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Using Genes to Explore the Effects of Cognitive and Non-cognitive Skills on Education and Labor Market Outcomes

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Using genes to explore the effects of cognitive and non-cognitive skills on education and labor market outcomes

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Abstract

A large literature establishes that cognitive and non-cognitive skills are strongly correlated with educational attainment and professional achievement. Isolating the causal effects of these traits on career outcomes is complicated by reverse causality and selection issues. We suggest a new approach: using within-family differences in the genetic tendency to exhibit the relevant traits as a source of exogenous variation. Genes are fixed over the life cycle and genetic differences between full siblings are random, making it possible to establish the causal effects of within-family variation in genetic tendencies. We link genetic data from individuals in the Swedish Twin Registry to government registry data and find evidence for causal effects of the genetic predispositions towards cognitive skills, personality traits, and economic preferences on professional achievement and educational attainment. Our results also demonstrate that education and labor market outcomes are partially the result of a genetic lottery.

Keywords: personality traits, economic preferences, cognitive skills, labor markets, education
JEL codes: J24, D91, I26

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1 Introduction

A large literature in economics and psychology documents that cognitive skills and non-cognitive traits such as extraversion and mental stability are strongly correlated with educational attainment and professional achievement (Heckman and Rubinstein, 2001; Mueller and Plug, 2006; Heckman, Stixrud, and Urzua, 2006; Almlund et al., 2011). Determining whether there is an underlying causal effect of these traits on education and labor market outcomes is challenging for two reasons. First, educational and professional settings might themselves affect these traits and, second, traits might be correlated with observable and unobservable characteristics, including the childhood environment, that independently affect outcomes.

We suggest a new approach to tackling this longstanding question: using the genetic tendency to exhibit the relevant cognitive and non-cognitive skills as a proxy for individual traits. Genes are fixed over the life cycle, precluding reverse causality issues. Moreover, genetic differences between full siblings are random, allowing for the establishment of causal effects (Davies et al., 2019). We use data from nearly 30,000 fully genotyped individuals in the Swedish Twin registry which we link to registry data on educational attainment and labor market outcomes. We first establish the conditional correlation between these outcomes and the genetic tendency towards a range of non-cognitive traits and cognitive skills, controlling for socio-economic background. We then use a restricted sample of dizygotic twin pairs, taking advantage of random within-family variation in genes to establish the causal effects of the genetic tendencies.

We take advantage of recently improved polygenic indices (PGIs) for individual traits including extraversion, mental stability, openness, narcissism, risk seeking, time preferences, and cognitive skills (Becker et al., 2021). While most individual characteristics are at least partly heritable (Turkheimer, 2000), complex traits tend to be influenced by many individual genes, each with a very small effect (Chabris et al., 2015). PGIs summarize these small correlations between each individual gene and a given trait in a single number that represents an individual's genetic tendency to exhibit a certain trait or outcome (Rietveld et al., 2013; Okbay et al., 2016; Lee et al., 2018; Harden and Koellinger, 2020). We then link these trait PGIs to government registry data on educational attainment, income, and occupational prestige across the life cycle. The data also include a PGI for educational attainment (EA) which likely captures many of the cognitive and non-cognitive skills which influence EA (Demange et al., 2021) and which we use an indicator of having won the "genetic lottery" for a predisposition to do well in one's career.

Economists have long been interested in the economic effects of cognitive and non-cognitive skills. There is ample evidence that individual traits strongly correlate with educational attainment and labor market outcomes. For instance, several of the "big five" personality traits (Goldberg, 1990) have been found to predict income (Almlund et al., 2011). Of the big five traits for which we have good PGIs available, neuroticism (the inverse of mental stability) has been found to be negatively associated with earnings while more extraverted individuals tend to earn more and be more entrepreneurial, and more open[1] individuals tend to be more highly educated (Judge et al., 1999; Mueller and Plug, 2006; Brandstätter, 2011; Deming, 2017; Alderotti, Rapallini, and Traverso, 2021; Buser, Niederle, and Oosterbeek, 2021). Narcissism is part of the so-called dark triad traits that have been very widely studied in the personality psychology literature (Emmons, 1987; Jones and Paulhus, 2014) but have received little attention in economics. Psychologists have, however, documented correlations between narcissism and career-relevant outcomes such as counter-productive behavior at work (Penney and Spector, 2002). In a survey of the literature on narcissism in organizational contexts, Campbell et al. (2011) emphasize that narcissism is linked with an inability to maintain healthy longterm relationships at work and a tendency to alienate colleagues, leading to lower ratings for interpersonal performance. Economists have also studied the link between economic preferences and career outcomes. Most relevant for our study, willingness to take risk has been been found to be associated with education and wage growth (Shaw, 1996) as well as occupational choice (Bellante and Link, 1981; Dohmen

[1]Openness is also referred to as openness to experience or intellectual openness. It is a multi-faceted trait that captures imagination, aesthetic sensitivity, adventurousness, and intellectual curiosity.

et al., 2011; Koudstaal, Sloof, and Van Praag, 2016; Buser, Niederle, and Oosterbeek, 2021), while discounting the future is associated with lower investments in human capital (Sutter et al., 2013; Golsteyn, Grönqvist, and Lindahl, 2014; Alan and Ertac, 2018; Angerer et al., 2021). Finally, cognitive skills are strongly positively associated with educational attainment and income (Murnane, Willett, and Levy, 1995; Cawley, Heckman, and Vytlacil, 2001; Hanushek, 2009).

Establishing whether these correlations are due to causal effects of the cognitive and non-cognitive traits on career outcomes is challenging. Cognitive and non-cognitive skills correlate with and are influenced by the childhood environment and socioeconomic status of the parents (Fletcher and Wolfe, 2016; Doepke, Sorrenti, and Zilibotti, 2019; Falk et al., 2021), which could lead to selection on observed and unobserved factors. That is, individual traits are likely correlated with difficult-to-observe aspects of an individual's background which independently affect how well someone does in education and the labor market. Reverse causality is another plausible concern. Individual traits, preferences and skills are themselves affected by education and by the professional environment (Roberts and Mroczek, 2008; Carlsson et al., 2015). Indirect evidence for causal effects of individual traits comes from studies of the effect on education and labor market outcomes of interventions aimed at boosting cognitive skills or fostering a specific non-cognitive trait (e.g. Alan and Ertac, 2018; Alan, Boneva, and Ertac, 2019). Other studies use a structural approach to estimate the effects of cognitive and non-cognitive skills while taking reverse causality into account (e.g. Heckman, Stixrud, and Urzua, 2006; Todd and Zhang, 2020).

Our approach to establishing the effects of cognitive and non-cognitive traits on schooling and labor market outcomes builds on recent advances in social science genomics (Harden and Koellinger, 2020). Recent studies have used within-sibling pair genetic variation to establish how much of the correlation between a PGI and the corresponding trait is due to a causal genetic effect and how much is due to correlations between genotype and the environment (Selzam et al., 2019; Linnér et al., 2019).[2] We do not actually observe the phenotypical traits in our data (that is, we do not have direct measures of the non-cognitive traits and cognitive skills captured by the PGIs). Rather, we use the corresponding PGIs as proxies for the tendency towards these traits which are fixed along the life cycle. We then estimate the effects of variation in the trait PGIs on education and labor market outcomes.

Studies in economics that use PGIs have not typically employed within-family designs but have used samples of unrelated individuals and controlled for background characteristics. Most relevant to our study is Papageorge and Thom (2020), who find that a PGI for EA predicts labor income even conditional on education and that the predictive power of the EA PGI for actual college graduation is stronger for individuals from a higher socioeconomic background. Barth, Papageorge, and Thom (2020) find that an EA PGI predicts wealth at retirement, partially via improved financial decision making.

We find strong evidence for a causal effect of the predisposition toward stronger cognitive skills on income, occupational status, and educational outcomes. We also find evidence for significant effects of the predispositions toward several non-cognitive traits: individuals who tend to be more risk seeking, mentally stable, and open tend to work in more prestigious occupations. The opposite is true for individuals with a tendency towards narcissism or discounting the future. A tendency towards being open and forward-looking also increases educational attainment (EA). Finally, we document large causal effects of the general genetic tendency towards higher EA on all the outcomes we study. This illustrates that success in education and professional careers is in part down to "genetic luck". We also investigate heterogeneity in these effects by gender and socioeconomic status (SES) of the parents. We find some evidence of a stronger effect of the predisposition toward cognitive skills for high-SES individuals, in particular on educational outcomes. We also find that the effects of the genetic tendencies on income tend to be stronger for women, implying hat gender differences in labor market outcomes are generally larger for less skilled

[2] Researchers have also constructed PGIs for economic outcomes and then used within-family regressions to establish causality. Several studies construct PGIs for educational attainment (EA) and use within-family variation to establish that the link between the genes summarized in the PGI and EA is causal (Rietveld et al., 2014; Lee et al., 2018; Kong et al., 2018). Kweon et al. (2020) construct a PGI for income and use within-sibling pair regressions to establish causality. They also show that EA is a likely pathway for the genetic effects on income.

individuals. The exception is the link between genetic tendencies and management positions: our results suggest that cognitive and non-cognitive skills strongly increase the likelihood for men to work in a management position but that effects are much weaker for women.

The rest of the paper is organized as follows. Section 2 explains how the PGIs are constructed, describes the data set, and lays out the empirical methods. Section 3 presents the results. Section 4 concludes.

2 Methods and Data

2.1 Polygenic Indices

Human DNA consists of around 3 billion nucleotide pairs, the overwhelming majority of which are shared across individuals. Genome-wide association studies (GWAS) look for genetic variants that are associated with a particular trait. They are based on variations in nucleotide pairs in which some people carry a different base at a particular location (e.g., AT instead of GC). These so-called single nucleotide polymorphisms (SNPs) are the most common form of genetic variation. Because individuals have two copies of each chromosome, they have either two ATs, two GCs, or one AT and one GC at each position in their DNA. SNPs can therefore be coded as 0, 1, or 2. Due to the very large number of SNPs that are potentially relevant for human behavior and economic outcomes, it is difficult to incorporate them jointly in an econometric model. Instead, the established way of exploiting the SNP data is to construct a polygenic index (PGI) that additively summarizes the effects of more than 1 million SNPs.

Formally, a PGI s_i is a weighted sum of SNPs:

$$s_i = \sum_{j=1}^{J} \hat{\beta}_j x_{ij}$$

where x_{ij} is individual i's genotype at SNP j. The weights $\hat{\beta}_j$ are estimated in a genome-wide association study (GWAS) which tests all measured SNPs for associations with the outcome of interest. Since the number of SNPs J is typically orders of magnitude greater than the number of individuals in the sample, it is impossible to fit all SNPs simultaneously in a multiple regression. Instead, the outcome is regressed on each SNP separately, resulting in J regressions in total.

As a simplified example, imagine there are just two SNPs in the genome, for which a given individual can have either zero, one or two minor alleles.[3] A GWAS for educational attainment (EA) shows that each additional minor allele in the first SNP is associated with a five days increase in educational attainment and each additional minor allele in the second SNP is associated with a 10 days increase. The resulting PGI for EA would then consist of adding the number of minor alleles for the first SNP multiplied by 5 and the number of minor alleles for the second SNP multiplied by 10. The resulting single number is then interpreted as a measure of an individual's genetic predisposition towards EA.

The polygenic indices we use stem from the work of the Social Science Genetic Association Consortium (SSGAC) (Becker et al., 2021). They use several data sets and employ a unified approach to estimate new, more predictive PGIs for a large range of traits and outcomes. They did not use the STR data we use for our analyses, meaning that the GWAS discovery for the PGIs we use was conducted on independent data. On top of the standard "single-trait" PGIs, Becker et al. (2021) also constructed so-called "multi-trait" PGIs for some traits. The idea behind a multi-trait PGI is to first look for other "supplementary" traits that have a large genetic correlation with the target trait (that is, they are partially predicted by the same SNPs).[4] The SNPs that predict the supplementary traits can then be used to boost the predictive power of the PGI for the target trait (Turley et al., 2018). Multi-trait

[3] An "allele" is one of the forms of a gene variant. A "minor allele" is the less common form.

[4] Becker et al. (2021) treat a trait as supplementary to a target trait if the pairwise genetic correlation between the traits is higher than 0.6.

PGIs are in general more predictive of the trait but cannot necessarily be interpreted in the same way. Because the multi-trait PGIs are based on a weighted average of GWAS estimates for several traits, they are more likely than single-trait PGIs to also capture other traits. We pre-registered our selection of PGIs but our pre-analysis plan does not specify whether we use single-trait or multi-trait PGIs in our analyses. We will therefore choose the more cautious approach and mainly focus on the single-trait results when describing our results and, where available, also present results for the multi-trait versions of the PGIs.

We are interested in PGIs for established personality traits and economic preferences. We pre-registered our selection of PGIs before we had access to the PGIs in the Twin Registry.[5] To avoid low-powered analyses, we only pre-registered traits where the PGI predicts the corresponding trait with an R^2 above two percent. This includes the personality traits extraversion (R^2 3.88%) and neuroticism[6] (R^2 5.67%), risk seeking (R^2 2.45%), as well as several measures of cognitive skills, of which we use cognitive performance (R^2 10.73%) and self-rated math ability (R^2 8.47%). Finally, we also use a PGI for educational attainment (EA) (R^2 7.27%) which likely captures a variety of cognitive and non-cognitive skills which influence EA and which we use an indicator of having won the "genetic lottery" for a predisposition to do well in one's career.[7]

On top of the pre-registered traits, the STR data contains two additional PGIs for standard traits from the personality psychology literature with an R^2 of between 1 and 2 percent (the STR set the cutoff for the inclusion of a PGI from the SSGAC at 1 percent), namely openness and narcissism. Both of these are very prominent in the personality psychology literature and are therefore interesting to study. As it turns out, there is enough variation in these traits to estimate precise effects and we therefore also conduct analyses using openness and narcissism, noting that the use of these traits was not pre-registered. We deviate from the pre-registered selection of PGIs in two additional ways. First, we use the self-rated math ability PGI rather than the PGI for highest math studied. This is because the highest math PGI turned out to be very highly correlated with the EA PGI, thereby capturing educational attainment rather than a separate math ability trait. Second, we do not use the delay discounting PGI which we pre-registered to study the effect of time preferences. This is because the single-trait version of this PGI has a very low R^2 and we realized that the more predictive multi-trait version relies so heavily on the EA and math attainment PGIs as to basically capture educational attainment rather than time preferences. The data contain a PGI with relatively high predictive power (R^2 5.43%) for having ever been a smoker, which can be seen as a proxy for heavily discounting the future (Khwaja, Sloan, and Salm, 2006; Chabris et al., 2008; Sutter et al., 2013). We use this PGI as an imperfect replacement for the delay discounting PGI.[8] The results for the PGIs that were not pre-registered should be interpreted more cautiously as these analyses are more exploratory.

The traits proxied by the PGIs are partially correlated with each other (see e.g. Buser, Niederle, and Oosterbeek, 2021) and it is therefore to be expected that some SNPs are associated with more than one trait, meaning that the trait PGIs are likely correlated with each other to some extent. Table 1 in the appendix shows the pairwise correlations of the nine single-trait PGIs in our data. Multi-trait PGIs are more likely than single-trait PGIs to correlate with other trait PGIs as they are based on a weighted average of GWAS estimates for several closely related traits.[9]

[5] https://osf.io/hf6uq/?view_only=4de6640024c641ef8c9ed47eabea5446

[6] In our analyses we use the inverse of neuroticism (usually referred to as "mental stability ").

[7] The R^2 for the different traits refers to the predictive power of the different PGIs for the corresponding trait as found by Becker et al. (2021).

[8] Smoking is genetically correlated with other behaviors such as substance abuse as well as with attention deficit/hyperactivity disorder (ADHD), meaning that some of the same genes that predict a tendency towards smoking also predict these other traits (Linner et al., 2020). This means that apart from a tendency to discount the future, the smoking PGI also captures other "externalizing" traits. Smoking could also affect outcomes through direct health effects and social effects (such as other people discriminating against smokers) which are unrelated to time preferences. We would expect this to be more of an issue for labor market outcomes than for educational outcomes.

[9] The multi-trait versions of each trait use the following supplementary traits. Extraversion: frequency of feeling left out of social activity. Neuroticism: depression, subjective well-being, loneliness. Risk: adventurousness. Cognitive performance: self-rated math ability, math attainment, educational attainment. Self-rated math ability: math attainment, cognitive performance. Educational attainment: math attainment, delay discounting, cognitive performance, age at first birth, religious attendance. Openness, narcissism

The main data sources used by Becker et al. (2021) to construct the PGIs are the UK Biobank (UKB) and 23andme, an online direct-to-consumer DNA testing service. For many traits, published meta-analysis results that included other samples were also included. The exact trait measure used for the same PGI can vary across datasets. Neuroticism is assessed through the 12-item EPQ-R Neuroticism scale (Eysenck, Eysenck, and Barrett, 1985; Lo et al., 2017) in the UKB sample and the widely used Big Five Inventory (BFI) (John, Donahue, and Kentle, 1991) in the 23andme sample. Extraversion and openness are available in 23andme and are assessed through the BFI. Narcissism is available in the 23andme data and is measured through a single Likert scale question: "How narcissistic (a narcissist is someone who is egotistical, self-focused, and vain) do you think that you are?". Risk seeking is assessed by a binary question in the UKB sample ("Would you describe yourself as someone who takes risks?") and a five-point Likert scale question in the 23andme sample ("In general, people often face risks when making financial, career, or other life decisions. Overall, do you feel comfortable or uncomfortable taking risks?"). Cognitive performance is available in the UKB sample and is based on the number of correct answers given to 13 fluid intelligence questions. Self-rated math ability is available in the 23andme sample and is based on a five-point Likert scale question ("How would you rate your mathematical ability?"). Finally, educational attainment is measured as years of education. See Becker et al. (2021) for further details on the data sources and methods underlying the PGIs.

2.2 Data

Carrying out our research agenda requires a dataset which contains polygenic indices for personality traits and cognitive skills for a large number of full sibling pairs as well as data on career outcomes and good indicators of socioeconomic background. The Swedish Twin Registry (STR) – the world's largest twin registry containing all twins born in Sweden from 1886 onwards (Lichtenstein et al., 2006) – is ideal in several ways. Approximately 43,000 of the twins in the registry are genotyped and the most recent PGIs from Becker et al. (2021) are available. STR data can be linked to administrative data through Statistics Sweden which allows us to construct indicators of educational attainment, income, and occupation. Individuals can be linked to the administrative data of their parents, allowing us to construct an indicator of parental socioeconomic status (SES).

We are interested in educational attainment and labor market success. We look at six pre-registered outcomes: three indicators of labor market achievement and three indicators of educational attainment. Our main indicator of labor market success is individual income, defined as the average income percentile relative to one's birth cohort across the life cycle from age 25 to 65. By using relative rather than absolute income, we avoid issues due to changes in the definition of the income variable across census years. We use work income data from the national censuses in 1970, 1975 and 1985 and the labor panel dataset (LISA) annually from 1990-2018, to construct this variable in the following way. First, we use population-wide income data to obtain birth year-specific income distributions. Second, we use this information to calculate the income percentile of each observation in the twin sample. Third, we take the average of all income percentile observations per individual.

We also look at two indicators of occupational status: the Treiman scale (Ganzeboom, De Graaf, and Treiman, 1992), which is an index of occupational status, and a binary indicator for ever having held a management position. The Treiman scale is constructed based on occupational codes retrieved from the censuses and the LISA database. All occupational codes are first converted to the 1996 version of the Swedish Standard for Occupational Classification. We then map the SSYK codes to the corresponding Treiman codes. Finally, we calculate the average value across all available years using the same method described for relative income. The translation scheme between the Swedish occupational codes and the Treiman scale is described in the appendix. We use the first digit in the Swedish occupational codes to define the management position indicator.[10]

and smoking are not available as multi-trait PGIs.

[10]The first digit/major groups in the Swedish occupational codes closely resemble the corresponding ISCO 88 codes, where 1 is equal

Our main indicator of educational attainment is years of education, which we construct from indicators of education level in the LISA database and the 1970 census for older individuals. The translation scheme between these variables and years of education can be found in the appendix. We also use this data to construct binary indicators for having graduated from university and finished high school.[11]

We use a measure of family SES that is constructed as an additive index of two items: highest parental education and average parental earnings. We use parental earnings data for the closest available year to the parent being aged 55, i.e. ten years before retirement. To adjust for differences in scales between the two variables, we initially standardize the subitems to have a mean of 0 and a standard deviation of 1. We use population data to obtain means and standard deviations for each birth year and then carry out the standardization separately for each cohort in order to take into account changes in average income and education level over time. Consequently, our measure of family SES takes a value of 0 for an individual from a family with an average score on each of the two items relative to other families in the same cohort. For individuals where parental education is missing, we use parental income only and vice versa. For a similar approach to measuring family SES using Swedish register data see Lindgren, Oskarsson, and Persson (2019).

2.3 Analysis

Naive regressions of outcomes on PGIs do not generally identify the causal effects of the SNPs summarized in the PGIs. GWAS results and, consequently, the resulting PGIs, may contain environmental confounds. This can be due to "genetic nurture" (Plomin and Bergeman, 1991; Kong et al., 2018). That is, the environment provided by parents might be correlated with and influenced by their genes (and therefore the genes of their children). Another potential confounder is assortative mating. If individuals with certain genetic tendencies select mates who have particular genetically influenced traits, this can induce spurious genetic correlations (Hartwig, Davies, and Davey Smith, 2018). Furthermore, different subgroups in a population that have different allele frequencies may have different outcomes due to other non-genetic factors such as cultural norms, policies, geographic environments, or economic circumstances. This can induce bias known as population stratification (Hamer and Sirota, 2000). At the GWAS stage, researchers typically try to limit bias from population stratification by restricting samples to a relatively homogenous population – usually by limiting the study sample to individuals of European descent – and by controlling for the leading principal components of the genetic-relatedness matrix (Price et al., 2006). However, this is not always sufficient for completely eliminating population stratification (Abdellaoui et al., 2013).

Because any difference in genes between full siblings is due to random differences in how the mother's and father's genes were combined at conception, the estimated effects of PGIs on outcomes using regressions that control for family fixed effects can be interpreted as causal. For these analyses, we have to restrict the sample to fully genotyped pairs of dizygotic twins. That is, we have to drop all observations from monozygotic (identical) twins and from dizygotic twins whose sibling was not genotyped. We also show results from regression analyses that use the full dataset of genotyped STR twins. This allows us to use a much larger sample, increasing statistical power to detect associations between the trait PGIs and outcomes, but these estimates are then potentially subject to the mentioned biases. To tackle this issue as thoroughly as possible, we control for parental SES, dummies for municipality of residence at age 16[12], and birth-year dummies interacted with gender, as well as the first 20

to "legislators, senior officers and managers". If we define the outcome as having belonged to this category at least once during the time period for which we have data (every fifth year between 1970 and 1990 and annually 2001-2018) around 10% of the sample falls into this category.

[11] These are constructed by using the first digit of the SUN system (Swedish educational nomenclature, a version of the ISCED) where the categories 3 and 5 correspond to high school and university respectively. We also pre-registered a more general "higher education" indicator defined as the SUN category 4, but it turned out that this group overlaps very strongly with the university graduates, leading to very similar results and insights.

[12] We have access to annual information on municipality of residence from 1968 and onwards. For 1960 and 1965 we can retrieve corresponding information from the quinquennial censuses. We use the information on municipality of residence from the census closest in time to the 16th birthday and use the information from the 1960 census for anyone born in or before 1946. We use the contemporary

genetic principal components. Selzam et al. (2019) show that much of the difference between within-family and between-family estimates can be eliminated by controlling for family SES. To the extent that genetic nurture is present within SES strata, we expect the within-family estimates to be smaller than the full-sample estimates. Note, however, that within-family estimates tend to be somewhat downward biased for other reasons (Trejo and Domingue, 2018; Young et al., 2019).

2.4 Sample

For the full-sample analyses looking at educational outcomes, we will limit the dataset to genotyped individuals born between 1934 and 1995 (that is, individuals who have likely completed their education) whom we can link to their parents' records for the construction of the socioeconomic controls.[13] This subsample contains 29,393 individuals. For the analyses looking at labor market outcomes, we will limit the dataset to individuals born between 1934 and 1990 (that is, individuals who have likely completed their education and worked for a few years). This subsample contains 25,515 individuals. For our causal analyses using within-family variation, we will limit the sample to complete sets of genotyped dizygotic twins. This sample contains 11,344 individuals (5,672 twin pairs) for the education analyses and 9,594 individuals (4,797 twin pairs) for the income analyses.

Table 2 in the appendix shows means and standard deviations of the outcome and control variables for the two samples (the full sample with socioeconomic controls and the restricted sample of dizygotic twin pairs used in the within-family fixed effects regressions). The two samples look very similar, meaning that the genotyped individuals in the sample whose dizygotic twin was also genotyped do not observably differ from the rest of the sample.

An important requirement for our strategy of using family fixed effects regressions to identify causal effects is that there is enough variation in the PGIs between full siblings. Figure 5 in the appendix shows cumulative distribution functions of the within-family difference in each of the nine PGIs. We also indicate the median difference on each graph. The median differences are between 0.64 and 0.68 standard deviations and, on each PGI, around 30 percent of sibling pairs differ from each other by more than one standard deviation.

3 Results

In this section, we present the results in two steps. First, we present the results for the impact of the PGIs on the six pre-registered education and labor market outcomes. Second, we explore whether these effects vary with SES and gender. All regression specifications are pre-registered.[14] Throughout, we use a strict significance threshold of 0.005 for designating a result as "statistically significant" and designate results that are significant at 0.05 as "suggestive", as recommended by Benjamin et al. (2018). All our hypothesis tests are two-sided and we use OLS with standard errors clustered at the family level for all regression analyses.

3.1 Main results

In this section, we will discuss the regression results documenting the effects of the genetic tendency towards eight non-cognitive and cognitive traits (extraversion, mental stability, openness, narcissism, risk seeking, time discounting as proxied by ever having been a smoker, cognitive performance, and math ability) on labor market outcomes and educational attainment. We consider three indicators of success in the labor market − average income percentile

division into 290 municipalities.

[13] We lose around a tenth of the genotyped individuals whom we cannot link to their parents and for whom we can therefore not calculate the socioeconomic controls.

[14] See Section 2 for a detailed description of how we deviate from the pre-registered selection of PGIs. In the appendix, we also show regression results for the original selection of PGIs. Tables 27 to 32 show full-sample conditional OLS results using the originally pre-registered PGIs. There, we use multi-trait PGIs because the single-trait PGI for delay discounting lacks predictive power and is therefore not available in the STR data.

relative to one's birth cohort across the life cycle, average percentile of occupational status relative to one's birth cohort across the life cycle, and a binary indicator for ever having held a management position – and three indicators of educational attainment – years of education, a binary indicator for having graduated from university, and a binary indicator for having finished high school.

Tables 3 to 14 in the appendix show full regression results for each of the six outcome variables using two different specifications. The first uses OLS regressions controlling for parental SES, dummies for municipality of residence at age 16, birth-cohort dummies interacted with gender, and the first 20 genetic principal components, using the full sample. The second restricts the sample to complete sets of dizygotic twins and uses OLS regressions controlling for family fixed effects and gender. For each specification and outcome, we run five regressions which include different PGIs: 1. personality traits (extraversion, mental stability, openness, and narcissism); 2. economic preferences (risk seeking and smoking, our proxy for time discounting); 3. cognitive skills (cognitive performance and self-rated math ability); 4. these eight PGIs simultaneously; and 5. educational attainment, which likely captures many cognitive and non-cognitive traits. Apart from the main results using single-trait PGIs, for each specification and outcome we also present tables using multi-trait PGIs for the traits for which they are available.

The main results are summarized in Figure 1, where we plot regression coefficients and confidence intervals (95 and 99.5 percent) for the effect of each single-trait PGI on each outcome using each of the two regression specifications (OLS with socio-economic controls and within-family regressions). The PGIs are standardized and the coefficients therefore represent the effect of a one-standard deviation increase in the PGI on the outcome variable.

The various PGIs differ in their predictive power for the trait of interest. This means that a one-standard deviation difference in one PGI might represent a larger or smaller difference in the underlying trait than is the case for a one-standard deviation difference in another PGI. The absolute and relative magnitudes of the PGI effects are therefore not necessarily representative of the actual absolute and relative impacts of the traits proxied by the PGIs. In Figure 2, we present the same results as in Figure 1 with each coefficient scaled by the inverse of the standardized beta coefficient from a regression of the actual trait on the PGI. That is, we multiply the relationship between each outcome and each PGI by the relationship between the PGI and the actual underlying trait.[15] The graphs in Figure 2 therefore show approximate impacts in terms of a one-standard deviation increase in the actual trait (rather than in the trait PGI as in Figure 1), keeping in mind that PGIs might partially capture unobserved genetically correlated traits and that estimates are likely downward biased by measurement error.[16]

Before we discuss the results in detail, we summarize them in three overall conclusions: 1. income and occupation are affected by both cognitive skills and non-cognitive traits. 2. educational outcomes are similarly affected by both non-cognitive traits and cognitive skills. 3. the coefficients generally look quite similar when we only use within-family variation in PGIs, providing new evidence for causal effects of non-cognitive traits and cognitive skills on education and labor market outcomes. While the family fixed-effects (FE) estimates are often similar in magnitude, they are less precisely estimated. For the results summarized above, the coefficients on genetic tendencies estimated through the full-sample OLS regressions conditional on SES are generally significant at our strict 0.5-percent threshold. The FE estimates are mostly significant at the 5-percent suggestive evidence threshold.

The upper-left panels of Figures 1 and 2 (plus Tables 3 and 4 in the appendix) show the effects of the PGIs on the average income percentile relative to one's birth cohort across the life cycle. We also consider two additional indicators of career success: the average percentile of occupational prestige, as measured by the Treiman scale, across the life cycle (the upper-right panels of Figures 1 and 2 plus Tables 5 and 6 in the appendix), and an indicator for ever having held a management position (the center-left panels of Figures 1 and 2 plus Tables 7 and 8 in the appendix).

[15] The STR data does not contain direct measurements for all of our cognitive and non-cognitive traits. To obtain an approximation of the standardized betas, we use the incremental R^2 for each PGI as reported by Becker et al. (2021) and make use of the fact that standardized beta coefficients are roughly equal to $\sqrt{\Delta R^2}$.

[16] When using PGIs as proxies for individual traits, measurement error occurs both because the traits are only partially heritable and because the PGIs only partially capture the heritable variation in the traits.

We find significant evidence that personality traits and economic preferences are associated with income and professional status. Increases in the mental stability and risk tolerance PGIs and decreases in the narcissism and smoking (our proxy for discounting the future) PGIs are associated with significantly higher lifetime income and occupational prestige. Individuals with a tendency towards greater openness hold more prestigious occupations but do not earn significantly more.[17] Looking at our third indicator of labor market success, we find that individuals with a tendency towards mental stability and risk taking are significantly more likely to have ever held a management position. The effects of the four personality PGIs and the two economic preference PGIs on labor market outcomes are also typically jointly statistically significant.

The causal FE estimates are generally similar in magnitude, if slightly smaller, but more noisily estimated. The FE coefficients are still often individually and jointly significant at the 5-percent level. The magnitude of the coefficients on the non-cognitive PGIs also tend to shrink when we include all eight trait PGIs simultaneously (column 4 in the regression tables). This is because the trait PGIs are correlated with each other. In particular, the openness, risk seeking and extraversion PGIs are all positively correlated with each other and the risk seeking PGI is also positively correlated with mental stability PGI (see Table 1 in the appendix).[18]

How economically meaningful are these effects of non-cognitive traits on labor market outcomes? To answer this question, we can use the scaled effects in Figure 2 as an approximation of the effect of the traits proxied by the PGIs. One-standard deviation differences in the mentioned non-cognitive traits are each associated with a 3-5 percentile difference in lifetime relative income and an up to 10 percentile difference in lifetime professional prestige.

We also find strong and significant effects of genetic tendencies towards cognitive skills on income and professional status, but less so on having held a management position. Among the PGIs based on the results of Becker et al. (2021), the cognitive PGIs tend to be more predictive of the associated trait than the PGIs for non-cognitive traits. Consequently, the effects we estimate for the cognitive skill PGIs are generally stronger and more precisely estimated than those for the non-cognitive trait PGIs. The scaled estimates in Figure 2, however, show that the effects of the underlying non-cognitive traits are likely of similar magnitude as the effects of the cognitive traits. Finally, variation in the genetic tendency toward higher educational attainment – which likely captures many relevant cognitive and non-cognitive traits – is strongly associated with higher lifetime income and professional status.

We will now look at the effects of the cognitive and non-cognitive traits on educational outcomes. The center-right panels of Figures 1 and 2 and Tables 9 and 10 in the appendix show the effects of the PGIs on years of education. We find strong and statistically significant effects for the cognitive skill PGIs, as well as for the genetic tendencies towards openness, narcissism, and being forward-looking (as proxied by not smoking). We also look at the likelihood of graduating from university and finishing high school (the two lower panels of Figures 1 and 2 plus Tables 11 and 14). The same genetic tendencies that significantly affect years of education tend to affect the likelihood of having a university degree. At the other end of the education spectrum, cognitive skills seem to matter more than non-cognitive traits for the likelihood of finishing high school. Our causal estimates using FE regressions tend to be slightly smaller but still sizable and statistically significant at the 5 or even 0.5 percent level, providing evidence for a causal impact of genetic predispositions towards both non-cognitive traits and cognitive skills on educational attainment.

The scaled estimates in Figure 2 show that the magnitudes of the effects are economically meaningful. A one-standard deviation difference in the cognitive performance PGI is associated with a roughly 10 percentage points increase in the likelihood of having graduated from university. The effect of math skills is roughly 5 percentage points. These two effects are estimated simultaneously, meaning that an individual with one-standard deviation

[17]This could be because open individuals tend to be attracted to artistic occupations (Judge et al., 1999), which might be prestigious but might not necessarily lead to high earnings. Buser, Niederle, and Oosterbeek (2021) similarly find that while more open individuals are more highly educated, they do not earn more conditional on education. We actually find that the openness PGI is negatively correlated with income but the sign reverses in the fixed effects regressions, one of very few instances where this happens.

[18]These correlations in PGIs are due to the underlying traits being correlated. For example, Buser, Niederle, and Oosterbeek (2021) similarly find that openness, risk seeking, extraversion, and mental stability are positively correlated with each other.

higher cognitive performance and math skills is around 15 percentage points more likely to graduate from university. The effects of the significant non-cognitive traits (openness, narcissism, and time discounting as proxied by smoking) are similarly large. Finally, a one-standard deviation increase in the educational attainment PGI is associated with 0.4 to 0.6 additional years of education.

Overall, our results suggest that both cognitive skills and non-cognitive traits causally affect the career trajectories of individuals. In most cases, the causal effects of the genetic tendencies obtained through the regressions using the restricted sample of dizygotic twins and controlling for family fixed effects are only slightly attenuated relative to the more precisely estimated coefficients obtained by OLS controlling for socioeconomic status, age, and gender. This indicates that our SES controls capture most of the spurious correlation between PGIs and outcomes that can occur due to selection of parents with certain genes into more favorable environments (see also Selzam et al., 2019). The exception is the smoking PGI that we use as a proxy for time preferences. Although the family FE estimates are often significant at the 5 or even 0.5 percent level, the magnitude of the effect is often quite a bit lower than the conditional OLS estimates. Smoking is an imperfect proxy for time preferences as it may affect outcomes in multiple ways, including through indirect health effects (smoking by parents might affect the health of children prenatally and at a young age). This confound is not present when controlling for family fixed effects and a bigger difference between the OLS and fixed effect results for smoking relative to the other trait PGIs is therefore to be expected.

The results presented so far are from linear regressions. In Figures 6 to 11 in the appendix, we show predicted values of each outcome at each quintile of each PGI. These predictions are based on OLS regressions using the same set of socio-economic controls as the regressions presented so far, but splitting each PGI into quintiles and including these as dummy variables in the regression. The main insight is that the relationships between traits and outcomes we discovered are almost always monotonous and often close to linear. We conclude that there appear to be no important non-linearities in the relationships between the PGIs and the outcomes we consider.

Our results also show the importance of the "genetic lottery" as a determinant of career trajectories. As an example, 12 percent of individuals in our sample have ever held a management position. This increases or decreases by nearly 3 percentage points (or roughly 25 percent) for someone whose genetic tendency for risk seeking and mental stability are both one standard deviation higher or lower. Or take the educational attainment PGI which likely summarizes many genetically influenced traits. The FE results show that for two siblings with the same parents, born on the same day, and raised in the same home, a one-standard deviation difference in the genetic predisposition towards educational attainment leads to a difference of 2 percentiles in life-time income and a 6 percentage points difference in the probability of graduating from university.[19]

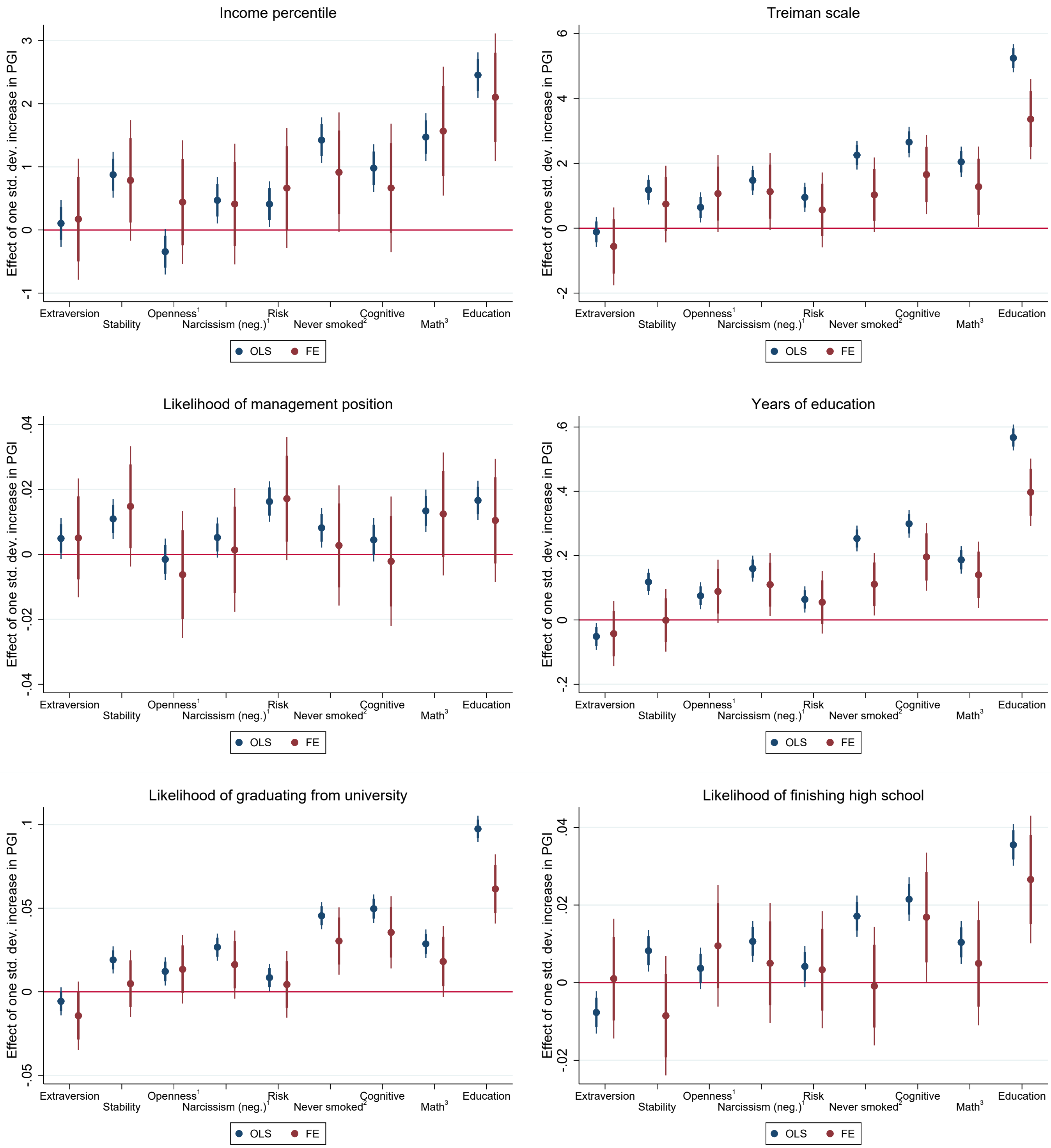
3.2 Heterogeneity by SES and Gender

We will now look at whether the estimated relationships vary with socio-economic background and gender. All of the outcomes we are interested in correlate strongly with socio-economic background. Individuals with higher-SES parents earn more, work in more prestigious occupations, are more likely to be managers, and are more highly educated. There are plausible reasons to expect the effects of cognitive and non-cognitive traits on these outcomes to be both stronger or weaker for higher-SES individuals. On the one hand, it may be that high-SES individuals can make up for lower skills through their other advantages whereas for low-SES individuals only those with high cognitive and non-cognitive skills make it to the top, leading to stronger genetic effects for low-SES individuals. On the other hand, it may be that advantaged individuals are better able to translate their genetic potential into education and labor market success, leading to stronger genetic effects for high-SES individuals.

Women in our sample on average earn less than men, work in less prestigious occupations, and are less likely to be

[19] Differences in the polygenic indices of such magnitude are not rare. Even among full siblings in our data, 28 percent of pairs differ in their educational attainment PGI by more than one standard deviation (see also Figure 5).

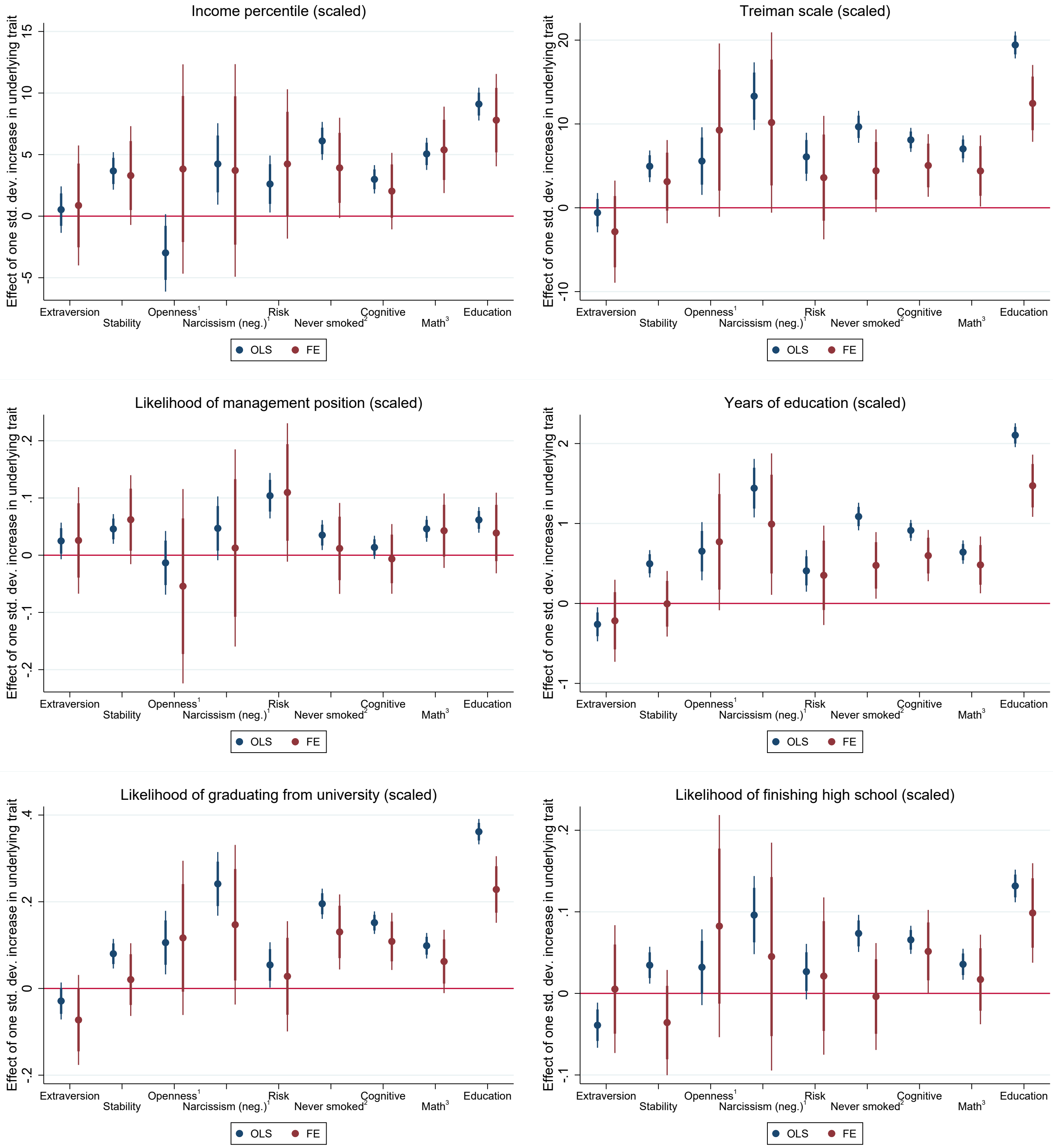
Figure 1: Main regression results



Note: Thick (thin) error bars represent 95% (99.5%) confidence intervals. The PGI coefficients were estimated in four separate regressions: personality traits (extraversion, stability, openness, and narcissism), economic preferences (risk taking and smoking), cognitive skills (cognitive performance and math ability), and educational attainment. The OLS regressions control for birth year dummies interacted with gender, dummies for municipality of residence at age 16, SES, and the first 20 genetic principal components. The FE regressions control for family fixed effects and gender. Standard errors are clustered at the family level.

[1]Trait not preregistered.
[2]PGI for ever having been a smoker replaces preregistered delay discounting PGI.
[3]PGI for self-judged math ability replaces preregistered PGI for highest math attained.

Figure 2: Main regression results (scaled)



Note: Thick (thin) error bars represent 95% (99.5%) confidence intervals. The PGI coefficients were estimated in four separate regressions: personality traits (extraversion, stability, openness, and narcissism), economic preferences (risk taking and smoking), cognitive skills (cognitive performance and math ability), and educational attainment. The OLS regressions control for birth year dummies interacted with gender, dummies for municipality of residence at age 16, SES, and the first 20 genetic principal components. The FE regressions control for family fixed effects and gender. Standard errors are clustered at the family level. The coefficients are scaled by the inverse of the effect of a one-standard deviation increase in the PGI on the standardized trait.

[1]Trait not preregistered.

[2]PGI for ever having been a smoker replaces preregistered delay discounting PGI.

[3]PGI for self-judged math ability replaces preregistered PGI for highest math attained.

managers. On the other hand, they have higher educational attainment. This indicates that, relative to education, women face higher barriers in their professional careers, for instance due to family obligations or discrimination (Bertrand, 2020). We therefore expect similar effects of traits on education for men and women but potentially different effects on income and occupation.

Tables 15 to 20 in the appendix repeat the full-sample OLS regressions but linearly interact each PGI with our indicator of parental SES. We summarize the regression results in Figure 3, where we show the estimated effect of each trait for individuals with parental SES one standard deviation below and one standard deviation above the mean.

We do not find robust evidence that the previously documented effects of cognitive and non-cognitive traits on labor market and education outcomes differ by socioeconomics background. The exception are the effects of the cognitive skill PGIs and the EA PGI on educational outcomes. High-SES individuals seem to be better able to translate genes that favor educational attainment into university degrees. On the other hand, the relationship between the same PGIs and the likelihood of finishing high school tends to be stronger for low-SES individuals. That is, the SES gap in university graduation is larger and the gap in high school graduation is smaller for individuals with genes that favor education. The latter is likely due to the fact that most individuals from a favorable socioeconomic background finish high school no matter what.[20]

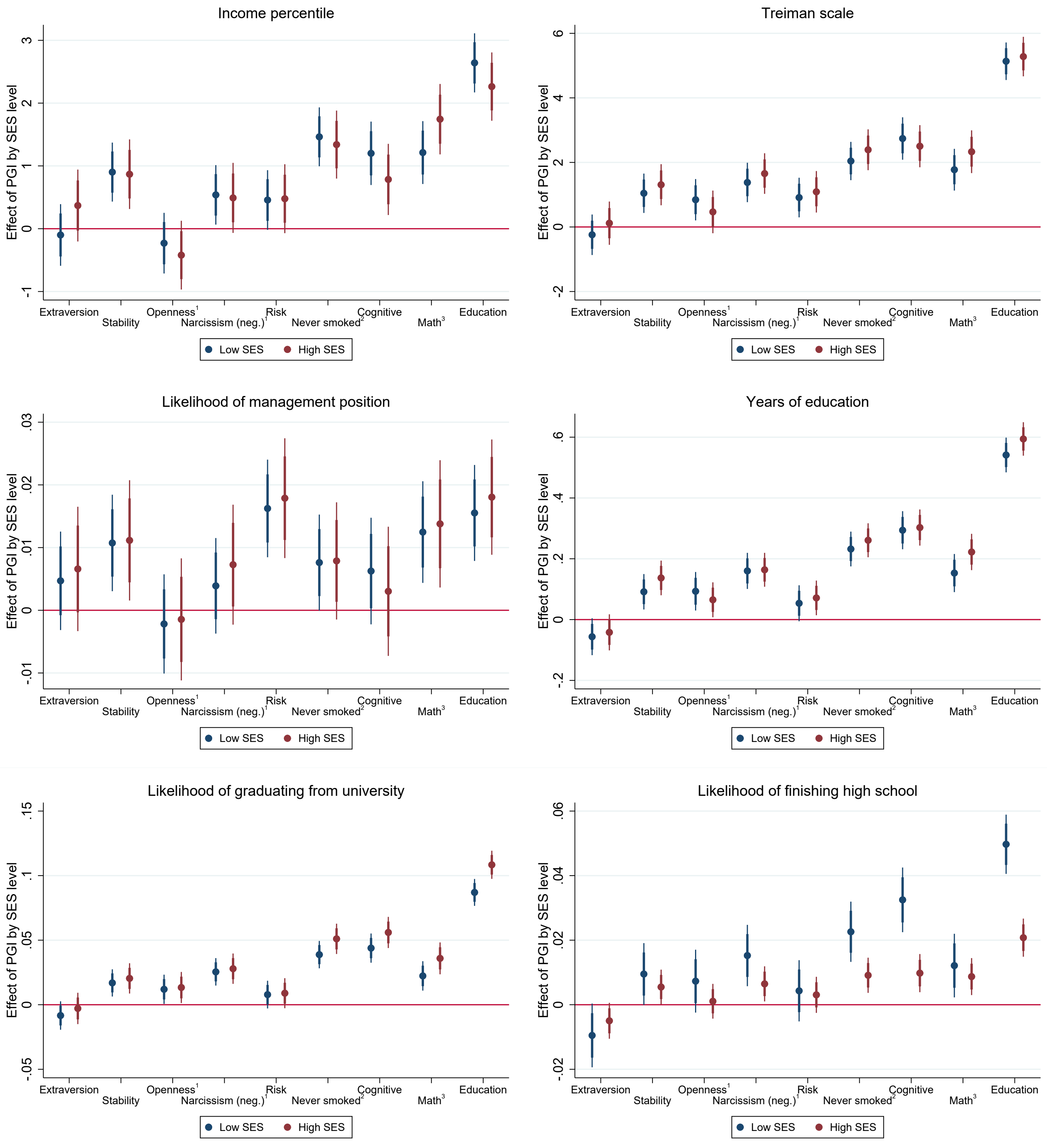
How meaningful are the magnitudes of these interactions? The estimates in column 4 of Table 19 show that – conditional on birth year interacted with gender, the leading genetic principal components, and all trait PGIs – a one-standard deviation difference in SES is associated with a 13.2 percentage points difference in the likelihood of holding a university degree. This SES-difference changes by 1.4 percentage points for a simultaneous one-standard deviation change in the cognitive performance and math ability PGIs. That is, the gap in university graduation between individuals with a socioeconomics background one standard deviation below and above the mean is 27.8 percentage points for individuals with genes that favor education (cognitive PGIs one standard deviation above the mean) and 25.0 percentage points for individuals with less favorable genes (cognitive PGIs one standard deviation below the mean). If we use the same method as in Figure 2 to scale the PGI effects, the joint effect of the two interactions increases from 1.4 to 4.5 percentage points. This means that the gap in university graduation between individuals with a socioeconomic background one standard deviation below and above the mean is 30.9 percentage points for individuals with genes that favor education (cognitive PGIs one standard deviation above the mean) and 21.9 percentage points for individuals who are less genetically predisposed towards educational attainment (cognitive PGIs one standard deviation below the mean).

It is also instructive to compare the main effects of the PGIs to the SES coefficient. If we take the EA PGI as an overall measure of the genetic predisposition to do well in one's career, we see that for most outcomes, the magnitude of the PGI coefficient is of very similar magnitude as the SES coefficient, meaning that a one-standard deviation difference in the genetic predisposition to education is as important for education and labor market outcomes as a one-standard deviation difference in our measure of socioeconomic background.

In Tables 21 to 26 in the appendix, we investigate heterogeneity by gender. The results are summarized in Figure 4. Despite being higher educated, women in our sample earn less, hold occupations with lower prestige, and are much less likely to be managers. We find suggestive evidence that some of the previously documented trait effects vary by gender. In particular, many of the significant relationships between traits and income are stronger for women, meaning that the gender-income gap is smaller for individuals who are genetically pre-disposed to being more stable, more risk tolerant, or less narcissistic. We also find a stronger relationship between the EA PGI and income for women, meaning that the gender gap is smaller among individuals who are genetically predisposed to being more highly educated. The gender-interaction effects are much weaker and not statistically significant when looking at occupational prestige rather than income. This makes sense as the 3 percentile gender gap in prestige

[20] 91 percent of individuals from the highest SES quartile finished high school but only 76 percent from the lowest quartile.

Figure 3: Heterogeneity results: SES



Note: Thick (thin) error bars represent 95% (99.5%) confidence intervals. The PGI coefficients were estimated in four separate regressions: personality traits (extraversion, stability, openness, and narcissism), economic preferences (risk taking and smoking), cognitive skills (cognitive performance and math ability), and educational attainment. The regressions control for birth year dummies interacted with gender and the first 20 genetic principal components. Standard errors are clustered at the family level.

[1] Trait not preregistered.

[2] PGI for ever having been a smoker replaces preregistered delay discounting PGI.

[3] PGI for self-judged math ability replaces preregistered PGI for highest math attained.

is much smaller than the 16 percentile gender gap in income. On the other hand, the effects of cognitive and non-cognitive traits on ever having been a manager are generally weaker for women than for men. That is, for men, certain skills seem to translate into a higher likelihood of becoming a manager, but this is the case to a much lesser extent for women. There are no consistent gender differences in the effects of the trait PGIs on educational attainment.

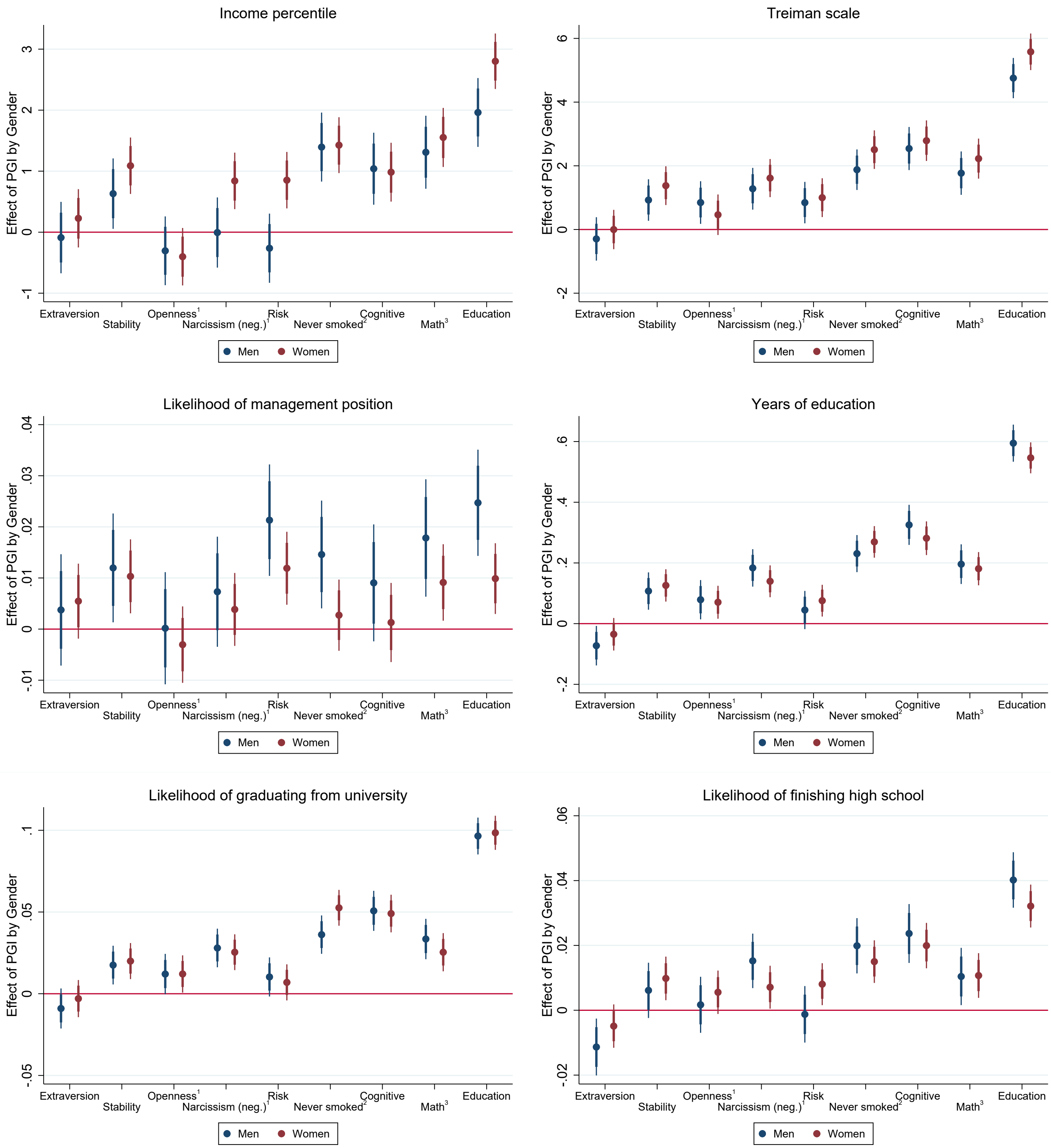
4 Conclusion

We use a new approach to tackle the longstanding question of whether there are causal effects of personality traits, economic preferences, and cognitive skills on education and labor market outcomes. Our method consists of using genetic predispositions – rather than contemporaneous measures – as proxies for the relevant traits. Using data from genotyped individuals in the Swedish Twin Registry, we link these genetic predispositions to government registry data on labor market outcomes and educational attainment. Because genes are fixed at conception, this approach allows us to exclude reverse causality whereby educational and professional experiences in turn affect traits and skills. While genes are fixed over the life cycle, selection on genes is still a potential issue (Kong et al., 2018). We use two approaches to deal with this.

The first approach is to control for parental background and genetic population stratification. Selzam et al. (2019) show that this approach can eliminate most of the bias due to selection on genes. Using this approach, we replicate many of the correlations established by the economics and psychology literatures using self-reported or experimental trait measures. For instance, we find that a predisposition toward mentally stability is associated with higher earnings (Mueller and Plug, 2006), a predisposition toward openness is associated with higher education (Mueller and Plug, 2006; Buser, Niederle, and Oosterbeek, 2021), a predisposition toward willingness to take risk is associated with working in a management position (Buser, Niederle, and Oosterbeek, 2021), and a predisposition toward greater patience is associated with both higher education and higher earnings (Sutter et al., 2013; Golsteyn, Grönqvist, and Lindahl, 2014; Alan and Ertac, 2018; Angerer et al., 2021). Some past studies have found a link between extraversion and labor market outcomes (Deming, 2017; Buser, Niederle, and Oosterbeek, 2021). Although less robust than other effects we estimate, we do find some suggestive evidence for a positive effect of the genetic tendency towards extraversion on labor market outcomes, in particular when using the multi-trait PGI. This question should be revisited in the future as more predictive PGIs for extraversion become available. Additionally, we find that a tendency towards narcissism is negatively associated with success in education and the labor market. Although narcissism is a prominent trait in personality psychology, it has been mostly ignored by economists. Our results suggest that it should be added to the list of personality traits and non-cognitive skills that are studied by education and labor economists and targeted in interventions. We also confirm past findings of a strong link between cognitive skills and both educational attainment and income (Murnane, Willett, and Levy, 1995; Cawley, Heckman, and Vytlacil, 2001; Hanushek, 2009). Finally, we find that the educational attainment (EA) PGI is strongly related to labor market and education outcomes and confirm the finding by Papageorge and Thom (2020) and Ronda et al. (2020) that this relationship between the EA PGI and college graduation is stronger for high-SES individuals. Most of these conditional relationships are statistically significant at our stricter 0.5 percent significance cutoff.

The second approach goes a step further towards establishing causality. Here, we use a restricted sample of dizygotic twins and take advantage of the fact that any genetic differences between full siblings are random. Controlling for family fixed effects allows us to cleanly identify the causal effects of genetic tendencies but restricts the sample size. For many traits, the fixed effects results are of similar magnitude to the full-sample conditional regression results, indicating that our SES controls capture most of the spurious correlations due to selection on genes. While the fixed-effect coefficients are less precisely estimated, they are still often significant at the 5-percent level, our threshold for suggestive evidence.

Figure 4: Heterogeneity results: Gender



Note: Thick (thin) error bars represent 95% (99.5%) confidence intervals. The PGI coefficients were estimated in four separate regressions: personality traits (extraversion, stability, openness, and narcissism), economic preferences (risk taking and smoking), cognitive skills (cognitive performance and math ability), and educational attainment. The regressions control for birth year dummies, municipality of residence at age 16, SES, and the first 20 genetic principal components. Standard errors are clustered at the family level.

[1]Trait not preregistered.

[2]PGI for ever having been a smoker replaces preregistered delay discounting PGI.

[3]PGI for self-judged math ability replaces preregistered PGI for highest math attained.

Taken together, these results obtained through our two empirical strategies represent evidence that genes which predispose individuals toward certain personality traits, certain economics preferences, and stronger cognitive skills causally increase education and labor market prospects. The magnitudes of these effects are economically meaningful. While our empirical approaches tackle the issue of selection on genes, a remaining potential issue is that the genetic tendencies measured by the trait PGIs might also partially capture the genetic predispositions towards related but unobserved traits. This is more of an issue for the multi-trait PGIs but also applies to the single-trait PGIs we use for our main analyses to some extent.[21]

Our results also emphasize the importance of the "genetic lottery" as a determinant of education and labor market outcomes. On top of polygenic indices for individual traits and skills, we also estimate the causal effects of a polygenic index for educational attainment which likely summarizes many traits and skills that predispose someone to have higher educational attainment. Our causal within-family estimates using pairs of dizygotic twins show that even among two full siblings born on the same day to the same parents, a one-standard deviation difference in the polygenic index for educational attainment leads to a 3 percentile difference in lifetime income, a 4 percentile difference in occupational prestige, and a 7 percentage points difference in the likelihood of graduating from university.

In summary, we present new evidence that cognitive skills and non-cognitive traits matter for important economic outcomes. Our results indicate that genes which predispose individuals towards certain traits – traits that past studies have indicated as potentially influential – causally affect education and labor market outcomes. While this is a direct indication that the genetically predetermined part of these traits matters, there is no reason to assume that environmentally determined variation in these traits would not have similar effects. Our results therefore support the notion that fostering cognitive and non-cognitive skills, particularly early in life, can have strong payoffs (see e.g. Heckman and Rubinstein, 2001; Kautz et al., 2014). Our results also indicate that differences in income and education are at least partially due to factors that are outside of people's control.

[21] See Becker et al. (2021) for estimates of genetic correlations between the trait PGIs used in this study and an extensive range of other genetic tendencies.

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Appendix: Tables

Descriptive statistics

Table 1: Correlations between PGIs

	Extra.	Mental st.	Open.	Narc.	Risk	Smoke	Cog. per.	Math	EA
Extraversion	1.0000								
Mental stability	0.1287	1.0000							
Openness	0.2380	0.0329	1.0000						
Narcissism	-0.0769	0.0494	-0.0879	1.0000					
Risk seeking	0.2269	0.2060	0.1623	-0.1363	1.0000				
Ever smoked	0.0793	-0.1066	0.0498	-0.0617	0.1091	1.0000			
Cognitive performance	-0.0572	0.0992	0.0506	-0.1300	-0.0212	-0.1350	1.0000		
Math ability	0.0230	0.1597	0.0350	-0.0450	0.1482	-0.2158	0.3556	1.0000	
Educational attainment	0.0034	0.0935	0.1171	-0.1817	0.0699	-0.2636	0.4571	0.3015	1.0000

Table 2: Descriptive statistics (outcome and control variables)

	(1) OLS sample	(2) FE sample
Income	55.323	54.822
	(21.316)	(21.217)
Treiman scale	51.778	50.870
	(24.801)	(24.987)
Management position	0.121	0.115
	(0.326)	(0.320)
Years of education	12.711	12.357
	(2.594)	(2.720)
University	0.412	0.372
	(0.492)	(0.483)
High school	0.887	0.849
	(0.316)	(0.358)
SES	50.329	49.443
	(23.582)	(24.130)
Birth year	1965.679	1961.835
	(17.905)	(19.499)
Female	0.565	0.551
	(0.496)	(0.497)
Observations	29393	11344

Main regression results

Table 3: Income (single trait PGIs)

Conditional correlations:

	(1)	(2)	(3)	(4)	(5)
Extraversion PGI (single)	0.111			0.265*	
	(0.133)			(0.134)	
Mental stability PGI (single)	0.888**			0.468**	
	(0.129)			(0.133)	
Openness PGI (single)	-0.349*			-0.414**	
	(0.129)			(0.129)	
Narcissism PGI (single)	-0.480**			-0.342*	
	(0.131)			(0.132)	
Risk seeking PGI (single)		0.409**		0.080	
		(0.129)		(0.137)	
Ever smoked PGI (single)		-1.427**		-1.002**	
		(0.128)		(0.132)	
Cognitive performance PGI (single)			0.981**	0.907**	
			(0.135)	(0.137)	
Math PGI (single)			1.477**	1.203**	
			(0.135)	(0.140)	
Educational attainment PGI (single)					2.459**
					(0.128)
N	25883	25883	25883	25883	25883
Joint sig 1	0.000			0.000	
Joint sig 2		0.000		0.000	
Joint sig 3			0.000	0.000	
Joint sig 1+2				0.000	
Joint sig all				0.000	

Standard errors in parentheses are clustered at the family level; * $p<0.05$,** $p<0.005$

Within-family regressions:

	(1)	(2)	(3)	(4)	(5)
Extraversion PGI (single)	0.171			0.245	
	(0.341)			(0.347)	
Mental stability PGI (single)	0.786*			0.402	
	(0.340)			(0.348)	
Openness PGI (single)	0.441			0.342	
	(0.348)			(0.349)	
Narcissism PGI (single)	-0.411			-0.297	
	(0.340)			(0.342)	
Risk seeking PGI (single)		0.664*		0.216	
		(0.338)		(0.360)	
Ever smoked PGI (single)		-0.914*		-0.519	
		(0.338)		(0.345)	
Cognitive performance PGI (single)			0.666	0.610	
			(0.362)	(0.367)	
Math PGI (single)			1.567**	1.350**	
			(0.364)	(0.377)	
Educational attainment PGI (single)					2.102**
					(0.360)
N	9722	9722	9722	9722	9722
Joint sig 1	0.042			0.371	
Joint sig 2		0.007		0.301	
Joint sig 3			0.000	0.000	
Joint sig 1+2				0.295	
Joint sig all				0.000	

Standard errors in parentheses are clustered at the family level; * $p<0.05$,** $p<0.005$

Table 4: Income (multi trait PGIs)

Conditional correlations:

	(1)	(2)	(3)	(4)	(5)
Extraversion PGI (multi)	0.095			0.346*	
	(0.134)			(0.137)	
Mental stability PGI (multi)	1.295**			0.734**	
	(0.134)			(0.138)	
Openness PGI (single)	-0.333*			-0.432**	
	(0.127)			(0.128)	
Narcissism PGI (single)	-0.510**			-0.301*	
	(0.130)			(0.133)	
Risk seeking PGI (multi)		0.428**		-0.036	
		(0.128)		(0.138)	
Ever smoked PGI (single)		-1.429**		-0.805**	
		(0.128)		(0.133)	
Cognitive performance PGI (multi)			1.286**	1.118**	
			(0.179)	(0.183)	
Math PGI (multi)			1.232**	1.029**	
			(0.177)	(0.179)	
Educational attainment PGI (multi)					2.760**
					(0.129)
N	25883	25883	25883	25883	25883
Joint sig 1	0.000			0.000	
Joint sig 2		0.000		0.000	
Joint sig 3			0.000	0.000	
Joint sig 1+2				0.000	
Joint sig all				0.000	

Standard errors in parentheses are clustered at the family level; $*$ $p<0.05$,$**$ $p<0.005$

Within-family regressions:

	(1)	(2)	(3)	(4)	(5)
Extraversion PGI (multi)	0.441			0.577	
	(0.356)			(0.368)	
Mental stability PGI (multi)	1.138**			0.635	
	(0.354)			(0.363)	
Openness PGI (single)	0.385			0.253	
	(0.342)			(0.343)	
Narcissism PGI (single)	-0.437			-0.238	
	(0.339)			(0.344)	
Risk seeking PGI (multi)		0.890*		0.279	
		(0.344)		(0.373)	
Ever smoked PGI (single)		-0.944*		-0.464	
		(0.338)		(0.346)	
Cognitive performance PGI (multi)			0.936*	0.812	
			(0.466)	(0.473)	
Math PGI (multi)			1.359**	1.171*	
			(0.462)	(0.468)	
Educational attainment PGI (multi)					2.460**
					(0.366)
N	9722	9722	9722	9722	9722
Joint sig 1	0.001			0.075	
Joint sig 2		0.002		0.352	
Joint sig 3			0.000	0.000	
Joint sig 1+2				0.039	
Joint sig all				0.000	

Standard errors in parentheses are clustered at the family level; $*$ $p<0.05$,$**$ $p<0.005$

Table 5: Treiman scale of occupational status (single trait PGIs)

Conditional correlations:

	(1)	(2)	(3)	(4)	(5)
Extraversion PGI (single)	-0.109			0.185	
	(0.164)			(0.165)	
Mental stability PGI (single)	1.194**			0.419*	
	(0.160)			(0.163)	
Openness PGI (single)	0.644**			0.464**	
	(0.165)			(0.164)	
Narcissism PGI (single)	-1.475**			-1.113**	
	(0.159)			(0.160)	
Risk seeking PGI (single)		0.952**		0.377*	
		(0.161)		(0.170)	
Ever smoked PGI (single)		-2.251**		-1.627**	
		(0.158)		(0.162)	
Cognitive performance PGI (single)			2.649**	2.424**	
			(0.168)	(0.170)	
Math PGI (single)			2.051**	1.601**	
			(0.167)	(0.173)	
Educational attainment PGI (single)					5.243**
					(0.154)
N	25515	25515	25515	25515	25515
Joint sig 1	0.000			0.000	
Joint sig 2		0.000		0.000	
Joint sig 3			0.000	0.000	
Joint sig 1+2				0.000	
Joint sig all				0.000	

Standard errors in parentheses are clustered at the family level; $*$ p<0.05,$**$ p<0.005

Within-family regressions:

	(1)	(2)	(3)	(4)	(5)
Extraversion PGI (single)	-0.561			-0.399	
	(0.427)			(0.431)	
Mental stability PGI (single)	0.743			0.312	
	(0.421)			(0.438)	
Openness PGI (single)	1.066*			0.940*	
	(0.424)			(0.425)	
Narcissism PGI (single)	-1.126*			-0.926*	
	(0.424)			(0.429)	
Risk seeking PGI (single)		0.563		0.159	
		(0.411)		(0.437)	
Ever smoked PGI (single)		-1.028*		-0.598	
		(0.409)		(0.425)	
Cognitive performance PGI (single)			1.653**	1.441**	
			(0.436)	(0.443)	
Math PGI (single)			1.278**	1.108*	
			(0.440)	(0.461)	
Educational attainment PGI (single)					3.357**
					(0.440)
N	9478	9478	9478	9478	9478
Joint sig 1	0.002			0.032	
Joint sig 2		0.024		0.369	
Joint sig 3			0.000	0.000	
Joint sig 1+2				0.041	
Joint sig all				0.000	

Standard errors in parentheses are clustered at the family level; $*$ p<0.05,$**$ p<0.005

Table 6: Treiman scale of occupational status (multi trait PGIs)

Conditional correlations:

	(1)	(2)	(3)	(4)	(5)
Extraversion PGI (multi)	-0.114			0.348^{*}	
	(0.168)			(0.170)	
Mental stability PGI (multi)	1.361^{**}			0.275	
	(0.167)			(0.170)	
Openness PGI (single)	0.654^{**}			0.352^{*}	
	(0.163)			(0.162)	
Narcissism PGI (single)	-1.481^{**}			-0.921^{**}	
	(0.159)			(0.161)	
Risk seeking PGI (multi)		0.922^{**}		0.201	
		(0.161)		(0.173)	
Ever smoked PGI (single)		-2.248^{**}		-1.184^{**}	
		(0.158)		(0.163)	
Cognitive performance PGI (multi)			3.860^{**}	3.455^{**}	
			(0.226)	(0.232)	
Math PGI (multi)			1.074^{**}	0.941^{**}	
			(0.226)	(0.228)	
Educational attainment PGI (multi)					5.762^{**}
					(0.154)
N	25515	25515	25515	25515	25515
Joint sig 1	0.000			0.000	
Joint sig 2		0.000		0.000	
Joint sig 3			0.000	0.000	
Joint sig 1+2				0.000	
Joint sig all				0.000	

Standard errors in parentheses are clustered at the family level; $*$ p<0.05,$**$ p<0.005

Within-family regressions:

	(1)	(2)	(3)	(4)	(5)
Extraversion PGI (multi)	-0.092			0.277	
	(0.448)			(0.455)	
Mental stability PGI (multi)	0.322			-0.334	
	(0.432)			(0.452)	
Openness PGI (single)	0.962^{*}			0.745	
	(0.418)			(0.420)	
Narcissism PGI (single)	-1.066^{*}			-0.680	
	(0.424)			(0.434)	
Risk seeking PGI (multi)		0.517		0.061	
		(0.417)		(0.444)	
Ever smoked PGI (single)		-1.026^{*}		-0.408	
		(0.409)		(0.424)	
Cognitive performance PGI (multi)			2.976^{**}	2.747^{**}	
			(0.583)	(0.598)	
Math PGI (multi)			0.252	0.314	
			(0.577)	(0.587)	
Educational attainment PGI (multi)					3.925^{**}
					(0.447)
N	9478	9478	9478	9478	9478
Joint sig 1	0.011			0.117	
Joint sig 2		0.028		0.628	
Joint sig 3			0.000	0.000	
Joint sig 1+2				0.230	
Joint sig all				0.000	

Standard errors in parentheses are clustered at the family level; $*$ p<0.05,$**$ p<0.005

Table 7: Ever worked in management position (single trait PGIs)

Conditional correlations:

	(1)	(2)	(3)	(4)	(5)
Extraversion PGI (single)	0.005*			0.004	
	(0.002)			(0.002)	
Mental stability PGI (single)	0.011**			0.006*	
	(0.002)			(0.002)	
Openness PGI (single)	-0.002			-0.003	
	(0.002)			(0.002)	
Narcissism PGI (single)	-0.005*			-0.003	
	(0.002)			(0.002)	
Risk seeking PGI (single)		0.016**		0.013**	
		(0.002)		(0.002)	
Ever smoked PGI (single)		-0.008**		-0.005*	
		(0.002)		(0.002)	
Cognitive performance PGI (single)			0.004	0.005*	
			(0.002)	(0.002)	
Math PGI (single)			0.013**	0.009**	
			(0.002)	(0.002)	
Educational attainment PGI (single)					0.017**
					(0.002)
N	25692	25692	25692	25692	25692
Joint sig 1	0.000			0.013	
Joint sig 2		0.000		0.000	
Joint sig 3			0.000	0.000	
Joint sig 1+2				0.000	
Joint sig all				0.000	

Standard errors in parentheses are clustered at the family level; ∗ $p<0.05$,∗∗ $p<0.005$

Within-family regressions:

	(1)	(2)	(3)	(4)	(5)
Extraversion PGI (single)	0.005			0.003	
	(0.007)			(0.007)	
Mental stability PGI (single)	0.015*			0.011	
	(0.007)			(0.007)	
Openness PGI (single)	-0.006			-0.008	
	(0.007)			(0.007)	
Narcissism PGI (single)	-0.001			0.000	
	(0.007)			(0.007)	
Risk seeking PGI (single)		0.017*		0.014	
		(0.007)		(0.007)	
Ever smoked PGI (single)		-0.003		0.000	
		(0.007)		(0.007)	
Cognitive performance PGI (single)			-0.002	-0.001	
			(0.007)	(0.007)	
Math PGI (single)			0.012	0.008	
			(0.007)	(0.007)	
Educational attainment PGI (single)					0.010
					(0.007)
N	9594	9594	9594	9594	9594
Joint sig 1	0.169			0.394	
Joint sig 2		0.039		0.143	
Joint sig 3			0.173	0.453	
Joint sig 1+2				0.163	
Joint sig all				0.136	

Standard errors in parentheses are clustered at the family level; ∗ $p<0.05$,∗∗ $p<0.005$

Table 8: Ever worked in management position (multi trait PGIs)

Conditional correlations:

	(1)	(2)	(3)	(4)	(5)
Extraversion PGI (multi)	0.007**			0.006*	
	(0.002)			(0.002)	
Mental stability PGI (multi)	0.009**			0.004	
	(0.002)			(0.002)	
Openness PGI (single)	-0.001			-0.004	
	(0.002)			(0.002)	
Narcissism PGI (single)	-0.005*			-0.002	
	(0.002)			(0.002)	
Risk seeking PGI (multi)		0.015**		0.011**	
		(0.002)		(0.002)	
Ever smoked PGI (single)		-0.008**		-0.003	
		(0.002)		(0.002)	
Cognitive performance PGI (multi)			0.009**	0.010**	
			(0.003)	(0.003)	
Math PGI (multi)			0.010**	0.007*	
			(0.003)	(0.003)	
Educational attainment PGI (multi)					0.019**
					(0.002)
N	25692	25692	25692	25692	25692
Joint sig 1	0.000			0.012	
Joint sig 2		0.000		0.000	
Joint sig 3			0.000	0.000	
Joint sig 1+2				0.000	
Joint sig all				0.000	

Standard errors in parentheses are clustered at the family level; $*$ p<0.05,$**$ p<0.005

Within-family regressions:

	(1)	(2)	(3)	(4)	(5)
Extraversion PGI (multi)	0.012			0.009	
	(0.007)			(0.007)	
Mental stability PGI (multi)	0.008			0.003	
	(0.007)			(0.007)	
Openness PGI (single)	-0.007			-0.010	
	(0.007)			(0.007)	
Narcissism PGI (single)	-0.001			0.002	
	(0.007)			(0.007)	
Risk seeking PGI (multi)		0.020**		0.018*	
		(0.007)		(0.007)	
Ever smoked PGI (single)		-0.003		-0.000	
		(0.007)		(0.007)	
Cognitive performance PGI (multi)			0.002	0.005	
			(0.009)	(0.010)	
Math PGI (multi)			0.011	0.006	
			(0.009)	(0.009)	
Educational attainment PGI (multi)					0.014*
					(0.007)
N	9594	9594	9594	9594	9594
Joint sig 1	0.164			0.415	
Joint sig 2		0.010		0.048	
Joint sig 3			0.178	0.301	
Joint sig 1+2				0.064	
Joint sig all				0.058	

Standard errors in parentheses are clustered at the family level; $*$ p<0.05,$**$ p<0.005

Table 9: Years of education (single trait PGIs)

Conditional correlations:

	(1)	(2)	(3)	(4)	(5)
Extraversion PGI (single)	-0.051**			-0.011	
	(0.015)			(0.015)	
Mental stability PGI (single)	0.119**			0.043**	
	(0.015)			(0.015)	
Openness PGI (single)	0.075**			0.059**	
	(0.015)			(0.015)	
Narcissism PGI (single)	-0.159**			-0.126**	
	(0.014)			(0.014)	
Risk seeking PGI (single)		0.064**		0.010	
		(0.015)		(0.015)	
Ever smoked PGI (single)		-0.253**		-0.190**	
		(0.014)		(0.015)	
Cognitive performance PGI (single)			0.299**	0.267**	
			(0.015)	(0.016)	
Math PGI (single)			0.187**	0.143**	
			(0.015)	(0.016)	
Educational attainment PGI (single)					0.568**
					(0.014)
N	29393	29393	29393	29393	29393
Joint sig 1	0.000			0.000	
Joint sig 2		0.000		0.000	
Joint sig 3			0.000	0.000	
Joint sig 1+2				0.000	
Joint sig all				0.000	

Standard errors in parentheses are clustered at the family level; * p<0.05,** p<0.005

Within-family regressions:

	(1)	(2)	(3)	(4)	(5)
Extraversion PGI (single)	-0.043			-0.023	
	(0.036)			(0.036)	
Mental stability PGI (single)	-0.001			-0.054	
	(0.035)			(0.036)	
Openness PGI (single)	0.089*			0.073*	
	(0.035)			(0.035)	
Narcissism PGI (single)	-0.110**			-0.081*	
	(0.035)			(0.035)	
Risk seeking PGI (single)		0.055		0.029	
		(0.035)		(0.037)	
Ever smoked PGI (single)		-0.111**		-0.071*	
		(0.035)		(0.036)	
Cognitive performance PGI (single)			0.196**	0.182**	
			(0.037)	(0.038)	
Math PGI (single)			0.140**	0.131**	
			(0.037)	(0.038)	
Educational attainment PGI (single)					0.397**
					(0.037)
N	11344	11344	11344	11344	11344
Joint sig 1	0.001			0.008	
Joint sig 2		0.003		0.123	
Joint sig 3			0.000	0.000	
Joint sig 1+2				0.011	
Joint sig all				0.000	

Standard errors in parentheses are clustered at the family level; * p<0.05,** p<0.005

Table 10: Years of education (multi trait PGIs)

Conditional correlations:

	(1)	(2)	(3)	(4)	(5)
Extraversion PGI (multi)	-0.065**			-0.007	
	(0.015)			(0.015)	
Mental stability PGI (multi)	0.139**			0.025	
	(0.015)			(0.015)	
Openness PGI (single)	0.075**			0.044**	
	(0.015)			(0.015)	
Narcissism PGI (single)	-0.158**			-0.102**	
	(0.014)			(0.014)	
Risk seeking PGI (multi)		0.067**		0.004	
		(0.014)		(0.015)	
Ever smoked PGI (single)		-0.253**		-0.141**	
		(0.014)		(0.015)	
Cognitive performance PGI (multi)			0.451**	0.398**	
			(0.021)	(0.021)	
Math PGI (multi)			0.065**	0.058*	
			(0.020)	(0.021)	
Educational attainment PGI (multi)					0.618**
					(0.014)
N	29393	29393	29393	29393	29393
Joint sig 1	0.000			0.000	
Joint sig 2		0.000		0.000	
Joint sig 3			0.000	0.000	
Joint sig 1+2				0.000	
Joint sig all				0.000	

Standard errors in parentheses are clustered at the family level; $*$ p<0.05,$**$ p<0.005

Within-family regressions:

	(1)	(2)	(3)	(4)	(5)
Extraversion PGI (multi)	-0.046			-0.008	
	(0.037)			(0.037)	
Mental stability PGI (multi)	0.001			-0.074*	
	(0.036)			(0.037)	
Openness PGI (single)	0.086*			0.065	
	(0.035)			(0.035)	
Narcissism PGI (single)	-0.107**			-0.068	
	(0.035)			(0.035)	
Risk seeking PGI (multi)		0.036		0.002	
		(0.035)		(0.037)	
Ever smoked PGI (single)		-0.109**		-0.045	
		(0.035)		(0.036)	
Cognitive performance PGI (multi)			0.266**	0.241**	
			(0.049)	(0.050)	
Math PGI (multi)			0.094*	0.110*	
			(0.048)	(0.048)	
Educational attainment PGI (multi)					0.439**
					(0.038)
N	11344	11344	11344	11344	11344
Joint sig 1	0.001			0.011	
Joint sig 2		0.006		0.447	
Joint sig 3			0.000	0.000	
Joint sig 1+2				0.035	
Joint sig all				0.000	

Standard errors in parentheses are clustered at the family level; $*$ p<0.05,$**$ p<0.005

Table 11: University (single trait PGIs)

Conditional correlations:

	(1)	(2)	(3)	(4)	(5)
Extraversion PGI (single)	-0.006			0.002	
	(0.003)			(0.003)	
Mental stability PGI (single)	0.019**			0.007*	
	(0.003)			(0.003)	
Openness PGI (single)	0.012**			0.010**	
	(0.003)			(0.003)	
Narcissism PGI (single)	-0.027**			-0.022**	
	(0.003)			(0.003)	
Risk seeking PGI (single)		0.009**		-0.001	
		(0.003)		(0.003)	
Ever smoked PGI (single)		-0.045**		-0.036**	
		(0.003)		(0.003)	
Cognitive performance PGI (single)			0.050**	0.044**	
			(0.003)	(0.003)	
Math PGI (single)			0.029**	0.021**	
			(0.003)	(0.003)	
Educational attainment PGI (single)					0.098**
					(0.003)
N	29393	29393	29393	29393	29393
Joint sig 1	0.000			0.000	
Joint sig 2		0.000		0.000	
Joint sig 3			0.000	0.000	
Joint sig 1+2				0.000	
Joint sig all				0.000	

Standard errors in parentheses are clustered at the family level; * p<0.05,** p<0.005

Within-family regressions:

	(1)	(2)	(3)	(4)	(5)
Extraversion PGI (single)	-0.014*			-0.009	
	(0.007)			(0.007)	
Mental stability PGI (single)	0.005			-0.004	
	(0.007)			(0.007)	
Openness PGI (single)	0.013			0.012	
	(0.007)			(0.007)	
Narcissism PGI (single)	-0.016*			-0.013	
	(0.007)			(0.007)	
Risk seeking PGI (single)		0.004		0.001	
		(0.007)		(0.008)	
Ever smoked PGI (single)		-0.030**		-0.024**	
		(0.007)		(0.007)	
Cognitive performance PGI (single)			0.036**	0.032**	
			(0.008)	(0.008)	
Math PGI (single)			0.018*	0.014	
			(0.008)	(0.008)	
Educational attainment PGI (single)					0.062**
					(0.007)
N	11344	11344	11344	11344	11344
Joint sig 1	0.025			0.142	
Joint sig 2		0.000		0.005	
Joint sig 3			0.000	0.000	
Joint sig 1+2				0.010	
Joint sig all				0.000	

Standard errors in parentheses are clustered at the family level; * p<0.05,** p<0.005

Table 12: University (multi trait PGIs)

Conditional correlations:

	(1)	(2)	(3)	(4)	(5)
Extraversion PGI (multi)	-0.007*			0.003	
	(0.003)			(0.003)	
Mental stability PGI (multi)	0.024**			0.005	
	(0.003)			(0.003)	
Openness PGI (single)	0.012**			0.008*	
	(0.003)			(0.003)	
Narcissism PGI (single)	-0.027**			-0.018**	
	(0.003)			(0.003)	
Risk seeking PGI (multi)		0.010**		-0.002	
		(0.003)		(0.003)	
Ever smoked PGI (single)		-0.046**		-0.028**	
		(0.003)		(0.003)	
Cognitive performance PGI (multi)			0.075**	0.065**	
			(0.004)	(0.004)	
Math PGI (multi)			0.010*	0.008*	
			(0.004)	(0.004)	
Educational attainment PGI (multi)					0.105**
					(0.003)
N	29393	29393	29393	29393	29393
Joint sig 1	0.000			0.000	
Joint sig 2		0.000		0.000	
Joint sig 3			0.000	0.000	
Joint sig 1+2				0.000	
Joint sig all				0.000	

Standard errors in parentheses are clustered at the family level; ∗ p<0.05,∗∗ p<0.005

Within-family regressions:

	(1)	(2)	(3)	(4)	(5)
Extraversion PGI (multi)	-0.013			-0.003	
	(0.007)			(0.008)	
Mental stability PGI (multi)	0.003			-0.009	
	(0.007)			(0.008)	
Openness PGI (single)	0.012			0.010	
	(0.007)			(0.007)	
Narcissism PGI (single)	-0.015*			-0.010	
	(0.007)			(0.007)	
Risk seeking PGI (multi)		-0.000		-0.005	
		(0.007)		(0.008)	
Ever smoked PGI (single)		-0.030**		-0.020*	
		(0.007)		(0.007)	
Cognitive performance PGI (multi)			0.050**	0.043**	
			(0.010)	(0.010)	
Math PGI (multi)			0.006	0.009	
			(0.010)	(0.010)	
Educational attainment PGI (multi)					0.069**
					(0.007)
N	11344	11344	11344	11344	11344
Joint sig 1	0.043			0.188	
Joint sig 2		0.000		0.019	
Joint sig 3			0.000	0.000	
Joint sig 1+2				0.047	
Joint sig all				0.000	

Standard errors in parentheses are clustered at the family level; ∗ p<0.05,∗∗ p<0.005

Table 13: High school (single trait PGIs)

Conditional correlations:

	(1)	(2)	(3)	(4)	(5)
Extraversion PGI (single)	-0.008**			-0.005*	
	(0.002)			(0.002)	
Mental stability PGI (single)	0.008**			0.003	
	(0.002)			(0.002)	
Openness PGI (single)	0.004			0.002	
	(0.002)			(0.002)	
Narcissism PGI (single)	-0.011**			-0.008**	
	(0.002)			(0.002)	
Risk seeking PGI (single)		0.004*		0.002	
		(0.002)		(0.002)	
Ever smoked PGI (single)		-0.017**		-0.013**	
		(0.002)		(0.002)	
Cognitive performance PGI (single)			0.021**	0.019**	
			(0.002)	(0.002)	
Math PGI (single)			0.010**	0.007**	
			(0.002)	(0.002)	
Educational attainment PGI (single)					0.035**
					(0.002)
N	29393	29393	29393	29393	29393
Joint sig 1	0.000			0.000	
Joint sig 2		0.000		0.000	
Joint sig 3			0.000	0.000	
Joint sig 1+2				0.000	
Joint sig all				0.000	

Standard errors in parentheses are clustered at the family level; ∗ $p<0.05$,∗∗ $p<0.005$

Within-family regressions:

	(1)	(2)	(3)	(4)	(5)
Extraversion PGI (single)	0.001			0.002	
	(0.005)			(0.006)	
Mental stability PGI (single)	-0.009			-0.012*	
	(0.005)			(0.006)	
Openness PGI (single)	0.009			0.008	
	(0.006)			(0.006)	
Narcissism PGI (single)	-0.005			-0.002	
	(0.006)			(0.006)	
Risk seeking PGI (single)		0.003		0.003	
		(0.005)		(0.006)	
Ever smoked PGI (single)		0.001		0.002	
		(0.005)		(0.006)	
Cognitive performance PGI (single)			0.017**	0.017**	
			(0.006)	(0.006)	
Math PGI (single)			0.005	0.006	
			(0.006)	(0.006)	
Educational attainment PGI (single)					0.027**
					(0.006)
N	11344	11344	11344	11344	11344
Joint sig 1	0.142			0.137	
Joint sig 2		0.808		0.781	
Joint sig 3			0.003	0.002	
Joint sig 1+2				0.259	
Joint sig all				0.015	

Standard errors in parentheses are clustered at the family level; ∗ $p<0.05$,∗∗ $p<0.005$

Table 14: High school (multi trait PGIs)

Conditional correlations:

	(1)	(2)	(3)	(4)	(5)
Extraversion PGI (multi)	-0.009**			-0.005*	
	(0.002)			(0.002)	
Mental stability PGI (multi)	0.010**			0.002	
	(0.002)			(0.002)	
Openness PGI (single)	0.003			0.001	
	(0.002)			(0.002)	
Narcissism PGI (single)	-0.010**			-0.006**	
	(0.002)			(0.002)	
Risk seeking PGI (multi)		0.005*		0.003	
		(0.002)		(0.002)	
Ever smoked PGI (single)		-0.017**		-0.010**	
		(0.002)		(0.002)	
Cognitive performance PGI (multi)			0.031**	0.027**	
			(0.003)	(0.003)	
Math PGI (multi)			0.002	0.002	
			(0.003)	(0.003)	
Educational attainment PGI (multi)					0.039**
					(0.002)
N	29393	29393	29393	29393	29393
Joint sig 1	0.000			0.002	
Joint sig 2		0.000		0.000	
Joint sig 3			0.000	0.000	
Joint sig 1+2				0.000	
Joint sig all				0.000	

Standard errors in parentheses are clustered at the family level; * p<0.05,** p<0.005

Within-family regressions:

	(1)	(2)	(3)	(4)	(5)
Extraversion PGI (multi)	-0.003			-0.003	
	(0.006)			(0.006)	
Mental stability PGI (multi)	-0.006			-0.011	
	(0.006)			(0.006)	
Openness PGI (single)	0.010			0.008	
	(0.006)			(0.006)	
Narcissism PGI (single)	-0.005			-0.002	
	(0.005)			(0.006)	
Risk seeking PGI (multi)		0.005		0.004	
		(0.005)		(0.006)	
Ever smoked PGI (single)		0.001		0.004	
		(0.005)		(0.006)	
Cognitive performance PGI (multi)			0.013	0.013	
			(0.008)	(0.008)	
Math PGI (multi)			0.010	0.012	
			(0.008)	(0.008)	
Educational attainment PGI (multi)					0.028**
					(0.006)
N	11344	11344	11344	11344	11344
Joint sig 1	0.153			0.133	
Joint sig 2		0.683		0.561	
Joint sig 3			0.001	0.000	
Joint sig 1+2				0.201	
Joint sig all				0.005	

Standard errors in parentheses are clustered at the family level; * p<0.05,** p<0.005

Heterogeneity results

Table 15: Income: heterogeneity by SES

	(1) est1	(2) est2	(3) est3	(4) est4	(5) est5
SES	3.450**	3.396**	3.275**	3.224**	3.056**
	(0.137)	(0.136)	(0.136)	(0.136)	(0.136)
Extraversion PGI (single)	0.135			0.281*	
	(0.133)			(0.134)	
Mental stability PGI (single)	0.885**			0.454**	
	(0.130)			(0.134)	
Openness PGI (single)	-0.326*			-0.393**	
	(0.129)			(0.129)	
Narcissism PGI (single)	-0.515**			-0.369*	
	(0.130)			(0.132)	
Risk seeking PGI (single)		0.467**		0.126	
		(0.130)		(0.138)	
Ever smoked PGI (single)		-1.401**		-0.980**	
		(0.129)		(0.132)	
Cognitive performance PGI (single)			0.993**	0.920**	
			(0.135)	(0.137)	
Math PGI (single)			1.478**	1.201**	
			(0.135)	(0.140)	
Educational attainment PGI (single)					2.452**
					(0.129)
ses * extraversion	0.234			0.246	
	(0.135)			(0.136)	
ses * stability	-0.017			-0.006	
	(0.129)			(0.133)	
ses * openness	-0.095			-0.093	
	(0.131)			(0.131)	
ses * narcissism	0.024			0.008	
	(0.130)			(0.132)	
ses * risk		0.010		-0.075	
		(0.129)		(0.137)	
ses * ever smoked		0.062		0.091	
		(0.126)		(0.131)	
ses * CP			-0.208	-0.181	
			(0.135)	(0.137)	
ses * math			0.266*	0.295*	
			(0.133)	(0.138)	
ses * EA					-0.189
					(0.127)
N	25986	25986	25986	25986	25986
Joint sig int 1	0.532			0.491	
Joint sig int 2		0.878		0.713	
Joint sig int 3			0.090	0.084	
Joint sig int 1+2				0.680	
Joint sig int all				0.356	

Standard errors in parentheses are clustered at the family level; $*$ p<0.05,$**$ p<0.005

Table 16: Treiman scale: heterogeneity by SES

	(1) est1	(2) est2	(3) est3	(4) est4	(5) est5
SES	7.288**	7.252**	6.984**	6.841**	6.473**
	(0.169)	(0.169)	(0.168)	(0.168)	(0.168)
Extraversion PGI (single)	-0.062			0.228	
	(0.164)			(0.165)	
Mental stability PGI (single)	1.177**			0.397*	
	(0.159)			(0.163)	
Openness PGI (single)	0.655**			0.484**	
	(0.164)			(0.163)	
Narcissism PGI (single)	-1.517**			-1.154**	
	(0.159)			(0.160)	
Risk seeking PGI (single)		1.001**		0.402*	
		(0.160)		(0.169)	
Ever smoked PGI (single)		-2.217**		-1.603**	
		(0.158)		(0.162)	
Cognitive performance PGI (single)			2.621**	2.397**	
			(0.167)	(0.169)	
Math PGI (single)			2.052**	1.607**	
			(0.166)	(0.172)	
Educational attainment PGI (single)					5.207**
					(0.154)
ses * extraversion	0.180			0.225	
	(0.163)			(0.164)	
ses * stability	0.132			0.115	
	(0.154)			(0.157)	
ses * openness	-0.188			-0.187	
	(0.164)			(0.162)	
ses * narcissism	-0.138			-0.144	
	(0.154)			(0.155)	
ses * risk		0.089		-0.004	
		(0.157)		(0.166)	
ses * ever smoked		-0.175		-0.144	
		(0.151)		(0.156)	
ses * CP			-0.119	-0.119	
			(0.163)	(0.166)	
ses * math			0.279	0.232	
			(0.163)	(0.170)	
ses * EA					0.072
					(0.147)
N	25615	25615	25615	25615	25615
Joint sig int 1	0.445			0.383	
Joint sig int 2		0.460		0.644	
Joint sig int 3			0.234	0.384	
Joint sig int 1+2				0.532	
Joint sig int all				0.415	

Standard errors in parentheses are clustered at the family level; $*$ $p<0.05$, $**$ $p<0.005$

Table 17: Ever worked in management position: heterogeneity by SES

	(1) est1	(2) est2	(3) est3	(4) est4	(5) est5
SES	0.033**	0.032**	0.032**	0.031**	0.030**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Extraversion PGI (single)	0.006*			0.004	
	(0.002)			(0.002)	
Mental stability PGI (single)	0.011**			0.006*	
	(0.002)			(0.002)	
Openness PGI (single)	-0.002			-0.004	
	(0.002)			(0.002)	
Narcissism PGI (single)	-0.006*			-0.003	
	(0.002)			(0.002)	
Risk seeking PGI (single)		0.017**		0.014**	
		(0.002)		(0.002)	
Ever smoked PGI (single)		-0.008**		-0.005*	
		(0.002)		(0.002)	
Cognitive performance PGI (single)			0.005*	0.005*	
			(0.002)	(0.002)	
Math PGI (single)			0.013**	0.009**	
			(0.002)	(0.002)	
Educational attainment PGI (single)					0.017**
					(0.002)
ses * extraversion	0.001			0.001	
	(0.002)			(0.002)	
ses * stability	0.000			0.000	
	(0.002)			(0.002)	
ses * openness	0.000			0.000	
	(0.002)			(0.002)	
ses * narcissism	-0.002			-0.002	
	(0.002)			(0.002)	
ses * risk		0.001		0.000	
		(0.002)		(0.002)	
ses * ever smoked		-0.000		-0.000	
		(0.002)		(0.002)	
ses * CP			-0.002	-0.002	
			(0.002)	(0.002)	
ses * math			0.001	0.001	
			(0.002)	(0.002)	
ses * EA					0.001
					(0.002)
N	25792	25792	25792	25792	25792
Joint sig int 1	0.915			0.908	
Joint sig int 2		0.931		0.979	
Joint sig int 3			0.796	0.779	
Joint sig int 1+2				0.980	
Joint sig int all				0.993	

Standard errors in parentheses are clustered at the family level; * $p<0.05$, ** $p<0.005$

Table 18: Years of education: heterogeneity by SES

	(1) est1	(2) est2	(3) est3	(4) est4	(5) est5
SES	0.799**	0.794**	0.761**	0.745**	0.698**
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Extraversion PGI (single)	-0.049**			-0.008	
	(0.015)			(0.015)	
Mental stability PGI (single)	0.114**			0.039*	
	(0.014)			(0.015)	
Openness PGI (single)	0.079**			0.064**	
	(0.015)			(0.015)	
Narcissism PGI (single)	-0.162**			-0.128**	
	(0.014)			(0.014)	
Risk seeking PGI (single)		0.063**		0.007	
		(0.014)		(0.015)	
Ever smoked PGI (single)		-0.247**		-0.183**	
		(0.014)		(0.015)	
Cognitive performance PGI (single)			0.298**	0.266**	
			(0.015)	(0.015)	
Math PGI (single)			0.188**	0.146**	
			(0.015)	(0.016)	
Educational attainment PGI (single)					0.568**
					(0.014)
ses * extraversion	0.007			0.011	
	(0.015)			(0.015)	
ses * stability	0.023			0.021	
	(0.015)			(0.015)	
ses * openness	-0.014			-0.015	
	(0.016)			(0.015)	
ses * narcissism	-0.002			0.001	
	(0.015)			(0.015)	
ses * risk		0.009		-0.001	
		(0.015)		(0.016)	
ses * ever smoked		-0.014		-0.004	
		(0.014)		(0.015)	
ses * CP			0.004	0.006	
			(0.015)	(0.016)	
ses * math			0.035*	0.031	
			(0.016)	(0.016)	
ses * EA					0.026
					(0.014)
N	29503	29503	29503	29503	29503
Joint sig int 1	0.476			0.492	
Joint sig int 2		0.531		0.952	
Joint sig int 3			0.041	0.088	
Joint sig int 1+2				0.720	
Joint sig int all				0.231	

Standard errors in parentheses are clustered at the family level; $*$ p<0.05,$**$ p<0.005

Table 19: University: heterogeneity by SES

	(1) est1	(2) est2	(3) est3	(4) est4	(5) est5
SES	0.140**	0.139**	0.134**	0.131**	0.122**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Extraversion PGI (single)	-0.006			0.002	
	(0.003)			(0.003)	
Mental stability PGI (single)	0.019**			0.007*	
	(0.003)			(0.003)	
Openness PGI (single)	0.013**			0.011**	
	(0.003)			(0.003)	
Narcissism PGI (single)	-0.027**			-0.022**	
	(0.003)			(0.003)	
Risk seeking PGI (single)		0.008**		-0.001	
		(0.003)		(0.003)	
Ever smoked PGI (single)		-0.045**		-0.035**	
		(0.003)		(0.003)	
Cognitive performance PGI (single)			0.050**	0.044**	
			(0.003)	(0.003)	
Math PGI (single)			0.029**	0.021**	
			(0.003)	(0.003)	
Educational attainment PGI (single)					0.098**
					(0.003)
ses * extraversion	0.003			0.004	
	(0.003)			(0.003)	
ses * stability	0.002			0.001	
	(0.003)			(0.003)	
ses * openness	0.001			0.001	
	(0.003)			(0.003)	
ses * narcissism	-0.001			-0.000	
	(0.003)			(0.003)	
ses * risk		0.001		-0.002	
		(0.003)		(0.003)	
ses * ever smoked		-0.006*		-0.004	
		(0.003)		(0.003)	
ses * CP			0.006*	0.006*	
			(0.003)	(0.003)	
ses * math			0.007*	0.006	
			(0.003)	(0.003)	
ses * EA					0.011**
					(0.003)
N	29503	29503	29503	29503	29503
Joint sig int 1	0.732			0.593	
Joint sig int 2		0.084		0.236	
Joint sig int 3			0.000	0.001	
Joint sig int 1+2				0.545	
Joint sig int all				0.005	

Standard errors in parentheses are clustered at the family level; $*$ $p<0.05$, $**$ $p<0.005$

Table 20: High school: heterogeneity by SES

	(1) est1	(2) est2	(3) est3	(4) est4	(5) est5
SES	0.046**	0.046**	0.044**	0.043**	0.041**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Extraversion PGI (single)	-0.007**			-0.005*	
	(0.002)			(0.002)	
Mental stability PGI (single)	0.007**			0.002	
	(0.002)			(0.002)	
Openness PGI (single)	0.004*			0.003	
	(0.002)			(0.002)	
Narcissism PGI (single)	-0.011**			-0.008**	
	(0.002)			(0.002)	
Risk seeking PGI (single)		0.004		0.001	
		(0.002)		(0.002)	
Ever smoked PGI (single)		-0.016**		-0.012**	
		(0.002)		(0.002)	
Cognitive performance PGI (single)			0.021**	0.019**	
			(0.002)	(0.002)	
Math PGI (single)			0.010**	0.008**	
			(0.002)	(0.002)	
Educational attainment PGI (single)					0.035**
					(0.002)
ses * extraversion	0.002			0.001	
	(0.002)			(0.002)	
ses * stability	-0.002			0.000	
	(0.002)			(0.002)	
ses * openness	-0.003			-0.003	
	(0.002)			(0.002)	
ses * narcissism	0.004*			0.003	
	(0.002)			(0.002)	
ses * risk		-0.001		0.000	
		(0.002)		(0.002)	
ses * ever smoked		0.007**		0.005*	
		(0.002)		(0.002)	
ses * CP			-0.011**	-0.010**	
			(0.002)	(0.002)	
ses * math			-0.002	-0.001	
			(0.002)	(0.002)	
ses * EA					-0.014**
					(0.002)
N	29503	29503	29503	29503	29503
Joint sig int 1	0.078			0.342	
Joint sig int 2		0.003		0.029	
Joint sig int 3			0.000	0.000	
Joint sig int 1+2				0.100	
Joint sig int all				0.000	

Standard errors in parentheses are clustered at the family level; $*$ p<0.05,$**$ p<0.005

Table 21: Income: heterogeneity by gender

	(1) est1	(2) est2	(3) est3	(4) est4	(5) est5
Female	-16.394**	-16.357**	-16.411**	-16.369**	-16.287**
	(0.258)	(0.258)	(0.257)	(0.257)	(0.257)
Extraversion PGI (single)	-0.088			0.161	
	(0.209)			(0.210)	
Mental stability PGI (single)	0.642**			0.342	
	(0.206)			(0.211)	
Openness PGI (single)	-0.300			-0.318	
	(0.201)			(0.201)	
Narcissism PGI (single)	0.007			0.086	
	(0.205)			(0.208)	
Risk seeking PGI (single)		-0.257		-0.471*	
		(0.202)		(0.214)	
Ever smoked PGI (single)		-1.402**		-0.970**	
		(0.202)		(0.208)	
Cognitive performance PGI (single)			1.050**	0.980**	
			(0.211)	(0.215)	
Math PGI (single)			1.310**	1.157**	
			(0.213)	(0.221)	
Educational attainment PGI (single)					1.968**
					(0.201)
female * extraversion	0.328			0.176	
	(0.269)			(0.271)	
female * stability	0.461			0.259	
	(0.262)			(0.270)	
female * openness	-0.115			-0.204	
	(0.260)			(0.261)	
female * narcissism	-0.866**			-0.769**	
	(0.260)			(0.264)	
female * risk		1.107**		0.915**	
		(0.260)		(0.276)	
female * ever smoked		-0.025		-0.034	
		(0.258)		(0.265)	
female * CP			-0.073	-0.078	
			(0.269)	(0.274)	
female * math			0.252	0.039	
			(0.272)	(0.282)	
female * EA					0.837**
					(0.254)
N	25883	25883	25883	25883	25883
Joint sig int 1	0.003			0.040	
Joint sig int 2		0.000		0.004	
Joint sig int 3			0.650	0.959	
Joint sig int 1+2				0.000	
Joint sig int all				0.001	

Standard errors in parentheses are clustered at the family level; * $p<0.05$, ** $p<0.005$

Table 22: Treiman scale: heterogeneity by gender

	(1) est1	(2) est2	(3) est3	(4) est4	(5) est5
Female	-2.849**	-2.814**	-2.915**	-2.824**	-2.622**
	(0.314)	(0.314)	(0.311)	(0.309)	(0.307)
Extraversion PGI (single)	-0.290			-0.050	
	(0.243)			(0.244)	
Mental stability PGI (single)	0.930**			0.251	
	(0.232)			(0.236)	
Openness PGI (single)	0.858**			0.682**	
	(0.238)			(0.237)	
Narcissism PGI (single)	-1.263**			-0.894**	
	(0.234)			(0.235)	
Risk seeking PGI (single)		0.851**		0.403	
		(0.232)		(0.244)	
Ever smoked PGI (single)		-1.876**		-1.321**	
		(0.227)		(0.234)	
Cognitive performance PGI (single)			2.542**	2.336**	
			(0.241)	(0.245)	
Math PGI (single)			1.769**	1.403**	
			(0.243)	(0.253)	
Educational attainment PGI (single)					4.755**
					(0.225)
female * extraversion	0.296			0.400	
	(0.325)			(0.326)	
female * stability	0.466			0.295	
	(0.315)			(0.321)	
female * openness	-0.401			-0.406	
	(0.327)			(0.325)	
female * narcissism	-0.363			-0.371	
	(0.314)			(0.316)	
female * risk		0.147		-0.063	
		(0.313)		(0.331)	
female * ever smoked		-0.634*		-0.506	
		(0.309)		(0.317)	
female * CP			0.242	0.213	
			(0.327)	(0.332)	
female * math			0.469	0.331	
			(0.326)	(0.338)	
female * EA					0.834*
					(0.298)
N	25515	25515	25515	25515	25515
Joint sig int 1	0.232			0.303	
Joint sig int 2		0.117		0.261	
Joint sig int 3			0.136	0.355	
Joint sig int 1+2				0.275	
Joint sig int all				0.153	

Standard errors in parentheses are clustered at the family level; * $p<0.05$, ** $p<0.005$

Table 23: Ever worked in management position: heterogeneity by gender

	(1) est1	(2) est2	(3) est3	(4) est4	(5) est5
Female	-0.088**	-0.088**	-0.088**	-0.088**	-0.087**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Extraversion PGI (single)	0.004			0.002	
	(0.004)			(0.004)	
Mental stability PGI (single)	0.012**			0.005	
	(0.004)			(0.004)	
Openness PGI (single)	0.000			-0.002	
	(0.004)			(0.004)	
Narcissism PGI (single)	-0.007			-0.004	
	(0.004)			(0.004)	
Risk seeking PGI (single)		0.021**		0.018**	
		(0.004)		(0.004)	
Ever smoked PGI (single)		-0.015**		-0.010*	
		(0.004)		(0.004)	
Cognitive performance PGI (single)			0.009*	0.009*	
			(0.004)	(0.004)	
Math PGI (single)			0.018**	0.012**	
			(0.004)	(0.004)	
Educational attainment PGI (single)					0.025**
					(0.004)
female * extraversion	0.002			0.002	
	(0.005)			(0.005)	
female * stability	-0.002			0.003	
	(0.005)			(0.005)	
female * openness	-0.003			-0.002	
	(0.005)			(0.005)	
female * narcissism	0.003			0.001	
	(0.005)			(0.005)	
female * risk		-0.010*		-0.009	
		(0.005)		(0.005)	
female * ever smoked		0.012*		0.010*	
		(0.004)		(0.005)	
female * CP			-0.008	-0.007	
			(0.005)	(0.005)	
female * math			-0.009	-0.006	
			(0.005)	(0.005)	
female * EA					-0.015**
					(0.004)
N	25692	25692	25692	25692	25692
Joint sig int 1	0.857			0.935	
Joint sig int 2		0.005		0.024	
Joint sig int 3			0.013	0.079	
Joint sig int 1+2				0.242	
Joint sig int all				0.030	

Standard errors in parentheses are clustered at the family level; * p<0.05,** p<0.005

Table 24: Years of education: heterogeneity by gender

	(1) est1	(2) est2	(3) est3	(4) est4	(5) est5
Female	0.226**	0.228**	0.219**	0.230**	0.251**
	(0.029)	(0.029)	(0.028)	(0.028)	(0.028)
Extraversion PGI (single)	-0.073**			-0.031	
	(0.023)			(0.023)	
Mental stability PGI (single)	0.108**			0.034	
	(0.022)			(0.022)	
Openness PGI (single)	0.079**			0.061*	
	(0.023)			(0.023)	
Narcissism PGI (single)	-0.183**			-0.144**	
	(0.022)			(0.022)	
Risk seeking PGI (single)		0.045*		-0.008	
		(0.022)		(0.024)	
Ever smoked PGI (single)		-0.230**		-0.160**	
		(0.022)		(0.022)	
Cognitive performance PGI (single)			0.326**	0.291**	
			(0.024)	(0.024)	
Math PGI (single)			0.195**	0.162**	
			(0.023)	(0.024)	
Educational attainment PGI (single)					0.595**
					(0.022)
female * extraversion	0.038			0.037	
	(0.030)			(0.030)	
female * stability	0.019			0.015	
	(0.029)			(0.029)	
female * openness	-0.010			-0.006	
	(0.030)			(0.030)	
female * narcissism	0.043			0.035	
	(0.029)			(0.029)	
female * risk		0.031		0.030	
		(0.029)		(0.031)	
female * ever smoked		-0.040		-0.051	
		(0.028)		(0.029)	
female * CP			-0.044	-0.038	
			(0.030)	(0.031)	
female * math			-0.014	-0.031	
			(0.030)	(0.031)	
female * EA					-0.049
					(0.028)
N	29393	29393	29393	29393	29393
Joint sig int 1	0.353			0.499	
Joint sig int 2		0.234		0.158	
Joint sig int 3			0.194	0.151	
Joint sig int 1+2				0.246	
Joint sig int all				0.195	

Standard errors in parentheses are clustered at the family level; * $p<0.05$, ** $p<0.005$

Table 25: University: heterogeneity by gender

	(1)	(2)	(3)	(4)	(5)
	est1	est2	est3	est4	est5
Female	0.096**	0.096**	0.094**	0.096**	0.100**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Extraversion PGI (single)	-0.009*			-0.003	
	(0.004)			(0.004)	
Mental stability PGI (single)	0.018**			0.005	
	(0.004)			(0.004)	
Openness PGI (single)	0.012*			0.009*	
	(0.004)			(0.004)	
Narcissism PGI (single)	-0.028**			-0.021**	
	(0.004)			(0.004)	
Risk seeking PGI (single)		0.010*		0.002	
		(0.004)		(0.005)	
Ever smoked PGI (single)		-0.036**		-0.025**	
		(0.004)		(0.004)	
Cognitive performance PGI (single)			0.051**	0.046**	
			(0.004)	(0.004)	
Math PGI (single)			0.033**	0.028**	
			(0.004)	(0.005)	
Educational attainment PGI (single)					0.097**
					(0.004)
female * extraversion	0.006			0.009	
	(0.006)			(0.006)	
female * stability	0.003			0.003	
	(0.006)			(0.006)	
female * openness	-0.000			0.002	
	(0.006)			(0.006)	
female * narcissism	0.002			-0.001	
	(0.006)			(0.006)	
female * risk		-0.003		-0.004	
		(0.006)		(0.006)	
female * ever smoked		-0.017**		-0.020**	
		(0.006)		(0.006)	
female * CP			-0.002	-0.003	
			(0.006)	(0.006)	
female * math			-0.008	-0.011	
			(0.006)	(0.006)	
female * EA					0.002
					(0.005)
N	29393	29393	29393	29393	29393
Joint sig int 1	0.821			0.569	
Joint sig int 2		0.009		0.001	
Joint sig int 3			0.283	0.083	
Joint sig int 1+2				0.020	
Joint sig int all				0.029	

Standard errors in parentheses are clustered at the family level; $*$ p<0.05,$**$ p<0.005

Table 26: High school: heterogeneity by gender

	(1) est1	(2) est2	(3) est3	(4) est4	(5) est5
Female	0.028**	0.028**	0.027**	0.028**	0.029**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Extraversion PGI (single)	-0.011**			-0.008*	
	(0.003)			(0.003)	
Mental stability PGI (single)	0.006*			0.001	
	(0.003)			(0.003)	
Openness PGI (single)	0.002			0.001	
	(0.003)			(0.003)	
Narcissism PGI (single)	-0.015**			-0.013**	
	(0.003)			(0.003)	
Risk seeking PGI (single)		-0.001		-0.003	
		(0.003)		(0.003)	
Ever smoked PGI (single)		-0.020**		-0.015**	
		(0.003)		(0.003)	
Cognitive performance PGI (single)			0.024**	0.020**	
			(0.003)	(0.003)	
Math PGI (single)			0.010**	0.008*	
			(0.003)	(0.003)	
Educational attainment PGI (single)					0.040**
					(0.003)
female * extraversion	0.006			0.005	
	(0.004)			(0.004)	
female * stability	0.004			0.003	
	(0.004)			(0.004)	
female * openness	0.004			0.003	
	(0.004)			(0.004)	
female * narcissism	0.008*			0.009*	
	(0.004)			(0.004)	
female * risk		0.009*		0.008*	
		(0.004)		(0.004)	
female * ever smoked		0.005		0.005	
		(0.004)		(0.004)	
female * CP			-0.004	-0.001	
			(0.004)	(0.004)	
female * math			0.000	-0.001	
			(0.004)	(0.004)	
female * EA					-0.008*
					(0.004)
N	29393	29393	29393	29393	29393
Joint sig int 1	0.044			0.081	
Joint sig int 2		0.020		0.044	
Joint sig int 3			0.648	0.889	
Joint sig int 1+2				0.015	
Joint sig int all				0.033	

Standard errors in parentheses are clustered at the family level; $*$ p<0.05,$**$ p<0.005

Regression results with originally pre-registered selection of PGIs

Table 27: Income: conditional correlations with originally pre-registered selection of PGIs

	(1)	(2)	(3)	(4)	(5)
Extraversion PGI (multi)	0.052			0.272*	
	(0.133)			(0.136)	
Mental stability PGI (multi)	1.277**			0.661**	
	(0.134)			(0.138)	
Risk seeking PGI (multi)		0.031		-0.247	
		(0.126)		(0.134)	
Delay discounting PGI (multi)		-2.599**		-0.595*	
		(0.129)		(0.282)	
Cognitive performance PGI (multi)			0.219	0.155	
			(0.188)	(0.194)	
Highest math (multi)			2.608**	1.997**	
			(0.188)	(0.289)	
Educational attainment PGI (multi)					2.760**
					(0.129)
N	25883	25883	25883	25883	25883
Joint sig 1	0.000			0.000	
Joint sig 2		0.000		0.020	
Joint sig 3			0.000	0.000	
Joint sig 1+2				0.000	
Joint sig all				0.000	

Standard errors in parentheses are clustered at the family level; $*$ p<0.05,$**$ p<0.005

Table 28: Treiman scale: conditional correlations with originally pre-registered selection of PGIs

	(1)	(2)	(3)	(4)	(5)
Extraversion PGI (multi)	0.060			0.390*	
	(0.165)			(0.167)	
Mental stability PGI (multi)	1.240**			-0.041	
	(0.167)			(0.168)	
Risk seeking PGI (multi)		0.199		0.060	
		(0.158)		(0.167)	
Delay discounting PGI (multi)		-5.207**		-2.401**	
		(0.156)		(0.346)	
Cognitive performance PGI (multi)			1.676**	1.346**	
			(0.236)	(0.242)	
Highest math (multi)			3.945**	2.061**	
			(0.236)	(0.359)	
Educational attainment PGI (multi)					5.762**
					(0.154)
N	25515	25515	25515	25515	25515
Joint sig 1	0.000			0.061	
Joint sig 2		0.000		0.000	
Joint sig 3			0.000	0.000	
Joint sig 1+2				0.000	
Joint sig all				0.000	

Standard errors in parentheses are clustered at the family level; $*$ p<0.05,$**$ p<0.005

Table 29: Ever worked in management position: conditional correlations with originally pre-registered selection of PGIs

	(1)	(2)	(3)	(4)	(5)
Extraversion PGI (multi)	0.007**			0.005*	
	(0.002)			(0.002)	
Mental stability PGI (multi)	0.009**			0.004	
	(0.002)			(0.002)	
Risk seeking PGI (multi)		0.013**		0.010**	
		(0.002)		(0.002)	
Delay discounting PGI (multi)		-0.016**		-0.002	
		(0.002)		(0.005)	
Cognitive performance PGI (multi)			0.005	0.007*	
			(0.003)	(0.003)	
Highest math (multi)			0.015**	0.010	
			(0.003)	(0.005)	
Educational attainment PGI (multi)					0.019**
					(0.002)
N	25692	25692	25692	25692	25692
Joint sig 1	0.000			0.010	
Joint sig 2		0.000		0.000	
Joint sig 3			0.000	0.005	
Joint sig 1+2				0.000	
Joint sig all				0.000	

Standard errors in parentheses are clustered at the family level; ∗ p<0.05,∗∗ p<0.005

Table 30: Years of education: conditional correlations with originally pre-registered selection of PGIs

	(1)	(2)	(3)	(4)	(5)
Extraversion PGI (multi)	-0.046**			-0.002	
	(0.015)			(0.015)	
Mental stability PGI (multi)	0.126**			-0.008	
	(0.015)			(0.015)	
Risk seeking PGI (multi)		-0.015		-0.012	
		(0.014)		(0.015)	
Delay discounting PGI (multi)		-0.568**		-0.339**	
		(0.015)		(0.031)	
Cognitive performance PGI (multi)			0.203**	0.150**	
			(0.021)	(0.022)	
Highest math (multi)			0.392**	0.135**	
			(0.022)	(0.032)	
Educational attainment PGI (multi)					0.618**
					(0.014)
N	29393	29393	29393	29393	29393
Joint sig 1	0.000			0.817	
Joint sig 2		0.000		0.000	
Joint sig 3			0.000	0.000	
Joint sig 1+2				0.000	
Joint sig all				0.000	

Standard errors in parentheses are clustered at the family level; ∗ p<0.05,∗∗ p<0.005

Table 31: University: conditional correlations with originally pre-registered selection of PGIs

	(1)	(2)	(3)	(4)	(5)
Extraversion PGI (multi)	-0.004			0.004	
	(0.003)			(0.003)	
Mental stability PGI (multi)	0.021**			-0.001	
	(0.003)			(0.003)	
Risk seeking PGI (multi)		-0.004		-0.006	
		(0.003)		(0.003)	
Delay discounting PGI (multi)		-0.096**		-0.062**	
		(0.003)		(0.006)	
Cognitive performance PGI (multi)			0.031**	0.021**	
			(0.004)	(0.004)	
Highest math (multi)			0.068**	0.021**	
			(0.004)	(0.007)	
Educational attainment PGI (multi)					0.105**
					(0.003)
N	29393	29393	29393	29393	29393
Joint sig 1	0.000			0.456	
Joint sig 2		0.000		0.000	
Joint sig 3			0.000	0.000	
Joint sig 1+2				0.000	
Joint sig all				0.000	

Standard errors in parentheses are clustered at the family level; ∗ p<0.05,∗∗ p<0.005

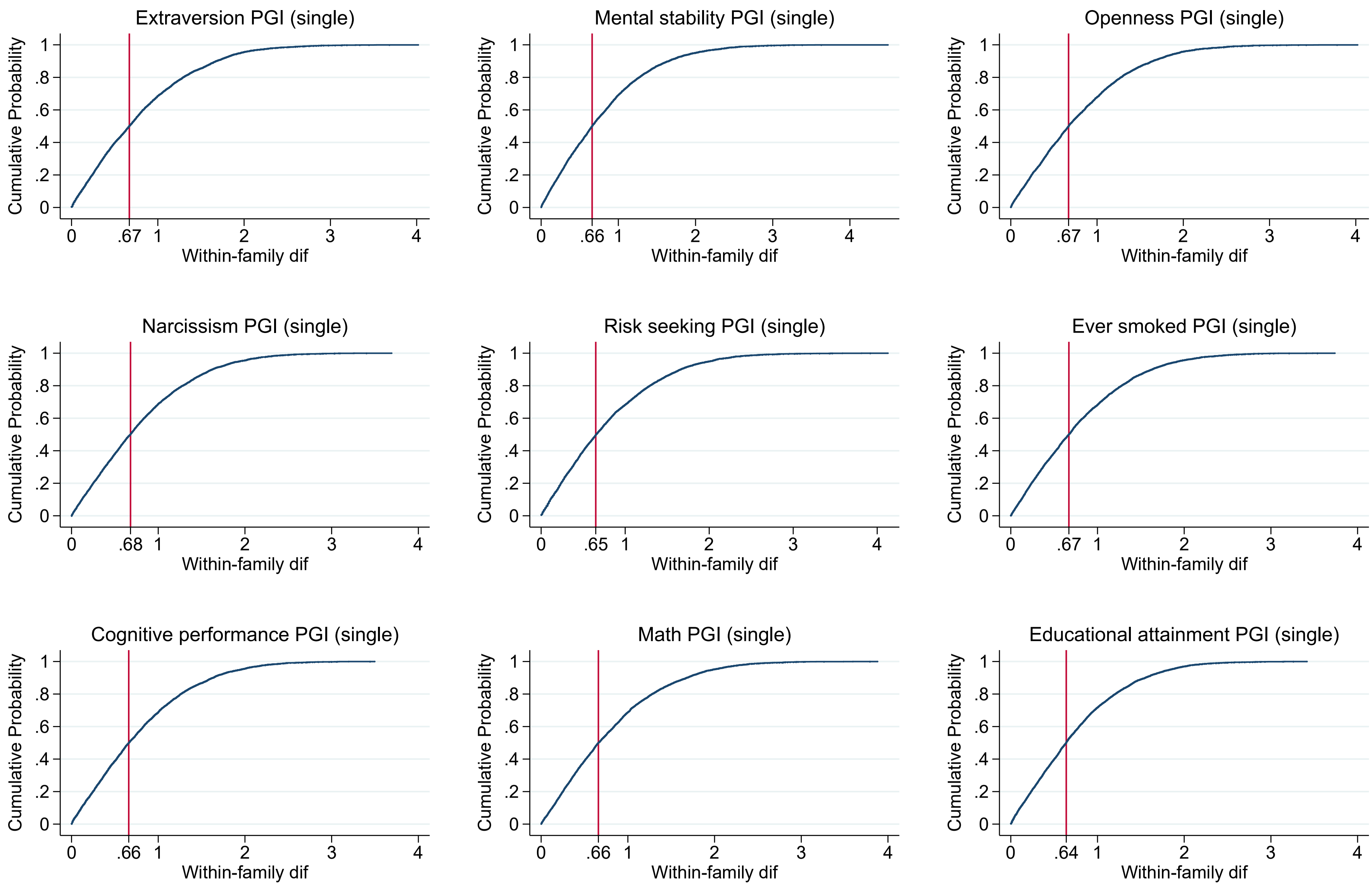
Table 32: High school: conditional correlations with originally pre-registered selection of PGIs

	(1)	(2)	(3)	(4)	(5)
Extraversion PGI (multi)	-0.008**			-0.005*	
	(0.002)			(0.002)	
Mental stability PGI (multi)	0.009**			0.001	
	(0.002)			(0.002)	
Risk seeking PGI (multi)		-0.000		0.001	
		(0.002)		(0.002)	
Delay discounting PGI (multi)		-0.035**		-0.016**	
		(0.002)		(0.004)	
Cognitive performance PGI (multi)			0.016**	0.013**	
			(0.003)	(0.003)	
Highest math (multi)			0.022**	0.010*	
			(0.003)	(0.004)	
Educational attainment PGI (multi)					0.039**
					(0.002)
N	29393	29393	29393	29393	29393
Joint sig 1	0.000			0.030	
Joint sig 2		0.000		0.001	
Joint sig 3			0.000	0.000	
Joint sig 1+2				0.000	
Joint sig all				0.000	

Standard errors in parentheses are clustered at the family level; ∗ p<0.05,∗∗ p<0.005

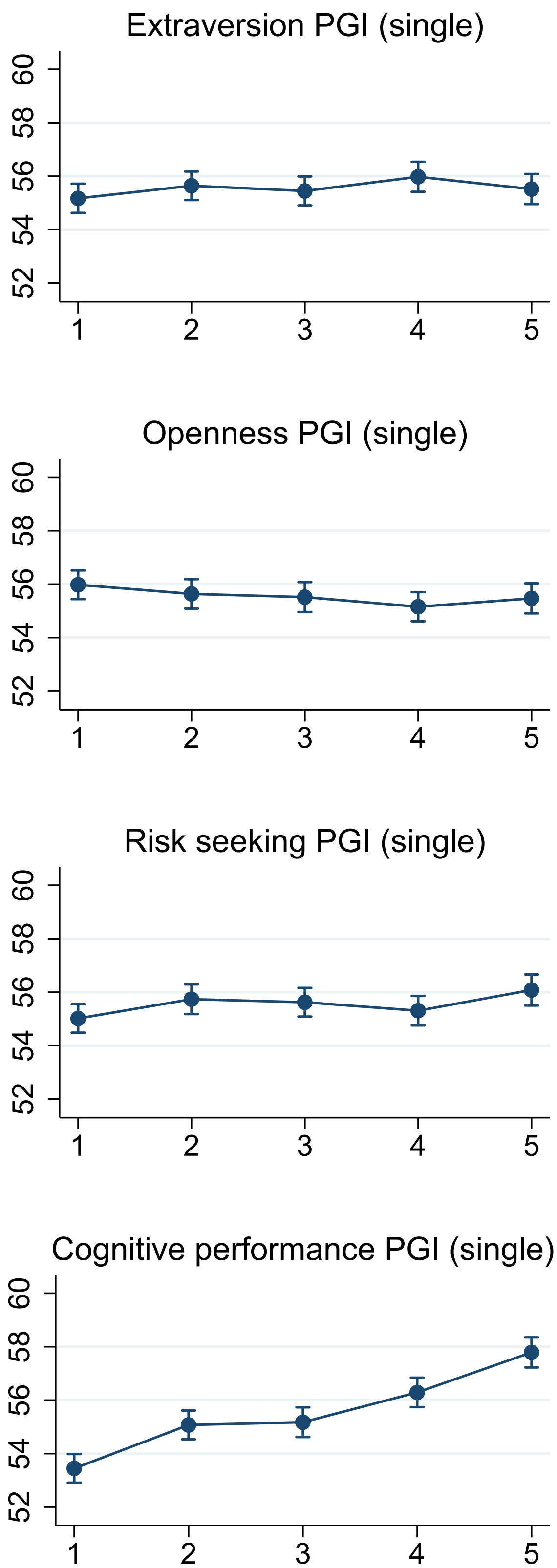
Appendix: Figures

Figure 5: CDFs of sibling differences in each PGI



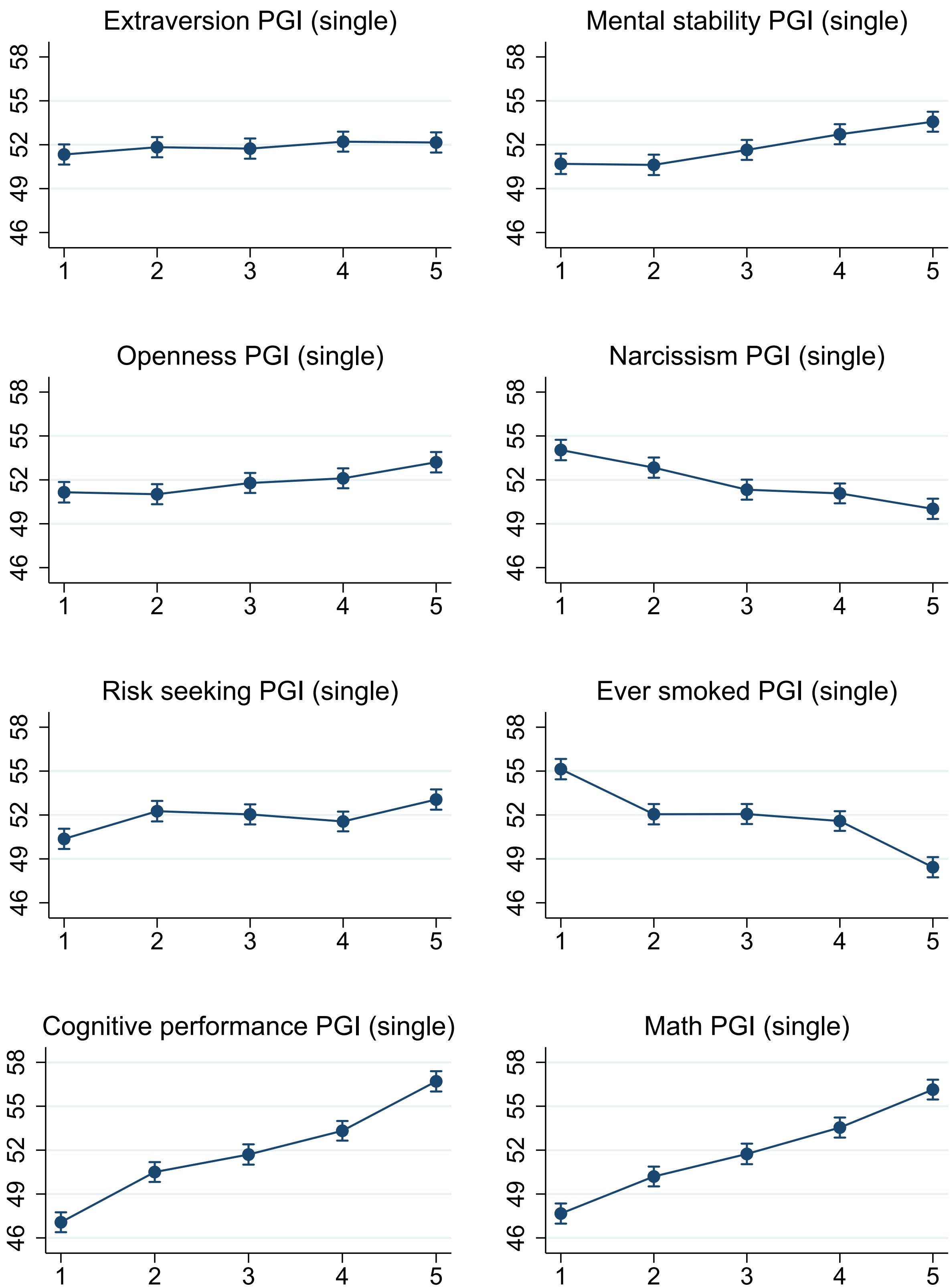
Outcomes by trait quintile conditional on gender, age and SES

Figure 6: Income



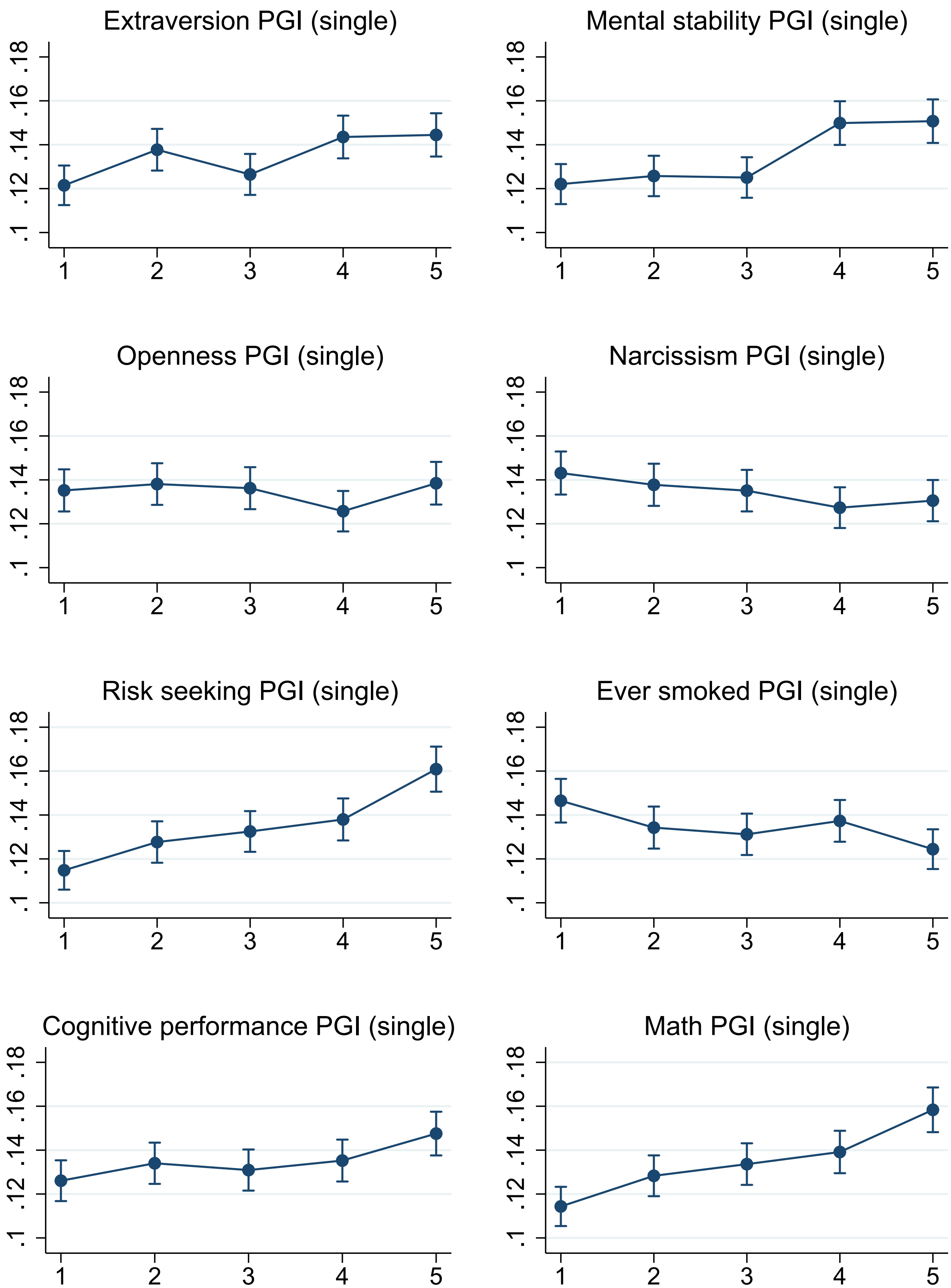
Note: error bars represent 95% confidence intervals.

Figure 7: Treiman scale



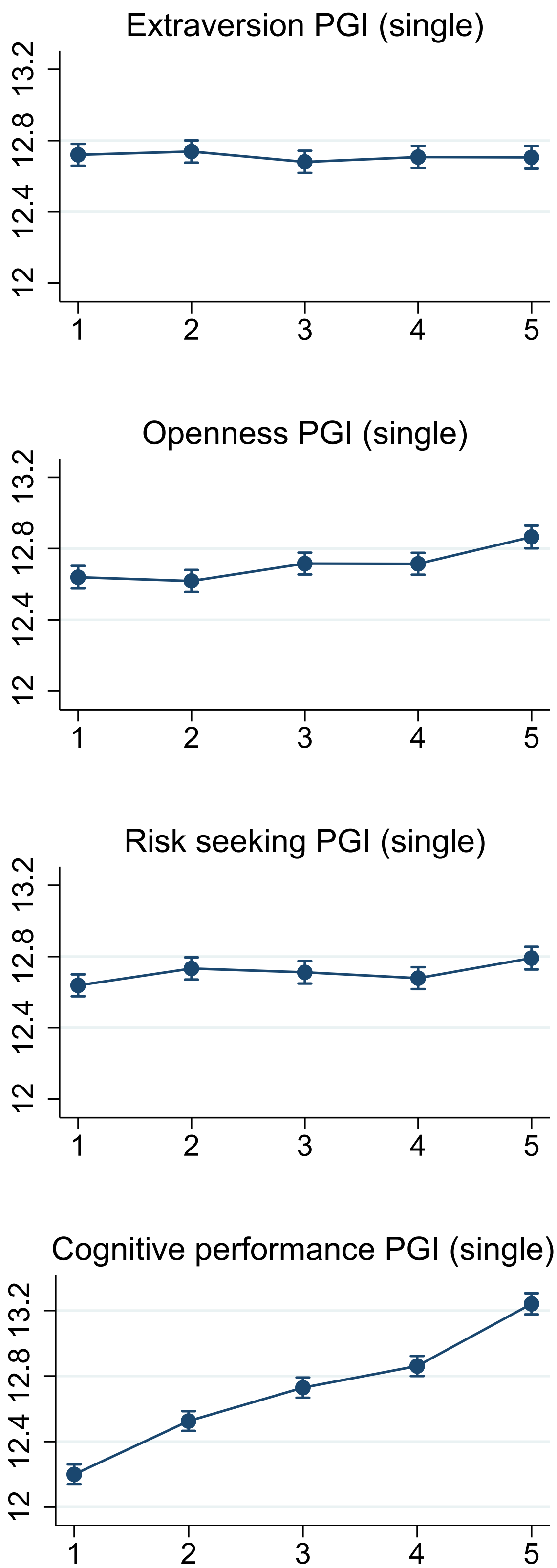
Note: error bars represent 95% confidence intervals.

Figure 8: Ever worked in management position



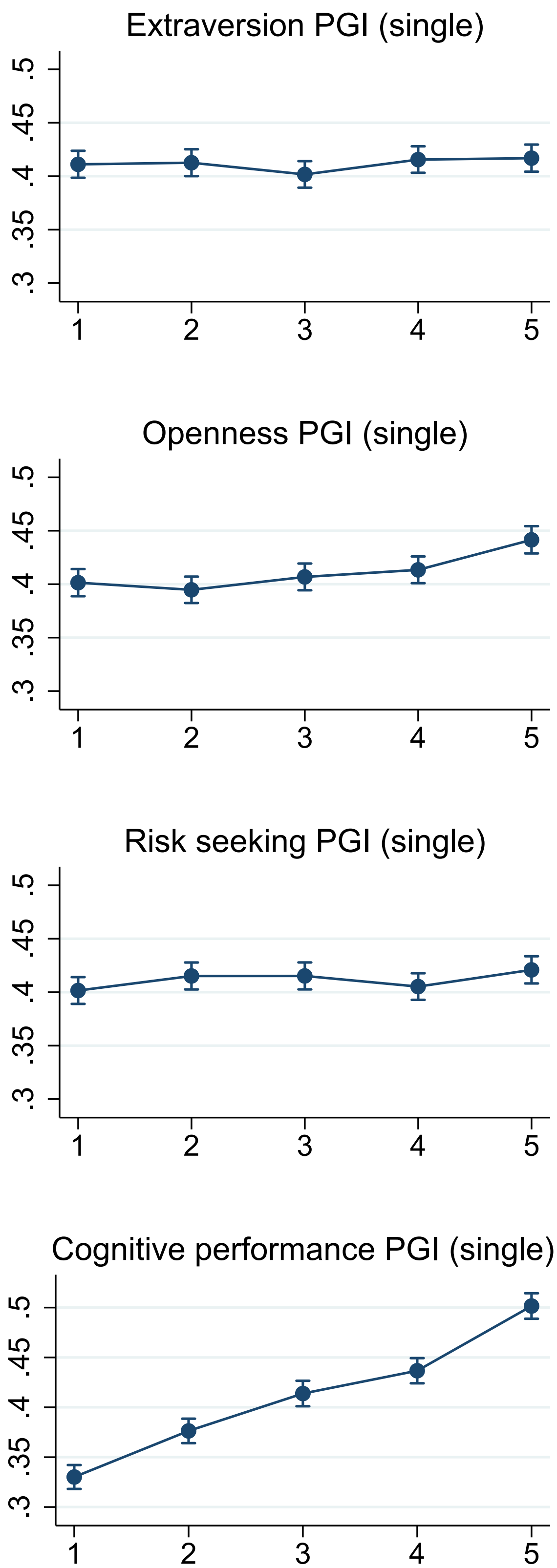
Note: error bars represent 95% confidence intervals.

Figure 9: Years of education



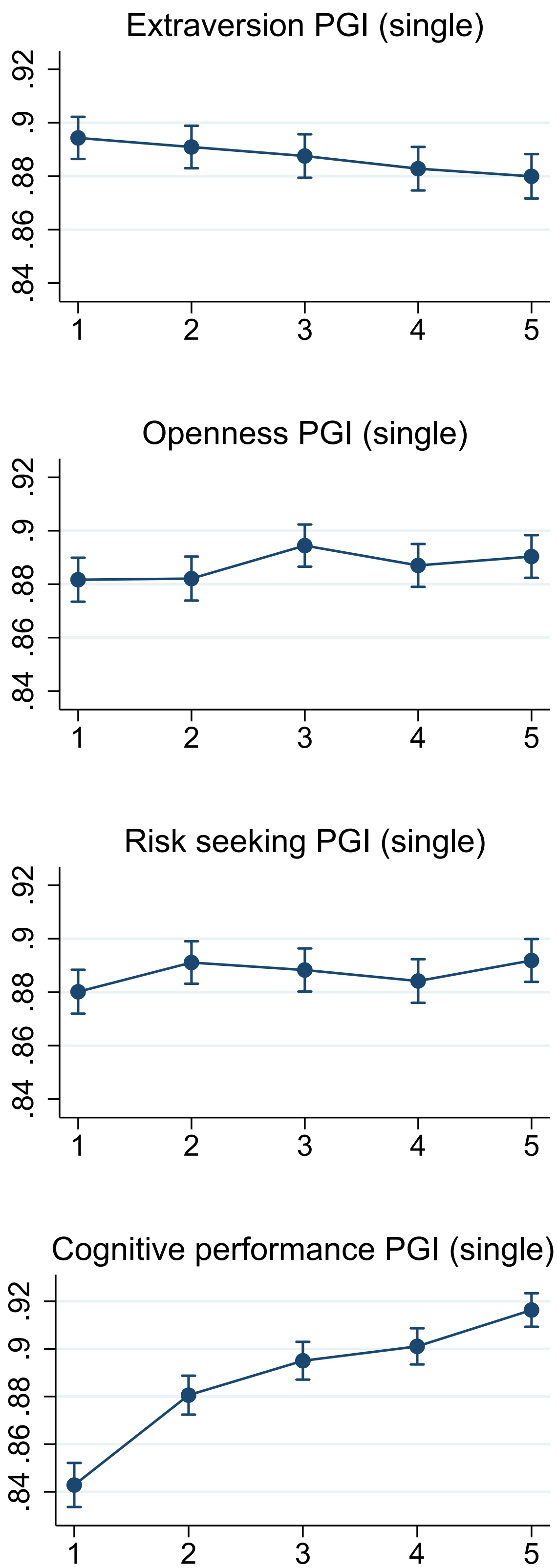
Note: error bars represent 95% confidence intervals.

Figure 10: University



Note: error bars represent 95% confidence intervals.

Figure 11: High school



Note: error bars represent 95% confidence intervals.

Appendix: Derived variable definitions

The translation scheme from the LISA register variable Sun200niva that we use is the following:

Utb2000niva	Years of education
<200	7
200-299	9
310-319	10
320-329	11
330-339	12
410-419	13
520-529	14
530-539	15
540-549	16
550-559	17
600-629	18
640-649	20

The translation scheme from the FOB census variable UtbNiva that we use is the following:

UtbNiva	Years of education
1	7
2	9
3	11
4	12
5	15
5	17
6	20

The translation scheme from the Swedish 3-digit occupational codes (Ssyk3) to the Treiman occupational status scale that we use is the following:

Ssyk3	Treimann		Ssyk3	Treimann		Ssyk3	Treimann
111	64		341	46		732	25
112	63		342	42		733	31
121	70		343	49		734	52
122	60		344	52		741	33
123	60		345	45		742	21
131	52		346	49		743	40
211	72		347	49		744	27
212	69		348	50		811	31
213	51		411	53		812	36
214	66		412	45		813	31
221	69		413	37		814	28
222	61		414	36		815	43
223	54		415	33		816	42
231	78		419	37		817	30
232	60		421	34		821	30
233	57		422	38		822	43
234	62		511	50		823	30
235	62		512	21		824	31
241	57		513	23		825	28
242	71		514	32		826	26
243	54		515	30		827	34
244	67		521	28		828	30
245	57		522	32		829	33
246	60		611	40		831	43
248	57		612	40		832	32
249	67		613	38		833	31
311	46		614	24		834	29
312	53		615	6		911	24
313	49		711	34		912	21
314	60		712	28		913	21
315	54		713	44		914	20
321	47		714	31		915	13
322	44		721	38		919	13
323	44		722	27		921	23
324	52		723	50		931	15
331	50		724	48		932	19
332	50		731	47		933	20