly assumed by macroeconomists. It may be due in part to the inclusion of the OLS tasks in this experiment, which cover a wider range of risk aversion than the standard H&L 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. Andersson 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 that 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 table 6), 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. Type 4 is close to risk neutrality and at the

[41] The average individual is defined as having average values of cognitive ability, personality, and each of the attributes—i.e., 46% male, 68% speaking English, etc.

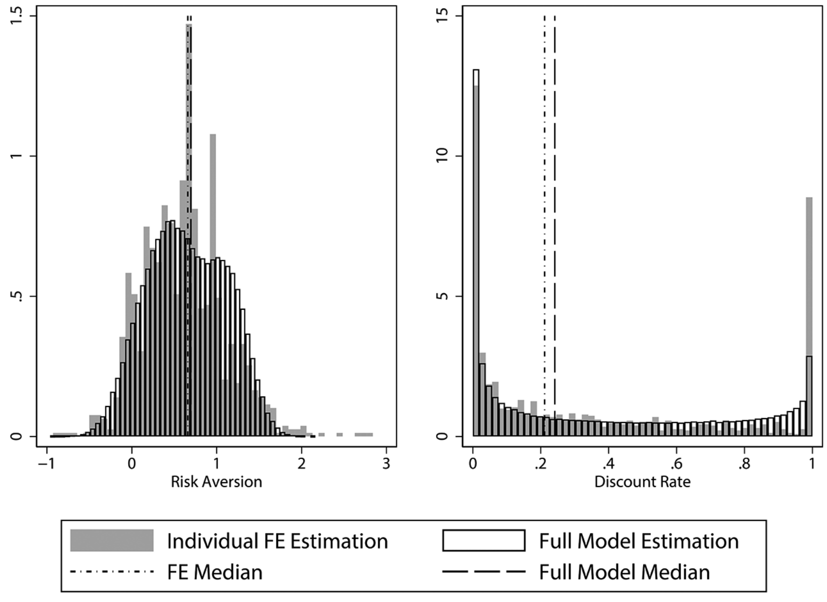

FIG. 3.—Sample distributions of risk and time preferences. FE = fixed effect.

same time very impatient. These "daredevils" represent 12% of the population. 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.

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.[42]

Figure 3 superposes the distributions of preference parameters estimated by alternatively using the fixed effects choice model and the full model.[43] They are remarkably similar and show that using only the coefficients from my structural model, information on observed heterogeneity,

[42] The simulation is performed exactly according to the model presented in sec. IV. 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.

[43] 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."

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 0.21 and 0.24, respectively.[44] Not only are the medians of the two distributions virtually identical for each preference parameter but the 25th percentile, the 75th percentile, the mean, and the standard deviation are as well.[45] In contrast, using observed and unobserved heterogeneity, Gaudecker, 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 elicit risk preferences.

Due to the presence of unobserved factors and types in the full model, it is not trivial to obtain a direct measure 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 (for an in-depth analysis, see sec. VI.D). 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 toward zero (patient individuals), but the full range up to one is covered and there is a spike at the upper end.[46] It reflects the fact that a nonnegligible portion of individuals choose either all earlier or all later payments as described in section III.

[44] For comparison purposes, Apesteguia, Ballester, and Gutierrez (2019) 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.

[45] 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), and 1.12 vs. 1.00 (75th percentile) for the full model and the fixed effects model, respectively. For the discount, 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. 0.21 (median), and 0.71 vs. 0.69 (75th percentile) for the full model and the fixed effects model, respectively.

[46] 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, also visible in raw choice data displayed in fig. 1. A similar finding is replicated in other experimental datasets (see, e.g., Apesteguia, Ballester, and Gutierrez 2019).

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 nonnegligible 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.[47]

Figure 4 illustrates the contribution of observed and unobserved heterogeneity to the overall cross-sectional variation in risk aversion. It includes the estimated marginal effects of sex and factors related to ability and personality traits,[48] as well as the percentage of variation in risk aversion attributed to observed heterogeneity that each of them explains.[49]

Observed heterogeneity explains one-quarter of the population variation in risk aversion.[50] A majority of the explained variation is attributed to factors related to personality. Among them, 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

[47] 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.

[48] 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 zero to one—male to female, in the 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 or 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 zero to one—male to female, in the case of sex).

[49] The explained percentage variation is obtained from the simulated dataset as the R^2 of the relevant linear regression of structural parameters on unobserved factors and unobserved types derived from eqq. (20)–(24).

[50] Values of risk aversion above three 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 choose the less risky alternative on virtually all of the 55 lottery choice tasks in the experiment.

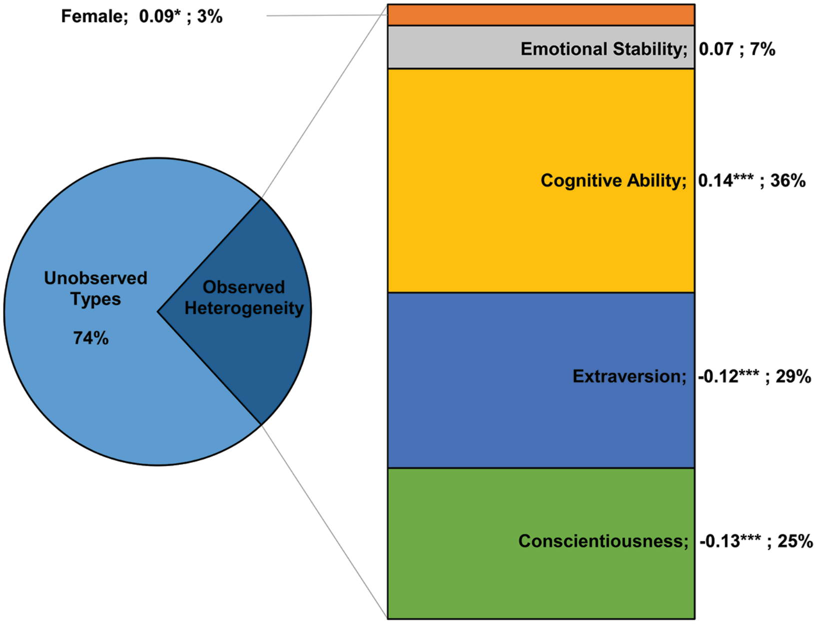

FIG. 4.—Heterogeneity in the coefficient of risk aversion. For observed heterogeneity, the first value corresponds to the marginal effect of changing each factor by 1 standard deviation (and sex from male to female) on risk aversion; the second value gives the percentage contribution of each heterogeneity component to the overall explanatory power of observed heterogeneity.

conscientious individuals taking a disciplined big-picture view and thus being able to look beyond short-term fluctuations that 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 with the simple correlations presented in table 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 Andersson et al. (2016) that can result from random errors correlated with cognitive ability combined with an experimental design skewed toward choices of one of the options (risky or safe). The correction is consistent with but stronger than that reported by Andersson et al. (2020). 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 with reduced-form techniques, which do not properly account for decision error (see table 1, online table 4). 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 debias estimates.

Observed heterogeneity explains 60% of the cross-sectional variation in discount rates. Once again, a majority of the explained variation is attributed to factors related to personality. This can be seen in figure 5.

The factor related to conscientiousness possesses by far the highest explanatory power, confirming its intuitive link with discount rates. It explains one-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 indicates 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. This illustrates the nuances in mappings between the economic and psychological systems for characterizing essential human differences. Table A4 shows the estimated raw structural coefficients for equations (20)–(24) along with their associated standard errors.

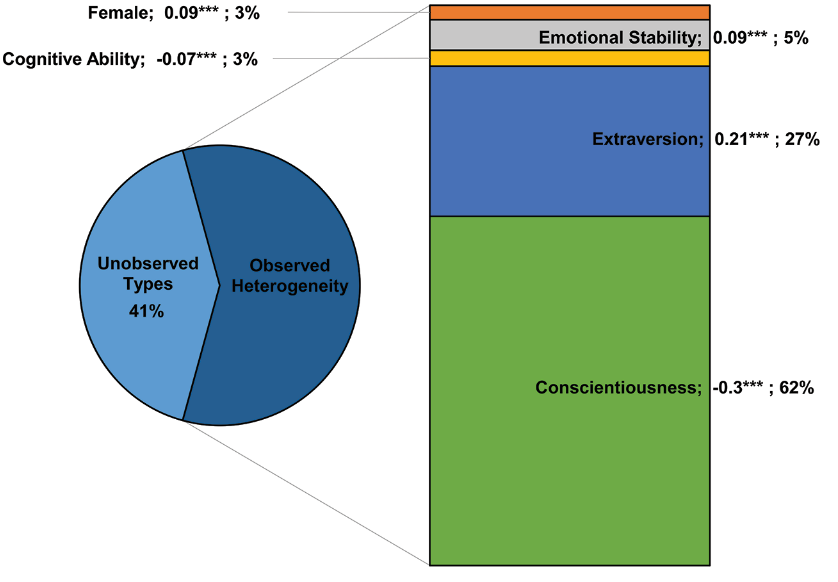

FIG. 5.—Heterogeneity in discount rates. For observed heterogeneity, the first value corresponds to the marginal effect of changing each factor by 1 standard deviation (and sex from male to female) on the discount rate; the second value gives the percentage contribution of each heterogeneity component to the overall explanatory power of observed heterogeneity.

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 parameter is the trembling hand parameter. It represents the percentage of time that an individual makes a mistake—that is, when he in fact chooses his less preferred option.

Estimates indicate a degree of apparent instability in individuals' preferences that means either that individuals are not fully self-aware or that their preferences fluctuate. In the words of Loomes and Sugden (1995, 643): "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 seen in table 3, the average individual has a standard deviation of 0.52 on his coefficient of risk aversion and 0.21 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 20% of the population (types 4 and 5) exhibits a low level of apparent instability in their risk preference with a standard deviation of around 0.3, 25% (type 2) exhibits an intermediate level of instability, and the remaining 50% (types 1 and 3) exhibits an elevated level of instability. The dispersion is even wider with discount rates: 40% of the population (types 1 and 5) exhibits stable time preference, 50% (types 2 and 3) exhibits moderate levels of apparent instability, and 12% (type 4) exhibits an elevated level of instability.

The trembling hand parameter varies less in the population. An average person chooses his less preferred option 4% of the time, which is consistent with the estimates in Apesteguia and Ballester (2018). Men make fewer mistakes than women. About two-thirds of the population make choices in line with their underlying preferences at least 95% of the time, while one-quarter (type 3) choose their less preferred option in over 10% of the choice tasks.

Figure 6 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 with the results of Apesteguia, Ballester, and Gutierrez

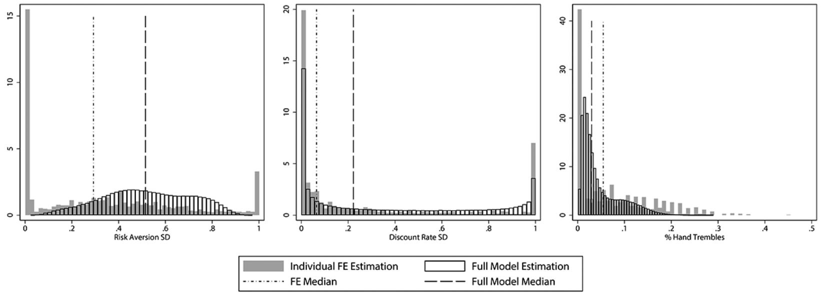

FIG. 6.—Sample distributions of consistency parameters. FE = fixed effect.

(2019), 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 toward zero but has a fat tail using estimates from both the fixed effects choice model and the full model. Finally, the distribution of the trembling hand parameter is also heavily skewed toward zero but has little mass beyond 0.3.

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 sec. IV.A.3), 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.[51] This should be less of an issue in the full model, which parameterizes the consistency parameters as a function of observed and unobserved heterogeneity and thus pools information from all individuals' choices.

[51] For this reason, the fixed effects estimation was also performed using a fixed value of 0.4 for the standard deviation of risk aversion and 0.3 for the standard deviation of the discount rate. Distributions of risk aversion, the discount rate, and the trembling hand parameter were qualitatively unchanged. Results are available from the author upon request.

TABLE 4
IMPLIED CHOICE INCONSISTENCY DUE TO PREFERENCE SHOCKS FOR MEDIAN INDIVIDUAL

	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10
	H&L-Type MPL Indifference Thresholds									
MPL 1–3	−1.71	−.95	−.49	−.14	.15	.41[b]	· .68[a]	.97	1.37	Infinity
	Binswanger-Type Binarized MPL Indifference Thresholds									
MPL 4			2.97	1.00	· .60[a]	.42[b]	.00			
MPL 5			4.73	1.69	1.06	.78[a]	· .00			
MPL 6			1.37	· .45[b]	.26	.17	.00			
MPL 7			4.46	1.50	.94[b]	.68[a]	· .00			
MPL 8			1.54	· .51[b]	.30	.20	.00			
	Temporal MPL Indifference Thresholds at Median Risk Aversion									
MPL 1–4	.02	.03	.07[b]	.18[a]	· .39[b]	.88				
MPL 5–8	.02	.03	.06[b]	.15[a]	· .27[a]	.45[b]				

[a] Inconsistent choices that the individual might make given draws from his risk aversion (or discount rate) distribution in the 68% interval.
[b] Additional inconsistent choices that the individual might make given draws from his risk aversion (or discount rate) distribution in the 95% interval.

1. Plausibility of Implied Preference Instability

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 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 0.08 and 0.33 and 95% of the time as if it were between 0.04 and 0.67.[52]

Table 4 illustrates what this implies in terms of choices on the employed experimental tasks. A middle dot between cells represents the theoretical switching point on each group of choice tasks under CRRA utility for the median individual in the absence of noise. Cells marked with a superscript "a" represent inconsistent choices that the individual might make given draws from his risk aversion (or discount rate) distribution in the 68% interval, while cells marked with a superscript "b" represent additional choice inconsistency that would result from draws within the 95% interval. On examination of table 4, it is clear that for the median

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

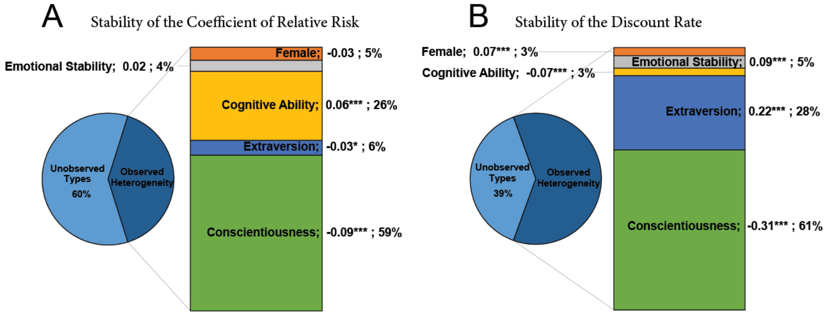

Fig. 7.—Heterogeneity in individuals' stability parameters. For observed heterogeneity, the first value corresponds to the marginal effect of changing each factor by 1 standard deviation (and sex from male to female) on the standard deviation of risk aversion; the second value gives the percentage contribution of each heterogeneity component to the overall explanatory power of observed heterogeneity.

individual, choice inconsistency generated by the estimated preference shocks is concentrated within one or two cells from the switch point implied by constant preferences set at their average value.

2. 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 7. A majority of the explained variation is attributed to factors related to personality, as was also the case for preference parameters. The factor related to conscientiousness is dominant and explains 60% of individual heterogeneity for both preferences.[53] The marginal effect of conscientiousness is stronger for the standard deviation of the discount rate, and accordingly the percentage of total explained cross-sectional variation is higher than for the standard deviation of risk aversion. Highly conscientious 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. (2020). The positive link between extraversion and time preference instability

[53] 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 that exhibits limit values of risk aversion.

seems more intuitive. Nevertheless, the explanatory power of these (and other) variables in terms of the overall heterogeneity in preference stability pales in comparison with that of the factor related to conscientiousness.

Propensity to make mistakes seems largely independent of personality, unlike the other preference and consistency parameters (see fig. 8). 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 approximately 15% of the total cross-sectional variation in the parameter. Unsurprisingly, individuals with higher cognitive ability are able to make choices that are more consistent with their underlying preferences—that is, they make decisions of higher quality. A 1 standard deviation increase in cognitive ability reduces the propensity to make mistakes by 1 percentage point, which corresponds to a 33% decrease from its estimated median value in the population and a 25% decrease from the average value. This suggests that some individuals face

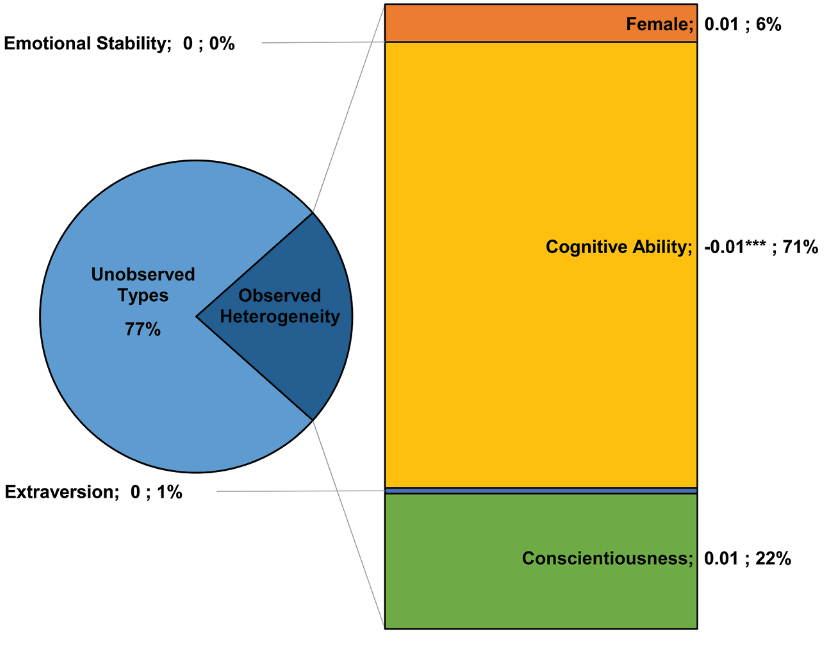

FIG. 8.—Heterogeneity in individuals' propensity to make mistakes. For observed heterogeneity, the first value corresponds to the marginal effect of changing each factor by 1 standard deviation (and sex from male to female) on the trembling hand parameter; the second value gives the percentage contribution of each heterogeneity component to the overall explanatory power of observed heterogeneity.

cognitive hurdles when evaluating the standard and relatively simple lottery and temporal choice tasks in this experiment.[54]

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 that 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.

C. *Robustness of Mappings*

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 based solely 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 that allows for the use of a coefficient of risk aversion greater than one in discount rate calculation, and (*i*) assuming E-P utility. Conclusions drawn from the main specification (RPM model with CRRA utility from eq. [1] and exponential discounting using the full sample and 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.

[54] 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.

The main insights on mappings also hold 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 print appendix section A3 and online appendix sections B.e.ii–B.e.ix.

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.[55]

Table 5 first presents the R^2 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 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 IV.A.3.

[55] These are simple linear regressions, and the model implies that the estimated parameters enter choices in a nonlinear fashion. Nevertheless, they serve as a useful approximation.

TABLE 5

Explanatory Power on Observed Choices of Preference and Consistency Parameters versus Demographic and Socioeconomic Variables

	Number of Safe Choices	Number of Impatient Choices	Number of Risk Reversals	Number of Time Reversals	Risk Switch Standard Deviation	Time Switch Standard Deviation
Demographic and socioeconomic variables (R^2)	.06	.07	.02	.02	.03	.02
All parameters (R^2)	.86	.63	.59	.04	.11	.16
Preference parameters (%)	91.7	98.6	.2	8.1	2.0	29.8
Consistency parameters (%)	8.3	1.4	99.8	91.9	98.0	70.2
Stability (%)	82.8	76.2	2.3	18.0	80.7	96.2
Mistakes (%)	17.2	23.8	97.7	82.0	19.3	3.8

Note.—The first two rows list the R^2 of the regression of the moment listed in each column title on 18 demographic and socioeconomic variables (first row) and the relevant structural parameters (second row) of the model. Demographic variables include the student's sex, age, language, number of siblings living with him, and 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 remaining rows represent the relative explanatory power of the relevant subgroups of parameters, expressed as a percentage. Outliers representing extreme values of risk aversion ($\Theta > 3$ and $\Theta < -1$) are excluded. This leaves 1,109 observations.

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 table A7. These results reveal that the fixed effects model has excellent predictive power with regard 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 table A7 for a breakdown by R^2 for each structural parameter.

E. Factor Determinants

The estimated coefficients from the factor equation (26) are displayed in table 6. 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 the orthogonal component of approximately 0.3, while the factor related to conscientiousness has an estimated standard deviation of the orthogonal component equal to 0.8. Being female is associated with lower values on the factor related to extraversion and higher values on the factor related to conscientiousness. Native English speakers and older individuals score higher on both of these personality traits.[56] The remaining coefficients are small.

Estimated factor loadings for each measure are positive, consistent with the assumption that each set of measures is associated with the relevant underlying factor.[57] As seen in appendix section A2, the magnitudes

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

[57] A factor loading is the structural coefficient on the relevant factor in the measurement eq. (25). It reflects the importance of the latent factor for a given proxy measure.

TABLE 6
Estimated Coefficients on Factor Components

	Female	English	Age = 17	Age = 18	Age ≥19	R^2	Standard Deviation	Implied Sample Average
Internal locus of control	−.07	−.01	.06	.06	.01	.01	.35	−.10
Cognitive ability	.02	.01	.08	.00	−.05	.03	.28	1.60
Extraversion	−.13	.03	.12	.16	.14	.05	.35	.13
Conscientiousness	.30	.14	.19	.21	.26	.05	.81	.13

Note.—Ages 15 and 16 are omitted.

of the loadings vary widely. This suggests that some questions are much better measures of cognitive ability and personality than others. Column 4 in table A2 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.[58] This confirms the usefulness of using a factor model to address measurement error inherent in indicators for cognitive ability and personality (see, e.g., Cunha and Heckman 2009). A simple additive score based on the measures of each trait, often used in the literature, appears insufficient.

VII. 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

[58] 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.

more closely by psychologists. Because preferences and traits, as well as the quality of decision-making, have been shown to predict outcomes and be highly heritable, these findings also have ramifications for understanding inequality and the mechanisms underlying the intergenerational transmission of socioeconomic status.[59] This is just the beginning of a larger effort to bring together competing classifications of human differences 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.

Following 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; Stango and Zinman 2023). 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 such as the stock market that tend to reward stable, long-term decisions. If cognitive ability and personality traits are assumed to also function as primitives of economic models through (or alongside) preferences, their combined impact on inequalities in outcomes, such as accumulated wealth, may be further magnified; for example, take a situation in which conscientiousness makes an individual do well financially both through its direct impact on his career success and indirectly through a lower associated discount rate 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 that is largely homogeneous in terms of educational level and age, I find significant dispersion in risk and time preferences, their individual-level precision, and 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

[59] Heritability estimates are about 50% for cognitive skill and personality (see, e.g., Bouchard and Loehlin 2001; 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 noncognitive traits (see, e.g., Beauchamp, Cesarini, and Johannesson 2017). Little is known regarding the heritability of decision-making quality. My results document 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.

parameters factor nonlinearly into a wide range of micro- and macroeconomic models, such a simplification is likely to have ramifications for predicting agents' responses to changes in economic conditions and calculating the welfare implications of new policy.

My results confirm that the RPM 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 that 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. Further research is needed 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 EU 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 (Tversky and Kahneman 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 noncognitive skills is a worthwhile exercise. Unfortunately, this dataset is not adapted to doing so. Based on the current state of the literature and 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.

VIII. 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 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 toward a unified framework for characterizing the number and nature of attributes driving behavior and heterogeneity in observed outcomes. It allows us to better comprehend the mechanism through which preferences, cognitive ability, and personality influence those outcomes. This seems crucial for understanding the origins of inequality and could lead to policy recommendations, which would target its fundamental human capital causes. For example, it could yield a list of competencies to target through schooling, while they are still malleable, and thus help reduce inequalities. Careful attention to measurement issues will be crucial in evaluating the effectiveness of any policy intervention.

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 socioeconomic 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 sociodemographics, I show that simply controlling for personality could go 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 degree a function of unobserved heterogeneity. This may be an artifact of the limitations of the present dataset, which allows for the identification of only basic risk and time preferences and contains rough proxy measures for three of the Big Five personality traits. Further research comparing an expanded set of both standard and nonstandard 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.

Data Availability

Code replicating the tables and figures in this article can be found in the Harvard Dataverse, https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/TU8V0C (Jagelka 2023).

Appendix A

A1. Sample Descriptive Statistics

TABLE A1
Sample Demographic and Socioeconomic Variables

	Observations	%	Mean	% If Male
Test subjects:				
Gender	1,224			
Male		46	NA	NA
Female		54	NA	NA
Age	1,224			
15–16		12	NA	11
17		67	NA	65
18		15	NA	17
≥19		6	NA	7
Language	1,224			
English		68	NA	69
Other		32	NA	31
Born in Canada	1,087	96	NA	96
Lives with siblings	1,224	75	NA	76
Parents:				
Age	1,068	NA	46	NA
Indigenous Canadian	1,224	7	NA	7
Number of children under 18	1,085	NA	2	NA
Thinks university is important	1,088	92	NA	91
High school dropout	1,224	12	NA	11
High school	1,224	52	NA	50
University	1,224	36	NA	39

TABLE A1 (*Continued*)

	Observations	%	Mean	% If Male
Annual income	976			
<$20,000		6	NA	6
$20,000–$40,000		13	NA	11
$40,000–$60,000		23	NA	24
$60,000–$80,000		19	NA	17
$80,000–$100,000		15	NA	17
>$100,000		24	NA	25

A2. *Experimental Measures of Cognitive Ability and Personality*

TABLE A2
FACTOR LOADINGS

Factor and Measure	Type (1)	Sign Reversal (2)	Loading (3)	Signal-to-Noise Ratio (4)
Emotional stability:				
1) When I make plans they work out as I expect	B		1.00	.12
2) My school was a place where I felt like an outsider or like I was left out of things	B	X	1.10	.15
3) I have a good idea of what I will be doing for an extended period of time	B		.87	.10
4) I worry I might be taken advantage of by a salesperson	B	X	.91	.10
5) You have little control over the things that happen to you	MV	X	2.48	.76
6) There is really no way you can solve some of the problems you have	MV	X	3.08	1.18
7) There is little you can do to change many of the important things in your life	MV	X	4.28	2.27
8) You often feel helpless in dealing with the problems of life	MV	X	4.41	2.42
9) Sometimes you feel that you are being pushed around in life	MV	X	2.22	.61
10) You can do just about anything you really set your mind to do	MV		1.23	.19
Cognitive ability:				
1) In your last year of high school, what was your overall grade average, as a percentage?	MV		1.00	.08
2) How would you rate your ability to use a computer (e.g., using software applications, programming, or using a computer to find or process information)?	MV		3.90	1.18
3) How would you rate your writing abilities (e.g., writing to get across information or ideas to others or editing writing to improve it)?	MV		3.69	1.06
4) How would you rate your reading abilities (e.g., understanding what you read and identifying the most important issues or using written material to find information)?	MV		1.86	.27
5) How would you rate your oral communication abilities (e.g., explaining ideas to others, speaking to an audience, or participating in discussions)?	MV		2.26	.40

TABLE A2 (*Continued*)

Factor and Measure	Type (1)	Sign Reversal (2)	Loading (3)	Signal-to-Noise Ratio (4)
6) How would you rate your ability to solve new problems (e.g., identifying problems and possible causes, planning strategies to solve problems, or thinking of new ways to solve problems)?	MV		1.71	.23
7) How would you rate your mathematical abilities (e.g., using formulas to solve problems, interpreting graphs or tables, or using math to figure out practical things in everyday life)?	MV		2.36	.43
8) Numeracy test score	C		1.46	.19
Extraversion:				
1) I am stronger than most people I know	B		1.00	.12
2) I believe I could defend myself if someone attacked me	B		1.18	.17
3) I am not very good at sports	B	X	1.08	.14
4) Likelihood of trying bungee jumping	B		3.38	1.39
5) Likelihood of speaking your mind about an unpopular issue at school	B		1.00	.12
6) I avoid activities where I might be embarrassed	B	X	1.06	.14
7) Likelihood of going camping in the wild	MV		1.95	.46
8) Likelihood of exploring an unknown city or section of town	MV		1.48	.27
9) Likelihood of periodically engaging in a dangerous sport (e.g., mountain climbing or sky diving)	MV		2.94	1.05
10) You can do just about anything you really set your mind to do	MV		.93	.11
Conscientiousness:				
1) I am not good about preparing in advance for things, even if they have direct bearing on my future	B	X	1.00	.65
2) I do things impulsively, making decisions on the spur of the moment	B	X	.51	.17
3) I select activities in terms of how beneficial they are to my future	B		.67	.30
4) I do not like to plan ahead	B	X	.90	.53
5) I meet obligations to friends and authorities on time	B		.68	.30
6) I follow through with a course of action if it will get me where I want to be	MV		.93	.56
7) I am able to resist temptations when I know there is work to be done	MV		.85	.47
8) During my last year of high school, I did as little work as possible; I just wanted to get by	MV	X	.67	.29
9) I set subgoals and consider specific means for reaching them	MV		.90	.53
10) I often think about what I will be doing 10 years from now	MV		.52	.18

NOTE.—B = binary; C = continuous; MV = multivalued.

TABLE A3
CORRELATIONS BETWEEN AVAILABLE PROXY MEASURES AND THE OFFICIAL BFI-2 QUESTIONNAIRE, CANADIAN SAMPLE

	Proxy Extraversion	Proxy Conscientiousness	Proxy Emotional Stability
BFI-2 extraversion and facets	.46		
Sociability	.34		
Assertiveness	.41		
Energy	.30		
BFI-2 conscientiousness and facets		.63	
Organization		.53	
Productiveness		.57	
Responsibility		.51	
BFI-2 emotional stability and facets			.48
Lack of anxiety			.24
Lack of depression			.59
Emotional stability			.36

A3. Structural Results

TABLE A4
ESTIMATED COEFFICIENTS ON PREFERENCE AND CONSISTENCY PARAMETERS USING THE FULL STRUCTURAL MODEL

	Risk Aversion	Discount Rate	Risk Aversion Standard Deviation	Discount Rate Standard Deviation	% Hand Trembles
Female	.09*	.30***	−.09	.27***	.12
	(.05)	(.06)	(.06)	(.05)	(.10)
Emotional stability	.19	.90***	.16	.92***	.03
	(.16)	(.21)	(.12)	(.08)	(.17)
Cognitive ability	.50***	−.82***	.56***	−.91***	−.71***
	(.19)	(.19)	(.17)	(.07)	(.14)
Extraversion	−.34***	2.07***	−.23*	2.34***	.09
	(.12)	(.15)	(.12)	(.08)	(.18)
Conscientiousness	−.16***	−1.36***	−.27***	−1.48***	.12
	(.06)	(.07)	(.08)	(.06)	(.17)

NOTE.—Robust standard errors clustered at the individual level are shown in parentheses.
* Significance at the 10% level.
*** Significance at the 1% level.

TABLE A5

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

	Risk Aversion	Discount Rate	Risk Aversion Standard Deviation	Discount Rate Standard Deviation	% Hand Trembles
Female	.09**	.28***	−.09	.35***	.11
	(.05)	(.06)	(.07)	(.05)	(.09)
Emotional stability	.27***	1.71***	.19	2.06***	−.23
	(.04)	(.11)	(.16)	(.14)	(.23)
Cognitive ability	.52***	−1.11***	.64***	−1.08***	−.64***
	(.11)	(.16)	(.15)	(.09)	(.20)
Extraversion	−.51***	1.99***	−.28**	2.37***	.18
	(.05)	(.11)	(.12)	(.09)	(.20)
Conscientiousness	−.09**	−1.36***	−.16***	−1.64***	.05
	(.04)	(.06)	(.06)	(.10)	(.16)

Note.—Personality measures were selected based on the strength of correlations with corresponding traits from the BFI-2 questionnaire in the validation study. Robust standard errors clustered at the individual level are shown in parentheses.

** Significance at the 5% level.

*** Significance at the 1% level.

TABLE A6

Cross-sectional Variation in Preference and Consistency Parameters Explained by Observed and Unobserved Heterogeneity: Robustness

	Risk Aversion	Discount Rate	Risk Aversion Standard Deviation	Discount Rate Standard Deviation	% Hand Trembles
Unobserved types (R^2)	.55	.23	.64	.23	.75
Observed heterogeneity (R^2)	.45	.77	.36	.77	.25
Female (%)	4	3	3	3	6
Emotional stability (%)	16	22	12	23	24
Cognitive ability (%)	25	3	43	2	59
Extraversion (%)	50	22	13	22	6
Conscientiousness (%)	5	49	28	50	6

Note.—Personality measures were selected based on the strength of correlations with corresponding traits from the BFI-2 questionnaire in the validation study. The first two rows list the R^2 of the relevant linear regression (derived from eqq. [20]–[24]) of the structural parameter listed in each column title on the five unobserved types (first row) or four unobserved factors (second row) in simulated data. The remaining rows represent the fraction of the explained cross-sectional variation in each structural parameter attributable to the four factors related to cognitive ability and personality.

TABLE A7

Explanatory Power of Individual Parameters with Regard to Individual Choices

	Number of Safe Choices	Number of Impatient Choices	Number of Risk Reversals	Number of Time Reversals	Risk Switch Standard Deviation	Time Switch Standard Deviation
All parameters (R^2)	.86	.63	.59	.04	.11	.16
Risk aversion (%)	95.4	4.4	.2	.0	3.7	7.3
Discount rate (%)		94.5		9.7		12.6
Risk aversion standard deviation (%)	3.8	.6	2.3	.3	77.7	.7
Discount rate standard deviation (%)		.2		15.9		76.3
% hand trembles	.8	.3	97.5	74.1	18.6	3.0

Note.—The first row lists the R^2 of the regression of the moment listed in each column title on all five preference and consistency parameters. The remaining rows represent the part of explained variation attributable to each parameter. Outliers representing extreme values of risk aversion ($\Theta > 3$ and $\Theta < -1$) are excluded. This leaves 1,109 observations.

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