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Interaction of family SES with children's genetic propensity for cognitive and noncognitive skills:

No evidence of the Scarr-Rowe hypothesis for educational outcomes

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Interaction of family SES with children's genetic propensity for cognitive and noncognitive skills: No evidence of the Scarr-Rowe hypothesis for educational outcomes

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Abstract

This study examines the role of genes and environments in predicting educational outcomes. We test the Scarr-Rowe hypothesis, suggesting that enriched environments enable genetic potential to unfold, and the compensatory advantage hypothesis, proposing that low genetic endowments have less impact on education for children from high socio-economic status (SES) families. We use a pre-registered design with Netherlands Twin Register data ($426 \leq n_{indivudals} \leq 3{,}875$). We build polygenic indexes (PGIs) for cognitive and noncognitive skills to predict seven educational outcomes across three designs (between-family, within-family, and trio) accounting for different confounding sources, totalling 2x7x3=42 analyses. Cognitive PGIs, noncognitive PGIs, and parental education positively predict educational outcomes. Supporting the compensatory hypothesis, 36/42 PGIxSES interactions are negative, but only three are significant after multiple-testing corrections (p-value < 0.007). In contrast, the Scarr-Rowe hypothesis lacks empirical support, with just three non-significant positive interactions. Overall, we emphasise the need for future replication studies in larger samples. Our findings suggest mixing social stratification and behavioural genetics theories to illuminate the complex interplay between genes and social environments.

Keywords: gene-environment (GxE) interaction, educational inequality, sociogenomics, genome-wide association studies, sociology, biological psychology

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Contents

1 Introduction

Educational attainment influences future individuals' socio-economic status (SES) and health outcomes. Therefore, extensive research has investigated the intergenerational determinants of educational success. In social stratification research, the importance of family SES[1] in reproducing educational opportunities over generations is a stylised fact (Blossfeld et al., 2016; Breen and Jonsson, 2005). Environmental inequalities in cultural and economic resources and investments would largely explain why children from high-SES families are more likely to succeed in schools than their low-SES peers (Jackson, 2013). At the same time, from behavioural genetics scholarship, it is well established that individual differences in nearly every phenotype of interest to social scientists are heritable to some degree (Van Hootegem et al., 2023; Polderman et al., 2015; Turkheimer, 2000). Classical twin studies (Silventoinen et al., 2020; Branigan et al., 2013) and novel molecular studies directly measuring the genome (Okbay et al., 2022; Angers et al., 2019; Lee et al., 2018) show that educational attainment is no exception, with genetics explaining between 40% and 16% of the variance, respectively.

While the fact that both genes and environments influence educational attainment within generations is clear (Nielsen, 2016; Conley et al., 2015; Diewald et al., 2015), an interdisciplinary research area on gene-environment interactions (G×E) further scrutinises whether the effect of genetic variants on a phenotype depends on the environment where individuals are raised or schooled—and vice versa (Conley et al., 2015; Shanahan and Hofer, 2005). Nevertheless, whether genetic propensity for education matters more among children from high or low-SES families is still an open question from a theoretical and empirical viewpoint (Domingue et al., 2020).

Theoretically, two main competing hypotheses from behavioural genetics and social stratification research streams predict G×E interactions on educational attainment, outlining different patterns and mechanisms (Ruks, 2022). The Scarr-Rowe hypothesis (Scarr-Salapatek, 1971) from behavioural genetics posits that enriched social environments allow individuals to fully express their genetic potential so that genes are more predictive of cognitive performance among socioeconomically advantaged families (Rowe, Jacobson and van den Oord, 1999). Alternatively, the compensatory advantage hypothesis (Bernardi, 2014) from social stratification predicts that negative traits or events for status attainment—e.g., a low genetic propensity for education—are less detrimental to high-SES children's educational attainment due to well-off parents' aversion to downward mobility and compensatory strategies (Holm, Hjorth-Trolle and Jaeger, 2019; Breen and Goldthorpe, 1997).

Empirically, a growing interdisciplinary literature spanning sociology, psychology and economics is accumulating evidence around G×E interactions. Previous research from classical twin models (Turkheimer and Horn, 2014; Turkheimer et al., 2003) and new advancements in molecular genetics scholarship (Conley et al., 2015) reach mixed conclusions on whether advantaged families fully express or compensate their children's genetic endowments for education. In line with the Scarr-Rowe hypothesis, several twin (Baier and Lang, 2019; Harden, Turkheimer, and Loehlin, 2007) and molecular genetics studies (Ronda et al., 2022; Uchikoshi and Conley, 2021) show that genes are more predictive of intelligence or educational attainment among socio-economically advantaged individuals. A meta-analysis by Tucker-Drob and Bates (2016) supports the Scarr-Rowe hypothesis for intelligence and test scores in the US, but it did not replicate in Western Europe or Australia. Conversely, in line with the compensatory hypothesis, other studies find a stronger genetic association among low-SES individuals, neighbourhoods, or schooling environments (Stienstra and Karlson, 2023; Arold, Hufe and Stoeckli, 2022; Baier et al., 2022; Cheesman et al., 2022; Knigge et al., 2022; Ruks, 2022; Harden et al., 2020; Lin, 2020; Trejo et al., 2018). Other authors find null effects or no consistent G×E

[1] From now on, for the sake of simplicity, we generically use parental or family SES to refer to children's social background even when in this article we measure it with the highest parental educational attainment.

interactions (Breinholt et al., 2023; Malanchini et al., 2023; Baier et al., 2022; Stienstra et al., 2021; Isungset et al., 2021; de Zeeuw et al., 2019; Figlio et al., 2017; Conley et al., 2015).

In this article, we examine whether parental SES moderates the effect of children's genetic propensity for education on different educational outcomes over the life course. Precisely, we contribute to the literature by testing whether previously mixed findings on G×E interactions in educational attainment might be related to three main aspects: (1) the type of research design implemented; (2) the measures of genetic endowments studied; and (3) the type and timing of the educational outcomes analysed.

First, we implemented several research designs. One central challenge in detecting unbiased G×E interactions is to control for the endogeneity between social contexts and genetic endowments, known as gene-environment correlations (rGE). Each parent transmits, on average, 50 % of their genetic material to their offspring, and some of these genes also affect the environment where children are raised, for instance, family SES and parenting practices (Marks and O'Connell, 2023). That leads to a correlation between the family's SES characteristics and the child's genetics, named passive rGE (Hart, Little, and van Bergen, 2021; Wertz et al., 2019; Plomin et al., 1977). Estimating gene-environment interactions in the presence of rGE can lead to false positive results (Keller, 2014). However, most previous studies employ a between-family analysis (Papageorge and Thom, 2020), which does not deal with rGE or unmeasured environmental factors across families (Fletcher and Conley, 2013). To address rGE, controlling for parental genotypes is a possible solution (Isungset et al., 2021; Breinholt and Conley, 2023). In the case of the within-family design, when sibling and genetic data are available (Fletcher et al., 2023), family fixed-effects models can exploit random segregation of alleles between siblings while controlling for all usually unmeasured (genetic and environmental) family circumstances shared within the household (Cheesman et al., 2022; Domingue et al., 2015). Still, there is evidence that passive rGE biases PGI coefficients in the within-family design (Trejo and Domingue, 2018). A trio design can be implemented under the rare but increasing availability of parental genetic information (Breinholt and Conley, 2023) to directly control for mothers' and fathers' genotypes and exploit random variation in non-transmitted alleles. In doing so, one can get a more robust estimation of G×E interactions since controlling for parents' PGIs makes it credible to assume that a child's PGI is exogenous to family characteristics (Isungset et al., 2021). Thus, in this article, we triangulate findings from these between-, within-family and trio research designs to shed light on different sources of variation and confounding to identify more robust G×E interactions (Demange et al., 2022).

Second, we study cognitive and noncognitive skills PGIs. Previous G×E interaction studies on educational outcomes mainly focus on the genetic propensity for adult educational attainment, using the PGI for total years of education (Lee et al., 2018). However, educational attainment can be further distinguished into cognitive and noncognitive skills (Demange et al., 2021), which are among the most predictive and closest traits in the causal chain explaining educational performance (McGue et al., 2020; Borghans et al., 2016). While cognitive skills are measured with validated intelligence and cognitive performance tests (Nisbet, 2012), noncognitive skills are a less-well-defined concept (Demange et al., 2021), including a wide range of traits generally improving one's educational performance (Jackson and Moullin, 2023), such as grit, conscientiousness, motivation, or social skills (Kevenaar et al., 2023; Smithers et al., 2018). As cognitive and noncognitive skills are two distinct latent constructs that can act as complements or substitutes in learning and educational performance (Light and Nencka, 2019), family SES might moderate (e.g., compensate or enhance) their (genetic) association with educational outcomes differently (Gil-Hernández, 2021; Holtman, Menze and Solga, 2021; Damian et al., 2015). The first GxE study using a PGI of noncognitive skills found no interaction with parental SES in explaining academic achievement from ages 7 to 16 in the United Kingdom (Malanchini et al., 2023). Building on this study, we use PGIs for both cognitive and noncognitive skills to untangle the genetic architecture of the main predictors of educational attainment and estimate G×E interactions over further educational outcomes, triangulating from different research designs.

Third, we investigate different educational outcomes. Previous studies independently covered several educational outcomes such as test scores in late primary and lower-secondary school (Breinholt et al., 2023; Malanchini et al., 2023; Cheesman et al., 2022; Isungset et al., 2021), high-school outcomes (e.g., persistence in mathematics; Harden et al., 2020), or college completion (Papageorge and Thom, 2020). Yet, adult educational attainment results from successive teacher assessments and transitions over the educational system with different selectivity and implications for social demotion (Blossfeld et al., 2016). For instance, Ghirardi and Bernardi (2023) hypothesised and evidenced that the interaction between PGIs and parental SES might depend on the selectivity of the educational outcomes investigated. Thus, we take a life-course approach (Blossfeld et al., 2019) investigating seven educational outcomes from childhood to adulthood: grades in mathematics and reading (age 7-10), high-stakes standardised test scores (CITO: age 12), school track in secondary school (age 12-18), and adult educational attainment (age ≥ 25). This life-course approach might shed further light on G×E interactions and mechanisms, while snapshots or single educational outcomes might give a distorted picture of potential G×E interactions.

In this study, we test two competing hypotheses on G×E interactions in educational outcomes, the compensatory and Scarr-Rowe hypotheses, asking the following research question: Does the effect of genetic propensity for cognitive and noncognitive skills on educational outcomes matter more for high- or low-SES children? We answer this question through a pre-registered research design and a genotyped panel of twins, siblings, and parents from the Netherlands Twin Register (NTR) (Ligthart et al., 2019). We use PGIs for cognitive and noncognitive skills to predict seven educational outcomes across three research designs, namely the between-family, within-family, and trio designs, conducting 42 distinguished analyses (i.e., 2 PGIs x 7 outcomes x 3 designs). While most previous research focused on comprehensive educational systems from the United States (US), UK, or Norway, we test the Scarr-Rowe and compensatory hypotheses in the context of the modern Dutch early tracked educational system, which is highly selective and horizontally stratified (Blossfeld et al., 2016).

The following sections outline our two hypotheses' theoretical framework, explain the data, methods and variables, and discuss our findings' implications for the interdisciplinary social stratification and sociogenomics literature.

2 Theoretical framework

The existing literature shows that genes and environments correlate and interact in a complex interplay to influence individuals' educational attainment (Papageorge and Thom, 2020; Belsky et al., 2018; Schmitz and Conley, 2017). This section discusses the main theories from behavioural genetics and social stratification accounting for the interaction between a family SES and genetic propensity for education.

2.1 The Scarr–Rowe hypothesis

The Scarr–Rowe hypothesis claims that the relative importance of genetics for cognitive ability is higher in socioeconomically advantaged families than in disadvantaged families (Rowe, Jacobson and van den Oord, 1999; Scarr-Salapatek, 1971). The underlying assumption of this interaction effect, in which genetic variation is suppressed in low-SES families, is that those children reared in deprived environments, generally characterised by material scarcity, chronic stress and low levels of cognitive stimulation (Mcewen and Mcewen, 2020), cannot fully express their genetic potential (Uchikoshi and Conley, 2021; Baier and Van Winkle, 2021). Contrastingly, children from advantaged families experience an enriched rearing environment where their genetic potential is fully expressed.

The Scarr-Rowe hypothesis was initially developed in studies about intelligence, using classical twin models of variance decomposition and finding support in the specific context of the US, a country characterised by high child poverty, meagre social policies and high-income inequality (Turkheimer and Horn, 2014), while its replication among Western European countries and Australia does not provide empirical support to this hypothesis (Tucker-Drob and Bates, 2016). Some authors argue that the genetic heritability of intelligence might not follow a linear pattern, being only suppressed in highly deprived environments to plateau after reaching a minimum environmental quality threshold (Nielsen, 2016; Pennington et al., 2009).

This hypothesis was extended by looking at other educational outcomes beyond IQ (Baier and Lang, 2019) and using molecular data—directly measuring the genome. Studies using molecular data have investigated this hypothesis across various educational outcomes such as school test scores (Isungset et al., 2021), school tracking (Uchikoshi and Conley, 2021; Harden et al., 2020), educational attainment (Lin, 2020), and years of education (Conley et al., 2015). Moreover, instead of examining the moderation of genetic expression by family SES, some studies further examine the moderating role of schools (Trejo et al., 2018), teachers (Arold, Hufe and Stoeckli, 2022), or neighbourhoods (Cheesman et al., 2022). However, the evidence regarding the Scarr-Rowe hypothesis is highly inconclusive, as reviewed in Table S1 in the annex.

Figure 1 Panel A illustrates an application of the Scarr-Rowe hypothesis for the relationship between genetic predisposition for cognitive and noncognitive skills and educational outcomes and its moderation by family SES. The line representing individuals with low SES is flatter, indicating that individuals with a high genetic propensity for cognitive and noncognitive skills do not realise their full genetic potential in disadvantaged socio-economic environments. According to the Scarr-Rowe hypothesis, we expect to observe in our study that:

H1. PGIs for cognitive and noncognitive skills are more predictive of educational outcomes for children with high-SES parents than low-SES parents.

2.2 The compensatory advantage hypothesis

In social stratification literature, the compensatory advantage hypothesis posits heterogeneity by parental SES in the penalty of a negative trait or event for status attainment at t_0 on a subsequent outcome at t_{+1}. According to this hypothesis and related findings, the educational and labour market trajectories of individuals from privileged backgrounds are less influenced by previous adverse events or traits (Bernardi and Gil-Hernández, 2021; Bernardi and Grätz, 2015; Bernardi, 2014), such as a low genetic propensity for education. This hypothesis was initially developed to examine educational inequalities, proposing and showing that children from higher social backgrounds are more likely to overcome the negative consequences of prior poor academic performance (e.g., bad grades, grade repetition) by progressing towards higher education (Bernardi and Triventi, 2018; Bernardi, 2012).

Thanks to their cultural and economic resources, high-SES families might (un)consciously nurture their low-endowed children's nature with compensatory investments[2] (Breinholt and Conley, 2023; Houmark et al., 2020). Thus, high-SES families would compensate for their children's unfavourable (genetic) traits to eventually develop higher—than usually predicted by low genetic potential—cognitive and noncognitive skills, academic performance (e.g., grades and test scores) or transition rates to academic tracks leading to college so to avoid downward educational mobility. In line with this hypothesis, some recent molecular genetics studies found a negative interaction between enriched environments and educational outcomes, showing the compensatory or substitutive role of

[2] This compensatory mechanism could work in absolute terms independently of relative within-family resource allocation patterns across siblings (i.e., parents investing relatively more in the sibling with higher PGI for education than in the sibling with lower PGI) (Engzell and Hällsten, 2022).

high-SES families, neighbourhoods and schools, or high-quality teachers to lift students with low genetic endowments for education (Arold et al., 2022; Cheesman et al., 2022; Harden et al., 2020; Lin, 2020). However, the evidence for the compensatory hypothesis is as mixed as with the Scarr-Rowe hypothesis, as reviewed in the introduction and Table S1 in the annex.

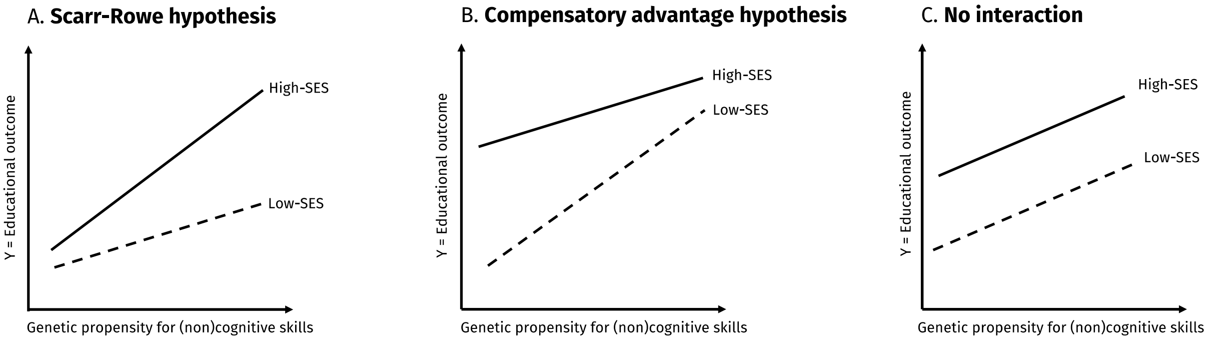
Specifically, the penalty in later educational outcomes associated with an initial negative trait or event is expected to be smaller for high-SES individuals due to class-based differences in motivation and resources. The compensatory advantage hypothesis is based on the Relative Risk Aversion model formalising SES inequalities in educational transitions (Breen and Goldthorpe, 1997). This model draws from prospect theory to propose that individuals are more sensitive to losses than gains due to evolutionary pressures so that, given their relative position in the class structure, high-SES subjects are more driven to avoid downward social mobility than low-SES subjects to move upward. For high-SES individuals, a previous adverse event or trait, such as low academic potential or performance, does not necessarily impact their later educational and occupational attainment because they stick to high educational expectations to maintain their privileged status (Bernardi and Valdés, 2021). In contrast, low-SES students would be more sensitive to a previous adverse event (Holm, Hjorth-Trolle and Jaeger, 2019), trait or contextual (i.e., macroeconomic) climate in their educational careers (Salazar et al., 2020), as relatively lower educational attainment would suffice to maintain or improve their status. Compared to disadvantaged parents, advantaged families have a large pool of economic, cultural and social resources (Lareau, 2015) to compensate for early adverse events through, for instance, private tutoring and schools, alternative educational pathways, or school involvement to influence teacher's track recommendations.

Figure 1 Panel B displays the compensatory advantage hypothesis applied to the association between genetic propensity for cognitive and noncognitive skills and educational outcomes and its heterogeneity by family SES. As can be seen, the slope is flatter for high-SES compared to low-SES children. According to this hypothesis, we expect to observe in our study that:

H2. PGIs for cognitive and noncognitive skills are less predictive of educational outcomes for children with high-SES parents than low-SES parents.

Finally, Figure 1 Panel C represents the null hypothesis of no interaction GxE interaction that would reject both the compensatory advantage and Scarr-Rowe hypotheses, where the genetic propensity for cognitive and noncognitive skills is equally predictive for high- and low-SES students, and their slopes are parallel.

Figure 1. *Hypotheses for the interaction between family SES and genetic propensity for cognitive and noncognitive skills on educational outcomes*



3 The context of the Dutch educational system

The modern Dutch educational system is primarily public and, despite some minor changes, relies on the 1968 Mammoth Act. This legal framework established free-of-charge compulsory education until the age of 16—if a degree is obtained or until 18 if no degree yet, and early tracking into different school tracks from the primary-to-secondary transition at age 12 (grade 6) (Luijkx and de Heus, 2008).

Primary education is compulsory from age 5 until age 12, but almost all children are enrolled from age 4, with a total duration of 8 grades (2 kindergarten and 6 elementary education grades). In secondary education, the system comprises three[3] main educational tracks in lower-secondary education from age 12 and grade 7 (Luijkx and de Heus, 2008), including (1) 4-year pre-vocational tracks (VMBO), further divided into four sub-tracks with different degrees of practical or theoretical focus; (2) a 5-year senior general education track (HAVO); (3) and a 6-year pre-university track (VWO).

The tracking process occurs at the end of primary school. It mainly depends on a combination of the student's high-stakes standardised CITO test scores (Dutch National Institute for Educational Measurement), measuring arithmetic and language competencies, and the teacher's recommendations based on a student's GPA and behaviour. The CITO test is administered in most Dutch schools, with scores ranging from 501 to 550, with a grade above 535 generally granting a recommendation to the two upper secondary tracks (HAVO and VWO). The CITO scores and track recommendations are strongly associated with final track enrolment.

Students enrolled in the pre-vocational tracks in lower secondary education most often transit into a vocational school (MBO) in upper secondary education, lasting between 1 and 4 years, depending on the specialisation. Access to higher education is granted either through a degree from the HAVO track, which provides access to universities of applied sciences (HBO), the most widespread option, or the completion of the VWO track leading to college or research-oriented universities (WO). However, achieving a level-4 MBO degree grants access to a university of applied sciences. At the end of the second phase of HAVO (years 4-5) and VWO (years 4-6), to access higher education, students must pass a standardised central exam for most of their subjects in combination with school-administered and designed tests for each subject to get a certificate and assign the final graduation grade.

Due to these institutional arrangements, parents of low-performing children may have less room to influence or bypass track decisions (Blossfeld et al., 2016). Thus, the Dutch educational system of early tracking is a stringent test for the compensatory advantage hypothesis. However, there is still some room for high-SES families with high educational expectations to deploy compensatory strategies if their children struggle at school or underperform to prevent them from downward mobility and enrol them into upper secondary tracks (Dronkers and Korthals, 2016). Among the possible mechanisms at play, high-SES parents might, for instance, help their kids with homework or pay for private tutoring to improve their performance in the CITO test, pressure teachers to get a higher recommendation (Timmermans et al., 2018), proactively search for alternative schools, or in case of a negative recommendation, push their children for upper-track mobility.

[3] In early secondary schools (grade 7 and 8), many students are in bridge classes typically that include two out of three tracks. Most bridge classes take one or two years, so by grade 9, most students have been funnelled into a single school track. Two adjacent tracks are often grouped, for instance, VMBO-t/HAVO classes or HAVO/VWO classes.

4 Data, samples and variables

This study's hypotheses and research design were pre-registered on the *Open Science Framework* repository before accessing the data and analyses: https://osf.io/yp4fk. Additional non-preregistered analyses are indicated as such below and should be considered exploratory. Additional deviations from the preregistration are detailed in Section 2 of the annex. All the statistical code necessary for replication will be available on the authors' GitHub repository. We cannot publish the NTR data, as participants did not consent to sharing their data publicly.

4.1 Data

The unique data of the *Netherlands Twin Register*[4] (NTR) (Ligthart et al., 2019) contains multiomics, phenotypic, and sociodemographic information about monozygotic (MZ) and dizygotic (DZ) twins (identical and opposite sex) and their family members, such as parents and siblings. The NTR's collection of blood and saliva DNA samples to identify single nucleotide polymorphisms (SNPs) allows us to construct PGIs for cognitive and noncognitive skills building on genome-wide association studies (GWAS) with large discovery samples of genetically unrelated individuals (Lee et al., 2018). From 1986 to 2017, the NTR recruited parents to register twins at birth or later throughout thirteen survey waves.

The NTR comprises two large sub-groups: families with young and adolescent twins (the Young Netherlands Twin Register) and families with adult twins (the Adult Netherlands Twin Register). First, the Young Netherlands Twin Register (YNTR) recruited families with young and adolescent twins born between the early 1980s and late 2000s (mean = 1993; SD = 5) based on birth cohort and age. The YNTR draws longitudinal information from parental reports from children aged 3 to 12, children's self-reports from age 14 to 18, and twins' full siblings' self-reports from age 14. Second, the Adult Netherlands Twin Register (ANTR) includes families with adult twins aged 25 or older born between 1914 and 1991 (mean = 1973 and SD = 12). Once they become adults, the YNTR twins and other individuals can join the ANTR, so a small subset of the YNTR is followed up from age 3 to adulthood. Here, we use both these datasets. YNTR is used as an unbalanced panel to study early educational outcomes, such as school grades, test scores (CITO) and secondary school track, while we use the ANTR to analyse adult educational attainment from age 25 among individuals born from 1980 to make the year of birth distribution comparable with the YNTR analyses.

The NTR covers 52% of all Dutch twin pairs born between 1987 and 2007, based on official statistics (Ligthart et al., 2019), while older adult cohorts are less well represented (under 30%). As with most twin registers, the NTR slightly overrepresents high-SES parents and high-achievers[5] compared to the general Dutch population. About 42% of the fathers and 32% of the mothers have higher education in our sample, while in the general equivalent population (aged 35-55 in 2005) to our birth cohorts, these figures reach 32% for men and 26% for women (Statistics Netherlands, 2023). Furthermore,

[4] Ethical approval for the NTR was provided by the Central Ethics Committee on Research Involving Human Subjects of the VU. University Medical Center, Amsterdam, and Institutional Review Board certified by the US Office of Human Research Protections (IRB number IRB-2991 under Federal-wide Assurance 3703; IRB/institute codes 94/105, 96/205, 99/068, 2003/182, 2010/ 359) and participants provided informed consent.

[5] Drawing from own analyses exploiting all the Dutch PISA study waves from 2000 to 2018 (mean year of birth = 1993; SD = 6), overlapping with the birth cohorts we analyse in the NTR data (mean year of birth = 1993; SD = 5), by grade 9, 44 % of Dutch 15-year-olds' pupils were enrolled in HAVO or VWO tracks, while 56 % were attending the VMBO tracks. In the YNTR data, 65 % of students attended the HAVO/VWO tracks, while 35 % the VMBO tracks. Furthermore, the sampled YNTR students took the CITO test from 2000, with a mean score of 532.1 versus a 532.5 average in 2005 for a large representative sample of students born in 1993 (Timmermans et al., 2015; Driessen et al., 2006). These figures imply that the distribution of CITO is representative of the student population, but there is a positive sample selection bias in the share of students attending upper secondary tracks in the NTR data.

the NTR data largely overrepresents children without a migration background. The average mother's age at first birth in the NTR data (mean = 30.6) largely overlaps with the population of reference in 2005 with a mean of 29.4 (Statistics Netherlands, 2023).

4.2 Samples

For the between-family analysis (see sections 5.1. and 5.3. below), we analyse all twins and their siblings with available information. However, we exclude one MZ co-twin randomly[6] in families with a pair of MZ-twins to avoid the lack of variation in the genetic characteristics (Mills et al., 2018), as the MZ-twins genetic correlation is ≈ 1. For the trio analysis, we follow the same criteria as the between-family analysis, except we limit the analysis to children with no missing information on parents' genotypes. In the within-family analysis (see section 5.2.), we keep a balanced sample of two family members by family to implement family fixed effects models by comparing (1) two DZ-twins in families where we observe the pair; (2) if one DZ co-twin is missing and there is only one full sibling observed within the family, we compare them and, if more than one sibling is observed, we pick a random sibling; (3) if two MZ-twins are observed in the same family, to avoid no within-family variation, we randomly selected one MZ-twin by family and assigned it a sibling if only one is observed, or a random one if more than one is available.

Table 1. *Analytical sample by research designs and outcomes*

		Research Design		
Age	**Outcome**	**Between**	**Within**	**Trio**
7	Mathematics grade	3,728	2,124	1,861
7	Reading grade	3,756	2,130	1,869
10	Mathematics grade	3,829	2,212	2,022
10	Reading grade	3,875	2,236	2,051
12	Test scores (CITO)	2,690	1,500	1,254
12-18	Upper secondary track	3,318	2,004	1,500
≥ 25	Educational attainment	1,224	426	576

After applying the selection criteria, excluding non-European ancestry individuals (less than 5% of the sample) due to population stratification issues, and deleting missing values in our variables of interest, the analytical samples range from 426 to 3,875 observations (see Table 1) depending on the research design (see section 5) and outcome analysed (see section 4.3.1). As the NTR does not require participation across all surveys, information on one or more analysed variables might be missing. We use different analytical samples by research design and outcomes to maximise sample

[6] In the annexary material, we display a robustness check analysis (section 5.2.) for the between-family and trio design analyses where we keep both MZ-twins and results hold.

size and power. [7] In addition, adult educational attainment is the only outcome from the ANTR cohort, with individuals born on average in 1973, while for the remaining outcomes taken from the YNTR, participants were born on average in 1993. Thus, to have a more homogenous sample in terms of its historical context, we restrict the sample to those born from 1980 for adult educational attainment within the ANTR cohort. We provide a table with all summary statistics for all sociodemographic, PGIs and outcomes by subsamples (by the outcome and research design), showing no considerable differences (see Excel file in the supplementary materials).

4.3 Variables

Dependent variables. We study seven educational outcomes[8] measured at different time points in the life course as dependent variables. First, we use school grades in mathematics and reading in primary education (at ages 7 and 10) measured on a 1-to-5 scale (1=poor; 2=weak; 3=fair; 4=good; 5=very good) as reported by mothers. [9] Second, we look at standardised national test scores (CITO) at age 12, a crucial outcome that influences teacher's track recommendation and student's track choice in lower-secondary education, ranging from 501 to 550 in its original scale, which we transformed into z-scores. Third, we take information about the type of secondary school attended using the last available information from age 12 to 18.[10] We coded as 1 those children who attend university preparation education (VWO) or senior general secondary education (HAVO) and as 0 those who attended pre-vocational secondary education or upper-secondary vocational education (MBO). Finally, we look at adult educational attainment from age ≥ 25 by distinguishing between those who have a university (wo) or university of applied sciences (HBO) degree (1) and those who finished secondary or primary education (0).

Independent and moderator variables. As the main independent variables, we use PGIs for cognitive and noncognitive skills. A PGI is a quantitative variable summarising the individual's genetic propensity for certain traits or behaviours (Mills and Tropf, 2020). Our PGIs for cognitive and noncognitive skills are based on the GWAS effect sizes estimated by Demange et al. (2022) and constructed using the GWAS-by-subtraction method by Demange et al. (2021).[11] PGIs were computed using Plink software version 1.9 based on weighted betas obtained using the LDpred v1.0.0 software, using infinitesimal prior, a linkage disequilibrium (LD) pruning window of 250kb and 1000Genomes phase 3 CEU population as LD reference. In the primary analysis, we use the PGI for cognitive and noncognitive skills as a continuous variable transformed into z-scores. We also categorise it in terciles in the robustness checks (see sections 5.1.2. and 5.1.3. in the annex) to account for potential nonlinearities. The PGI for cognitive skills measures the genetic variance of cognitive performance as tagged by common genetic variations (common SNPs). The PGI for noncognitive skills reflects the

[7] To get an idea of the required sample size to study GxE interactions with enough statistical power, we reviewed the most recent studies examining the interaction between educational PGIs and parental SES (see Table S1 in the annex). Following simulations by Domingue et al. (2020:473-475), we expect a needed sample about 1.500 observations to detect interaction beta of 0.1 with power 80%. Thus, most of our subsamples are powered to detect true effects reliably, but we should be particularly cautious for the subsamples on educational attainment.

[8] In the pre-registration, we included teachers' recommendation for the type of secondary school at age 12 as an additional outcome. However, the analytical sample sizes of this variable are very low, thus, we do not include it in the final analyses (see Section 2 in the annex).

[9] These variables might be problematic since they are not coming from register data, but self-reported by parents. In case of systematic misreporting by family SES, we might observe a biased GxE interaction but, to our knowledge, there is no evidence on data quality issues in the NTR data.

[10] In our sample, 90 % of students, on average, remain on the same track from age 14 to 18.

[11] The summary statistics of the genome-wide association study (GWAS) for cognitive and non-cognitive skills can be found at the following link: https://dataverse.nl/dataset.xhtml?persistentId=doi:10.34894/MMXYPL

genetic variance of educational attainment independent of cognitive performance, as tagged by SNPs (Demange et al., 2021).

As the main measure of a family's SES, we use a dichotomous variable distinguishing between high- and low-educated parents (1=university; 0=primary, secondary education, and higher vocational schooling), taking this information in the first year available (e.g., at age 3 for YNTR participants). Using a dominance approach, we look at the highest educational level among fathers and mothers. As a robustness check, we replicate the analyses using parental highest occupation (1=higher-grade professionals) as an alternative measure of a family's SES, and we find robust results (see section 5.3. of the annex).

Control variables. To minimise unobserved confounding in the between-family analysis, we account for the following control variables: gender, birth year, mother's age, and the number of children in the family. In the within-family analysis, we control only for variables that may vary, such as gender, mother's age, and birth year (only among non-twin siblings). In the trio analysis, we control for all the covariates used in the between-family analysis and include the mother's and father's PGIs for cognitive and noncognitive skills. The mother's and father's PGIs have been constructed following the same procedure used to operationalise the children's PGIs (see section 4.3.2. above). In all three designs, we also control for ancestry's first 10 genetic principal components (PCs) and the genotyping platform, a standard practice in the genomics literature (see Okbay et al., 2016).

5 Methods

5.1 Between-family analysis

We estimate equation (1a) where *i* is a child, and $\boldsymbol{Z}_i$ is a vector of controls (child's gender, year of birth, mothers' age at first birth, number of children in the family, 10 genetic principal components, genotyping platform). Specifically, to assess the predictive power of children's PGI for cognitive and noncognitive skills, in baseline equation (1a), we include the PGI for cognitive skills, PGI for noncognitive skills and family's SES. We expect β1, β2 and β3 to be positive and statistically significant in equation (1a).

$$Y_i = \alpha + \beta_1 PGI\ Cog_i + \beta_2 PGI\ NonCog_i + \beta_3 SES_i + \boldsymbol{Z}_i + \varepsilon_i\ (Eq. 1a)$$

The below equations formalise the two-way interactions between a child's PGI for cognitive (1b) or noncognitive skills (1c) and parental SES. According to the *Scarr-Rowe hypothesis* (H1), we expect β4 (equations 1b and 1c) to be positive and significant, so PGIs for cognitive or noncognitive skills are more predictive among high-SES children. Alternatively, according to the *compensatory advantage hypothesis* (H2), β4 is expected to be negative and statistically significant, so PGIs for cognitive or noncognitive skills are less predictive for high-SES children's educational outcomes than low-SES children.

$$\begin{aligned} Y_i = \alpha + \beta_1 PGI\ Cog_i + \beta_2 PGI\ NonCog_i + \beta_3 SES_i + \beta_4 SES_i\ x\ PGI\ Cog_i + \beta_5 SES_i\ x\ \boldsymbol{Z}_i \\ + \beta_6 PGI\ Cog_i\ x\ \boldsymbol{Z}_i + \boldsymbol{Z}_i + \varepsilon_i\ (Eq. 1b) \end{aligned}$$

$$\begin{aligned} Y_i = \alpha + \beta_1 PGI\ Cog_i + \beta_2 PGI\ NonCog_i + \beta_3 SES_i + \beta_4 SES_i\ x\ PGI\ NonCog_i + \beta_5 SES_i\ x\ \boldsymbol{Z}_i \\ + \beta_6 PGI\ NonCog_i\ x\ \boldsymbol{Z}_i + \boldsymbol{Z}_i + \varepsilon_i\ (Eq. 1c) \end{aligned}$$

Comparing SES inequality *vis-à-vis* gender and migration inequalities also result in a striking portrait. SES gaps in ICT literacy and other domains are astounding in effect size compared to gaps by gender or migration background. Boys seem to perform better than girls in math, mirroring a common finding in the literature. This gap remains constant up to grade 9 but strikingly lower in magnitude (0.35 SD approximately) compared to gradients by parental education or occupational status. All in all, there are no meaningful differences by gender or migration background in math, science, or reading. ICT literacy is no exception; boys and girls seem to perform equally on average, as do migrants and natives. What is more, inequality by gender or migration background in ICT literacy (like science and reading) do not emerge while children navigate throughout primary schooling and even when they are tracked in secondary schooling.

5.2 Within-family design

We implement an additional research design to account for potential bias due to rGE and exploit random variation in siblings' genetic endowments. We apply the within-family design with twin and sibling FE. Using this design, we can assume that variation in siblings' PGIs for cognitive and noncognitive skills is exogenous (direct genetic effects) (Demange et al., 2022) since each sibling randomly gets 50% of their genetic makeup in the process of reproduction, being unconfounded by parental SES.

$$Y_{ij} = \alpha + \beta_1\, PGI\ Cog_{ij} + \beta_2\, PGI\ NonCog_{ij} + \boldsymbol{Z}_{ij} + \delta_j + \varepsilon_{ij}\ (Eq. 2a)$$

In equation 2a, *i* is a child within family *j*, δ_j represents the family fixed effect and $\boldsymbol{Z}_{ij}$ is a vector of controls including the child's gender, birth year (only among twins and siblings comparisons), 10 principal genetic components and genetic testing platform. We run family-FE models, including children's PGIs for cognitive and noncognitive skills and controls in the main model in equation (2a) above. Again, in line with previous between-family models, we expect β1 and β2 to be positive and statistically significant in equation (2a). However, effect sizes might be slightly smaller due to attenuation bias, partial control for gene-environment correlations and other family-constant factors. Since parental SES is the same for twins and siblings within the same family, its constitutive term can not be estimated in the within-family design.

Finally, we estimate the interactions between children's PGIs for cognitive and noncognitive skills and family SES in equations (2b) and (2c), respectively. We expect the interaction between parental SES and children's PGIs in β3 (equations 2b-2c) to be positive and statistically significant under the Scar-Rowe hypothesis (H1) so that the effect of PGIs on outcomes is higher for high-SES in comparison with low-SES families. On the other hand, we expect the interaction between parental SES and children's PGIs in β3 (equations 2b-2c) to be negative and statistically significant under the compensatory advantage hypothesis (H2) so that the effect of PGIs on outcomes is lower for high-SES in comparison with low-SES families.

$$\begin{aligned} Y_{ij} = \alpha + \beta_1\, PGI\ Cog_{ij} + \beta_2\, PGI\ NonCog_{ij} + \beta_3 PGI\ Cog_{ij}\ x\ SES_i + \beta_4 SES_i\ x\ \boldsymbol{Z}_{ij} + \beta_5 PGI\ Cog_{ij}\ x\ \boldsymbol{Z}_{ij} \\ + \boldsymbol{Z}_{ij} + \delta_j + \varepsilon_{ij}\ (Eq. 2b) \end{aligned}$$

$$\begin{aligned} Y_{ij} = \alpha + \beta_1\, PGI\ Cog_{ij} + \beta_2\, PGI\ NonCog_{ij} + \beta_3 PGI\ NonCog_{ij}\ x\ SES_i + \beta_4 SES_i\ x\ \boldsymbol{Z}_{ij} \\ + \beta_5 PGI\ NonCog_{ij}\ x\ \boldsymbol{Z}_{ij} + \boldsymbol{Z}_{ij} + \delta_j + \varepsilon_{ij}\ (Eq. 2c) \end{aligned}$$

5.3 Trio design

To perform the trio design, we restrict the samples to children with available parental genetic information. We estimate the models above in the between-family analysis and additionally control for parents' and mothers' PGIs for cognitive and noncognitive skills to control for rGE.

$$Y_i = \alpha + \beta_1 PGI\ Cog_i + \beta_2 PGI\ NonCog_{\ i} + \beta_3 SES_i + \boldsymbol{Z}_i + \varepsilon_i\ (Eq.3a)$$

Firstly, we estimate the model expressed in equation (3a) where *i* is child, and $\boldsymbol{Z}_i$ is a vector of controls (child's gender, year of birth, mothers' age at first birth, number of children in the family, 10 genetic principal components, genetic testing platform).

$$\begin{aligned} Y_i = \alpha + \beta_1 PGI\ Cog_i + \beta_2 PGI\ NonCog_{\ i} + \beta_3 SES_i + \beta_4 Parents\ PGI\ Cog_i + \beta_5\ Parents\ PGI\ NonCog_i \\ + \boldsymbol{Z}_i + \varepsilon_i\ (Eq.3b) \end{aligned}$$

Then, in equation (3b), we add the father's and mother's PGIs for cognitive and noncognitive skills to account for rGE. The coefficients β1 and β2 should remain positive and statistically significant in the presence of direct genetic effects of children's PGI for cognitive and noncognitive skills on educational outcomes.

$$\begin{aligned} Y_i = \alpha + \beta_1 PGI\ Cog_i + \beta_2 PGI\ NonCog_{\ i} + \beta_3 SES_i + \beta_4 Parents\ PGI\ Cog_i + \beta_5\ Parents\ PGI\ NonCog_i \\ + \beta_6 SES_i\ x\ PGI\ Cog_i + \beta_7\ SES_i\ x\ \boldsymbol{Z}_i + \beta_8 PGI\ Cog_i\ x\ \boldsymbol{Z}_i + \beta_9\ SES_i\ x\ Parents\ PGI\ Cog_i \\ + \beta_{10}\ SES_i\ x\ Parents\ PGI\ NonCog_i + \beta_{11} PGI\ Cog_i\ x\ Parents\ PGI\ Cog_i \\ + \beta_{12} PGI\ NonCog_i\ x\ Parents\ PGI\ Cog_i + \boldsymbol{Z}_i + \varepsilon_i\ (Eq.3c) \end{aligned}$$

$$\begin{aligned} Y_i = \alpha + \beta_1 PGI\ Cog_i + \beta_2 PGI\ NonCog_{\ i} + \beta_3 SES_i + \beta_4 Parents\ PGI\ Cog_i + \beta_5\ Parents\ PGI\ NonCog_i \\ + \beta_6 SES_i\ x\ PGI\ NonCog_i + \beta_7\ SES_i\ x\ \boldsymbol{Z}_i + \beta_8 PGI\ NonCog_i\ x\ \boldsymbol{Z}_i \\ + \beta_9\ SES_i\ x\ Parents\ PGI\ Cog_i + \beta_{10}\ SES_i\ x\ Parents\ PGI\ NonCog_i \\ + \beta_{11} PGI\ Cog_i\ x\ Parents\ PGI\ Cog_i + \beta_{12} PGI\ NonCog_i\ x\ Parents\ PGI\ Cog_i + \boldsymbol{Z}_i \\ + \varepsilon_i\ (Eq.3d) \end{aligned}$$

Finally, in the trio design, we look at the two-way interactions between a child's PGI for cognitive (equation 3c) or noncognitive skills (equation 3d) and parental SES. As for the between- and within-family designs described above, we expect the interaction between parental SES and children's PGI in β6 to be positive and statistically significant under the Scarr-Rowe hypothesis (H1), and positive and statistically significant under the compensatory advantage hypothesis (H2).

6 Results

6.1 Cognitive and noncognitive skills PGIs and educational outcomes

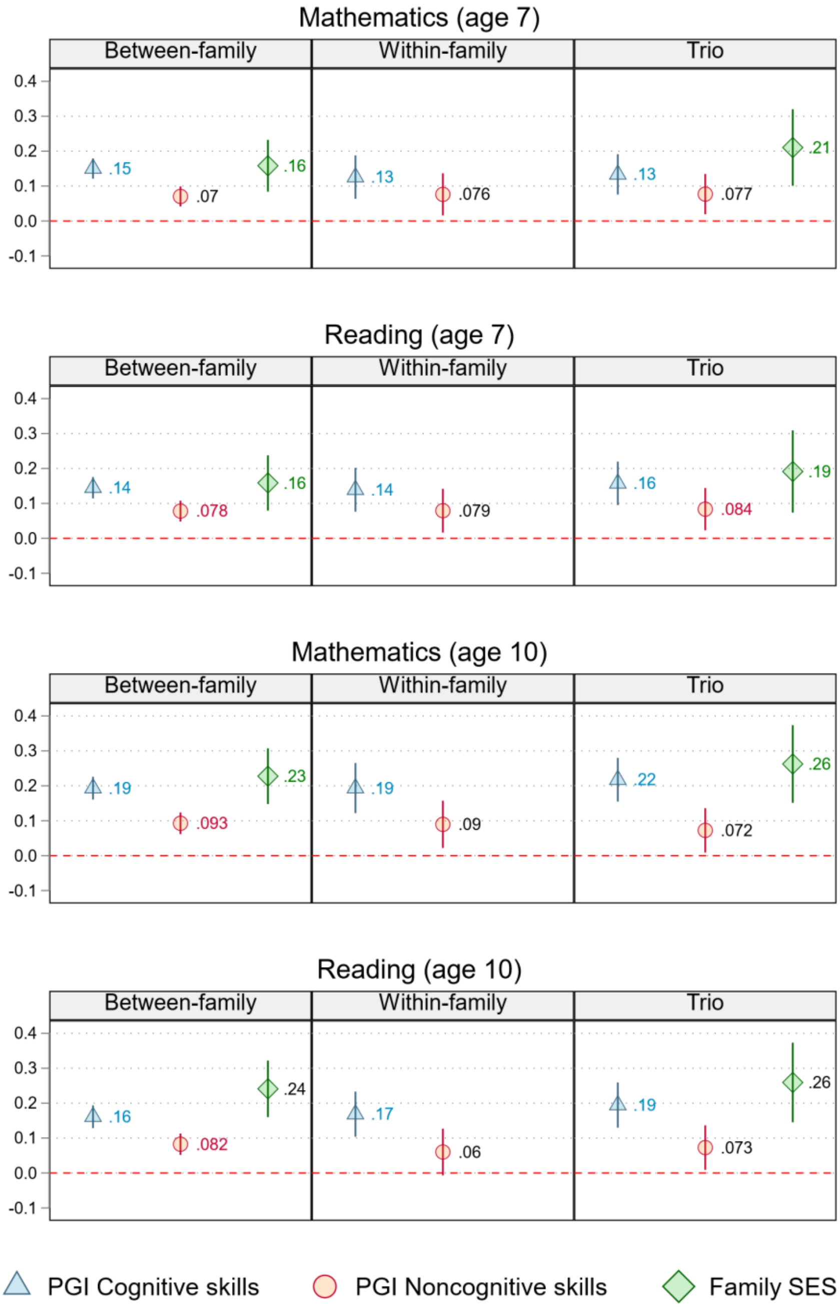
We first evaluate whether the PGIs for cognitive and noncognitive skills and family SES predict educational outcomes, as illustrated in Figures 2 and 3 by research designs (see Tables S2-S3, S5, S7-S9 in the annex). The PGIs for cognitive and noncognitive skills and family SES positively predict educational outcomes regardless of the research design implemented, namely between-family, within-family, and trio designs.

Children with higher PGIs for cognitive skills have higher educational outcomes net of their family's SES. The PGI for cognitive skills positively and significantly predict all outcomes except for adult educational attainment in the within-family design. Specifically, as shown in Figures 2 and 3, a one-unit SD increase in the PGI for cognitive skills is associated with an increase of 0.13-0.22 points on a 1-to-5 scale (SD~0.9) for school grades, a 0.2-0.25 SD increase in CITO test scores, a 9-10 % higher chance of attending upper secondary tracks, or 7-9 % higher likelihood of attaining higher education in adulthood.

Similarly to PGI for cognitive, children with higher PGIs for noncognitive skills have higher educational outcomes net of their family's SES. A one-unit SD increase in the PGI for noncognitive skills is associated with an increase of 0.06-0.09 points on a 1-to-5 scale (SD~0.9) for school grades, a 0.09-0.17 SD increase in CITO test scores, a 5-8 % higher chance of attending upper secondary tracks, or 6-9 % higher likelihood of attaining higher education in adulthood. One can note that the coefficients for the noncognitive skills PGI are, depending on the outcome, from 15 to 60 % smaller when compared to the cognitive skills PGI. However, they are still positive and statistically significant at 5% across the different designs after adjusting for the family's SES and all covariates, except for reading at age 10 and educational attainment in the within-family analysis, and for educational attainment in the trio analysis, most likely due to small sample sizes.

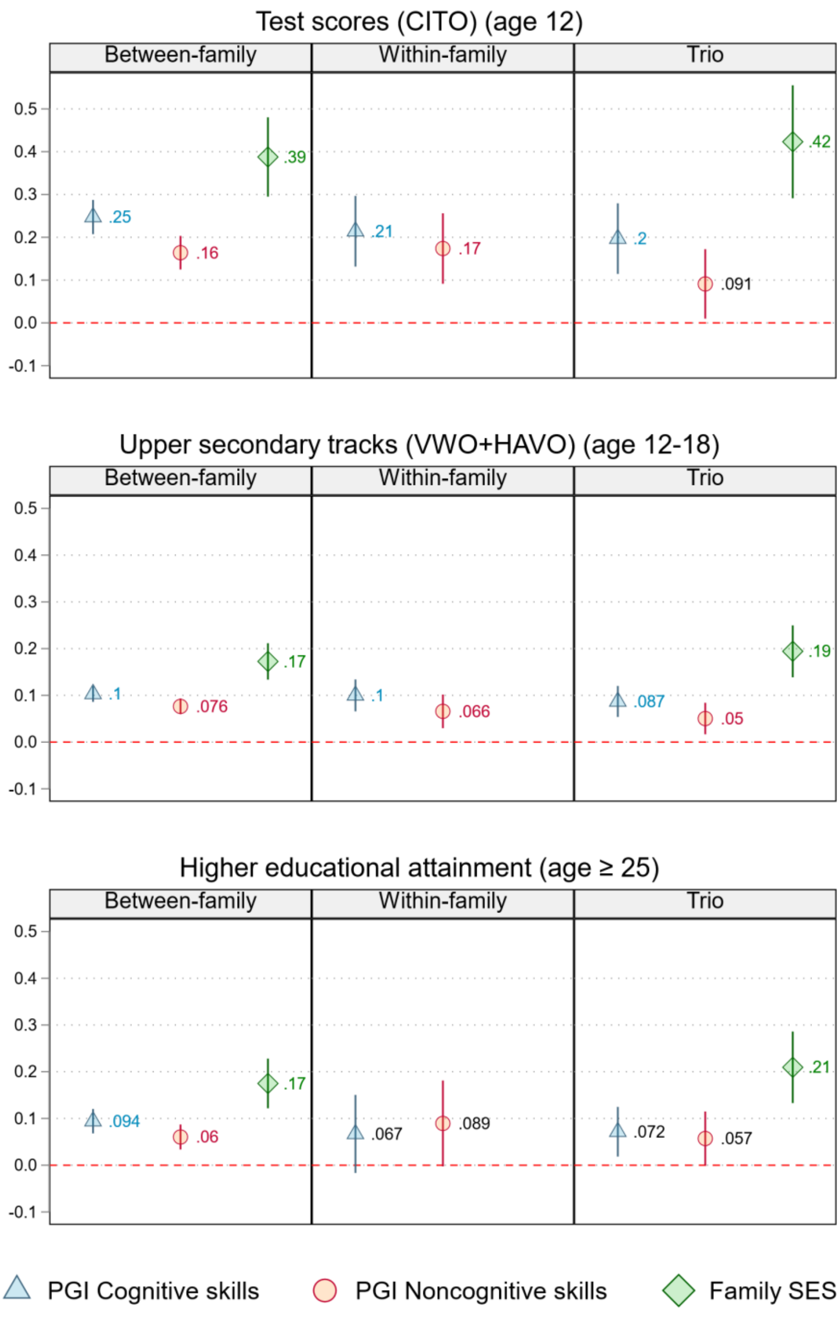
Family SES is also positively associated with children's educational outcomes. Controlling for children's PGIs for cognitive and noncognitive skills—and parents' PGIs in the trio design, individuals with highly educated parents get 0.16-0.26 points higher school grades, score 0.4 SD higher in the CITO exam, and have a 20% higher likelihood to attend upper secondary tracks or university education than their least advantaged peers. One can notice that the PGIs and family SES estimates are remarkably similar across the three designs, going against the expectation that rGE upwardly biases between-family estimates considerably.

Figure 2. *Children's cognitive and noncognitive PGIs, and family SES (inestimable in the within-family analysis) coefficients on school grades in the three designs (between, within and trio)*



Note: 95% confidence intervals. Standard errors clustered by families. We run OLS (for between and trio analysis) and family fixed-effects (for within-analysis) models. Controls in the between-family analysis: sex, birth year, mother's age, number of children, first 10 genetic PCs and testing platform. Controls for the within-family analysis: sex, birth year (only for twin and sibling comparisons), first 10 genetic PCs and testing platform. Controls in the trio analysis: sex, birth year, mother's age, number of children, mother's and father's PGIs for cognitive and noncognitive skills, first 10 genetic PCs and testing platform. See sample sizes in Table 1. PGIs and CITO scores are z-standardised. See Tables S2-S3, S5, S7-S9 in the annex for full output. SES is fixed in the within-family models, so not shown in this figure. In black are the coefficients that are not statistically significant anymore after correcting for multiple testing (p-value < 0.007).

Figure 3. *Children's cognitive and noncognitive PGIs, and family SES (inestimable in the within-family analysis) coefficients on CITO test scores, upper secondary tracks attendance, and higher educational attainment in the three designs (between, within and trio analysis)*

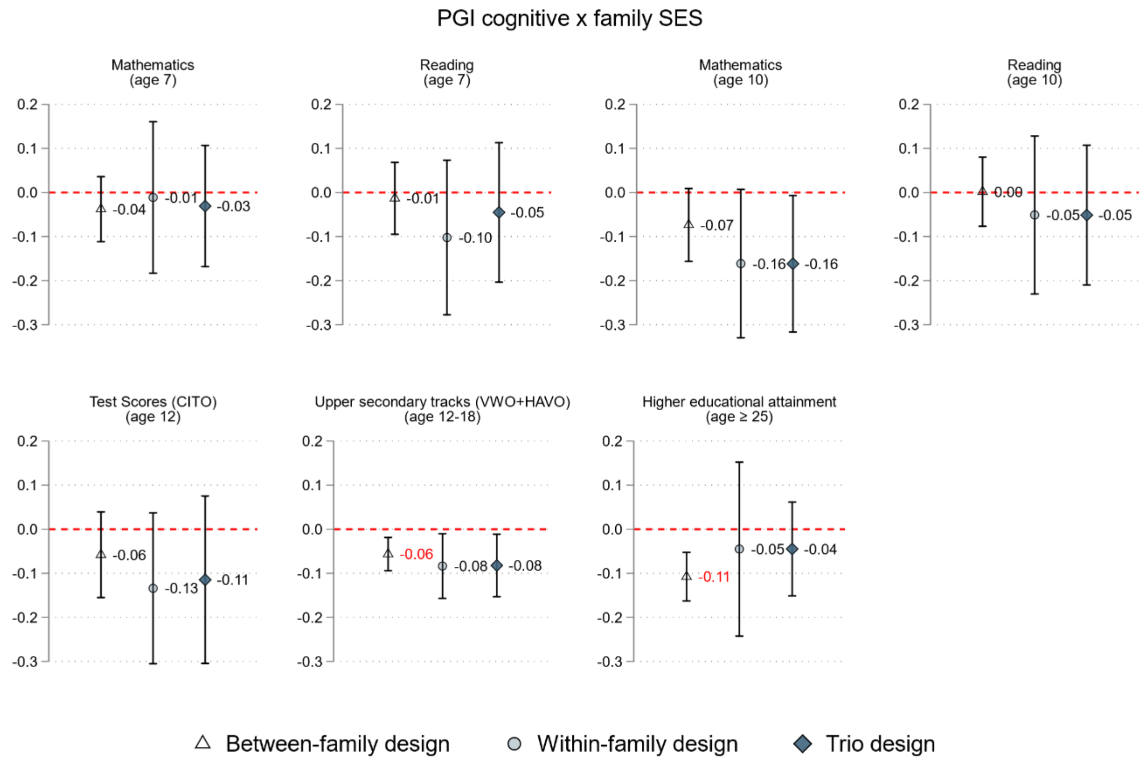


Note: 95% confidence intervals. Standard errors clustered by families. We run OLS or LPM (for between and trio analysis) and family fixed-effects (for within-analysis) models. Controls in the between-family analysis: sex, birth year, mother's age, number of children, first 10 genetic PCs and testing platform. Controls for the within-family analysis: sex, birth year (only for twin and sibling comparisons), first 10 genetic PCs and testing platform. Controls in the trio analysis: sex, birth year, mother's age, number of children, mother's and father's PGI for cognitive and noncognitive skills, first 10 genetic PCs and testing platform. See sample sizes in Table 1. PGIs and CITO scores are z-standardised. See Tables S2-S3, S5, S7-S9 in the annex for full output. SES is fixed in the within-family models, so not shown in this figure. In black are the coefficients that are not statistically significant anymore after correcting for multiple testing (p-value < 0.007).

6.2 Heterogenous genetic associations on educational outcomes by family SES

We test whether the impact of PGIs for cognitive and noncognitive skills on educational outcomes varies according to the family SES. Figure 4 shows the coefficients of the interactions between the PGIs for cognitive skills and the family's SES. Focusing on school grades, we find a negative and statistically significant (p-value < 0.05) interaction only for mathematics at age 10 in the trio design. Regarding CITO scores, the coefficients are substantial and have a negative sign in all three designs but are not statistically significant. We find a negative and statistically significant interaction (p-value < 0.05) for upper secondary tracks across all three designs; this interaction is significant after multiple testing correction in the between-family design (p-value < 0.007). Concerning educational attainment, there is a negative interaction statistically significant (p-value < 0.007) only in the between-family design, while in the within-family and trio designs, the estimates are non-significant and decrease by half but keep their negative sign. Tables S4, S6, and S10 in the annex show the interaction coefficients of these analyses for each model.

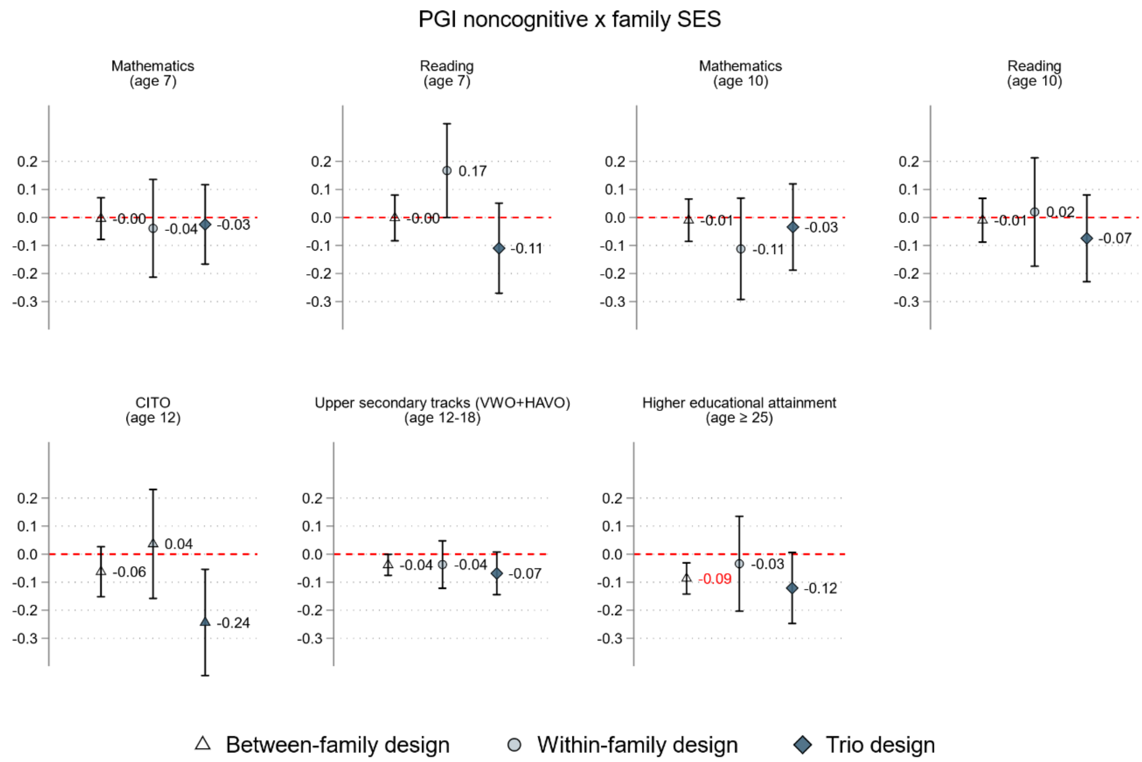
Figure 4. *Interaction coefficients between PGI for cognitive skills and family's SES on educational outcomes in the three designs (between, within and trio analysis)*



Note: 95% confidence intervals. Standard errors clustered by families. We run OLS or LPM (for between and trio analysis) and family fixed-effects (for within-analysis) models. Controls in the between-family analysis: sex, birth year, mother's age, number of children, first 10 genetic PCs and testing platform. Controls for the within-family analysis: sex, birth year (only for twin and sibling comparisons), first 10 genetic PCs and testing platform. Controls in the trio analysis: sex, birth year, mother's age, number of children, mother's and father's PGI for cognitive and noncognitive skills, first 10 genetic PCs and testing platform. Following Keller (2014), gene-covariates (cognitive skills PGI) and environment-covariates (family's SES) interactions are included. See sample sizes in Table 1. PGIs and CITO scores are z-standardised. See Tables S4, S6, and S10 in the annex for full output. In red are the coefficients that are statistically significant after correcting for multiple testing (p-value < 0.007).

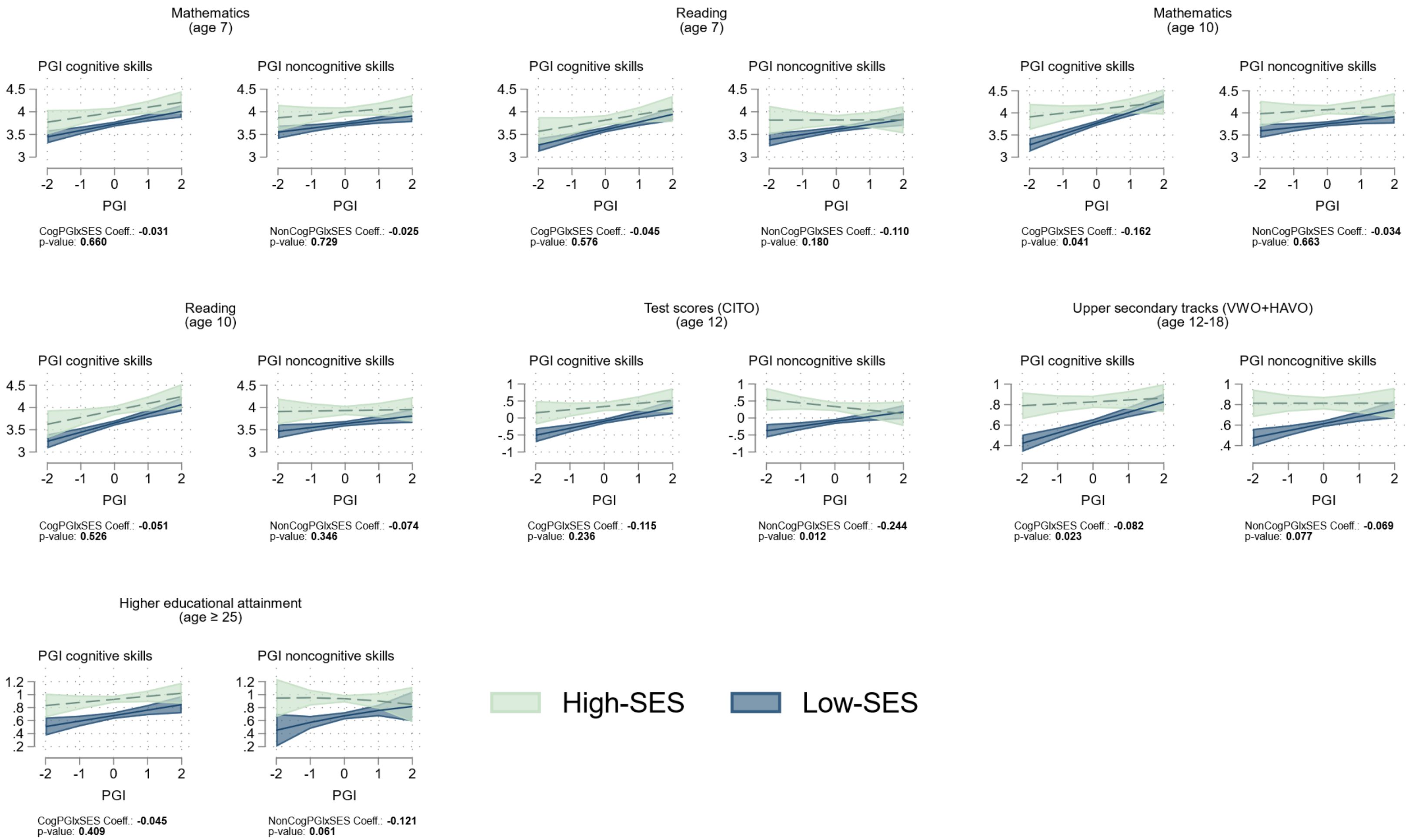
The pattern is less clear when looking at the interaction between PGI for noncognitive skills and the family's SES, as shown in Figure 5. If we focus on school grades, we observe no consistent and statistically significant interactions with any of these outcomes across research designs. Regarding the remaining outcomes, the trio design detects a statistically significant (p-value<0.05) negative interaction for CITO test scores and a suggestively significant (p-value<0.10) negative interaction for upper secondary tracks and educational attainment. Interestingly, the interaction with CITO test scores and upper secondary tracks is absent in the between- and within-family design, while it is significant after multiple testing correction for educational attainment (p-value < 0.007). Tables S4, S6, and S10 in the annex show the interaction coefficients of these analyses for each model.

Figure 5. *Interaction coefficients between PGI for noncognitive skills and family's SES on educational outcomes in the three designs (between, within and trio analysis)*



Note: 95% confidence intervals. Standard errors clustered by families. We run OLS or LPM (for between and trio analysis) and family fixed-effects (for within-analysis) models. Controls in the between-family analysis: sex, birth year, mother's age, number of children, first 10 genetic PCs and testing platform. Controls for the within-family analysis: sex, birth year (only for twin and sibling comparisons), first 10 genetic PCs and testing platform. Controls in the trio analysis: sex, birth year, mother's age, number of children, mother's and father's PGI for cognitive and noncognitive skills, first 10 genetic PCs and testing platform. Following Keller (2014), gene-covariates (noncognitive skills PGI) and environment-covariates (family's SES) interactions are included. See sample sizes in Table 1. PGIs and CITO scores are z-standardised. See Tables S4, S6, and S10 in the annex for full output. In red are the coefficients that are statistically significant after correcting for multiple testing (p-value < 0.007).

Figure 6. *Predicted grades in mathematics and reading, CITO scores, and predicted probabilities of upper secondary tracks attendance and higher educational attainment by cognitive and noncognitive PGIs for children from low- and high-SES families (trio analysis)*



Note: 95% confidence intervals. Standard errors clustered by families. We run OLS and LPM models. Controls: sex, birth year, mother's age, number of children, mother's and father's PGI for cognitive and noncognitive skills, first 10 genetic PCs and testing platform. Following Keller (2014), gene-covariates (noncognitive skills PGI) and environment-covariates (family's SES) interactions are included. See sample sizes in Table 1. PGIs and CITO test scores are z-standardised

For a clearer understanding of our findings, Figure 6 shows the predicted grades and probabilities of upper secondary tracks attendance and higher educational attainment by cognitive and noncognitive PGIs and family SES in the trio design since this is the most reliable model (Breinholt and Conley, 2023). We here focus on upper secondary tracks among the various outcomes since, as already shown in Figures 4 and 5, the negative interaction between the family SES and PGI for cognitive skills predicting attendance to the academic upper secondary tracks is the most consistent result across all the research designs, and robust also to multiple testing in the between-family design. Looking at upper secondary education in Figure 6, indeed, it is evident that the slope of the PGI for cognitive skills is considerably flatter among high-SES children compared to low-SES peers, meaning that a low genetic propensity for cognitive skills is less consequential for advantaged children compared with disadvantaged pupils. While about 80 % of high-SES students with low PGI for cognitive skills attend the upper secondary tracks, only 40 % of low-SES with low PGI for cognitive skills do the same. Therefore, educational inequalities by family background seem to be the largest among students at the bottom of the genetic distribution for cognitive skills, while this SES gap narrows progressively the higher the PGI for cognitive skills.

Figure 6 also shows a similar pattern for the other two outcomes: mathematics at age 10, and test scores (CITO). Looking at the interaction between family SES and the cognitive skills PGI on mathematics at age 10, we can see that the cognitive skills PGI is more predictive among low-SES than high-SES. Interestingly, the interaction between noncognitive skills PGI and family SES is negative and statistically significant also on test scores (CITO), with the PGI for noncognitive skills positively predicting the outcome for low-SES and the opposite for high-SES.

All in all, 86 % (36/42) of the estimated interactions between PGIs and SES are negative, contrasting with the Scarr-Rowe hypothesis (H1). Indeed, with only 3/42 non-significant positive interactions, the Scarr-Rowe hypothesis lacks substantial empirical support. On the other hand, the overall negative direction in 36 out of 42 PGIxSES interactions, with 8 interaction terms being statistically significant at 5%, seems in line with the compensatory advantage hypothesis (H2). However, only 3 out of 8 negative and statistically significant coefficients (p-value < 0.05) in the largest samples of the between-family design survive multiple testing corrections (p-value < 0.05/(7 outcomes by PGI) = 0.007) to prevent false positives due to chance. We fully recognise the need for caution in interpreting these results as they are not fully robust to multiple testing, and the smaller samples of the within-family and trio designs and adult educational attainment could undermine the statistical power to identify false negatives reliably.

6.3 Robustness checks

We run several robustness checks to assess the credibility of our findings. First, using a linear model in studying interactions may lead to bias and false discovery in dichotomous or categorical outcomes (Domingue et al., 2022; Rohrer and Arslan, 2021; Mize, 2019). Thus, we (re)estimate our analysis using logistic models for dichotomous outcomes and nonparametric PGIs specified in terciles to successfully replicate the compensatory patterns found in the main analyses (see Figures S1-S12 and Tables S11-S14 in the annex). These results do not substantially differ from the main analysis, and they confirm the negative interaction between family SES and PGI cognitive skills on the upper secondary track, which remains statistically significant across all these model specifications.

Second, we replicate the models using alternative definitions of our samples. On the one hand, we run the between-family and trio analyses without excluding one random MZ twin per family (see Tables S15-S20 in the annex). We find consistent results with the main samples and analyses, and again, the interaction between family SES and PGI cognitive skills is negative and statistically significant in both the between-family (p-value < 0.05) and in the trio design (p-value < 0.10). On the other hand, regarding educational attainment, we run additional analyses with (1) the full ANTR sample without excluding individuals born before 1980 and (2) excluding those born after 1980 (see Tables S21-S26 in the annex). Splitting the educational attainment subsamples shows stable negative interaction coefficients in the between-family models but not in the within-family and trio designs, where its sign varies by birth cohort. Interestingly, focusing on the trio-design results and the subsample of cohorts born before 1980, the interaction coefficient becomes positive and statistically significant (p-value <0.05) for the cognitive skills PGI in line with the Scarr-Rowe hypothesis. This latter pattern suggests that there might be heterogeneity in the GxE by birth cohorts and that this also could reflect changing selectivity in attaining a university degree in older cohorts (Ghirardi and Bernardi, 2023).

Finally, we replicate our analyses by building alternative definitions of parental and children's educational attainment. We use the highest parental occupation drawing from the earliest available information, as with parental education (see Tables S27-S29 in the annex). Results align with the main analysis concerning the G×E interactions for the upper secondary track, while the results for the G×E interaction on school grades for cognitive skills PGI in mathematics at age 10 and noncognitive skills PGI for CITO test scores are not statistically significant. Then, we repeat the analysis without dichotomising the children's educational attainment outcome variable. We still distinguish between the sample used in the main analysis (born from 1980) and the other two split samples presented above (i.e., the overall sample and those born before 1980). In this robustness check, educational attainment consists of the following four categories: primary school only, lower vocational school and lower secondary school, intermediate vocational school and intermediate or higher secondary school, higher vocational school, and university. Findings align with the main results (see Tables S30-32 in the annex).

7 Conclusion and discussion

This article examines the intergenerational transmission of educational inequality by testing whether genetic endowments for education matter differently by family SES. We investigate GxE interactions framed in behavioural genetics and social stratification theories to examine the competing Scarr-Rowe (H1) and compensatory advantage hypotheses (H2). While the former expects a positive interaction, arguing that high-SES families enhance full children's genetic expression, the latter predicts a negative pattern where high-SES families compensate for their children's low genetic endowments.

We provide three contributions to shed new light on previously mixed findings on these hypotheses. First, we look at GxE on educational phenotypes by untangling the genetic architecture of educational attainment—total years of education in adulthood—into cognitive and noncognitive skills, the main predictors of learning and educational performance. Second, due to data constraints, most studies implemented between- or within-family research designs that cannot fully account for gene-environment confounding. Few studies applied the trio design to enhance causal identification, which is ideal for combining parental genetic information with between-family models. Its application was limited to the US and Norway, countries with comprehensive educational systems. Hinging on Dutch panel family data, we triangulate findings from between-, within-family, and trio designs to bypass rGE in an early-tracked educational system. Third, while most previous research only looked at single outcomes with cross-sectional data, we analysed seven childhood-to-adulthood educational outcomes with different selectivity and implications for social demotion avoidance: grades and high-stakes test scores in primary education, school tracking in secondary schools and adult attainment.

We report four main findings and discuss their implications for future research. First, the evidence presented in this study shows no empirical support for the Scarr-Rowe hypothesis (H1) since most GxE interactions estimated between cognitive and noncognitive skills PGIs and family SES were of negative sign (3 non-significant positive interactions out of 42). The weight of the evidence leans more into the competing compensatory advantage hypothesis (H2), with 36/42 negative GxE interaction coefficients that hold generally consistent across different research designs and PGIs. Still, we should be particularly cautious if we take our findings at face value. Out of 36 negative GxE interaction terms, only eight are statistically significant at the conventional 5% threshold, and barely three survived the stringent multiple-testing corrections criteria (p-value < 0.007) we applied to prevent false positives.

Second, our findings suggest that previously mixed findings on G×E interactions on educational attainment might relate to the type of outcomes investigated. We found evidence for GxE interactions among specific outcomes, only documenting a sound negative G×E interaction—robust across research designs and surviving multiple testing corrections—for the cognitive skills PGI and attendance to school tracks leading to college. In line with this finding, previous social stratification studies found that high-SES parents tend to compensate for their children's low academic ability and performance (i.e., GPA, test scores, grade repetition) to keep progressing into academic pathways bound to college (Bernardi and Triventi, 2018).

Still, focusing on the trio as the most robust design accounting for parental genetics, findings suggest a negative G×E interaction for the noncognitive skills PGI when predicting high-stakes test scores at age 12 and for the cognitive skills PGI when predicting math grades at age 10. These findings align with previous evidence showing that high-SES schools can compensate for a low PGI for educational attainment in terms of mathematics persistence across secondary school in the US (Harden et al., 2020) or test scores in Norway (Cheesman et al., 2022). Examining single outcomes with snapshots might conceal that educational attainment results from successive academic achievements and transitions over the educational system. A life course approach based on longitudinal data allows for tracing educational careers and focusing on those educational outcomes that are especially critical for social demotion avoidance and future SES attainment (i.e., early track choice). This life-course approach might shed further light on G×E interactions and mechanisms in future studies.

Third, we expected an inflation of our between-family estimates due to rGE, which would be visible by an attenuation of these estimates in the within-family and trio design. However, the direction and magnitude of the estimated coefficients are broadly consistent across research designs. In the case of the main effects of PGIs for cognitive and noncognitive skills and family SES on educational outcomes, this suggests that parental education fully accounts for passive rGE mechanisms influencing children's education (Selzam et al., 2019). Likewise, adjusting for family SES and its interactions with covariates might suffice to control for inflation of GxE interactions due to rGE. Exploring the replication of this result with alternative polygenic scores or various environmental factors could yield further insights.

Fourth, we found more robust GxE interactions for the genetic propensity for cognitive skills than noncognitive skills. This pattern might be related to the higher predictive power of the PGI of cognitive skills or due to the definition of noncognitive skills used in the GWAS (residual variance of adult educational attainment), which might make this PGI less reflective of noncognitive aspects of childhood education (Demange et al. 2021). This pattern calls for further research to study complementarity or substitution dynamics between cognitive and noncognitive genetic endowments and skill formation over the life course. In this direction, Malanchini et al. (2023) suggest that the contribution of the PGI for noncognitive skills to academic achievement is most prominent later in life.

This study has some limitations that should be considered for improvement in future research. First, interaction analyses are sensitive to the definition and distribution of outcome variables (Domingue et al., 2022). Using a linear model in studying GxE interactions with censored outcomes may lead to bias and false discovery when the outcome is dichotomous or categorical. Our sensitivity analyses estimating nonlinear specifications showed consistent results with the main linear analyses. Still, our study could be refined in future replication analyses to keep up with the continuous methodological advancements in sociogenomics in PGIs prediction and interaction estimation.

The second limitation is the small number of observations in some subsamples, especially for the within-family and trio designs and the adult educational attainment outcome. The larger the sample size, the higher the reliability in detecting GxE interactions (Domingue et al., 2020). Thus, we caution that our findings might be underpowered and subject to replication when bigger samples are available in our country's case, the Netherlands (or other countries), hopefully to detect false negatives better and minimise the risk of false positives.

Third, we use different analytical samples and units of analysis according to the research design and outcome examined. Thus, the differences in the results by outcome and over the between-, within-family, and trio designs might be due to successfully isolating different confounding sources, statistical power, as outlined above, or sample selection bias. However, as briefly discussed previously, this does not seem to be a concern since there are not considerable sociodemographic, genetic and educational differences between the various subsamples used in this study (see Excel file in the supplementary materials).

Fourth, the Netherlands Twin Registry study does not fully represent the Dutch population, raising concerns about positive selection and external validity as in most twin studies. Furthermore, as standard in sociogenomics studies relying on PGIs, our analysis is restricted to individuals with European ancestry since most GWAS comprise European ancestry participants, but genetic variant associations might vary across populations with different ancestries (Martin et al., 2019). We hope future G×E studies will combine large-scale genotyped family data with longitudinal administrative information to improve power and population coverage and extend these analyses to be more inclusive of racial and ethnic minorities.

While acknowledging these limitations to guide future research, this study indicates that the Scarr-Rowe hypothesis lacks empirical support. In contrast, its competing compensatory advantage hypothesis finds partial support, suggesting that advantaged families might offset the impact of low genetic propensity for cognitive and noncognitive skills and contribute to the intergenerational reproduction of educational inequality. At the same time, these findings, limited to parental education and occupation as proxies of the family SES environment, spark investigation of enriched learning environments, for instance, in schooling systems, and its policy potential to lift students with low genetic endowments for educational skills. Looking at mechanisms explaining our findings was beyond the scope of this study. Thus, we hope future studies will investigate the mechanisms underlying the interaction process between family SES and genetic propensity for education, such as parental educational investments and expectations, to shed light on the complex intertwining between DNA and social environments.

8 References

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9 List of abbreviations and definitions

PGI	Polygenic Index
SES	Socio-Economic Status
GWAS	Genome-Wide Association Study
SNP	Single Nucleotide Polymorphism
G×E	Gene-Environment Interaction
NTR	Netherlands Twin Register
CITO	Dutch National Institute for Educational Measurement
MZ	Monozygotic twins
DZ	Dizygotic twins

10 Annexes

1 Literature review

Table S1: Literature review about studies that investigate the interaction between genetic propensity to educational attainment, cognitive and non-cognitive skills and socio-economic background using molecular data.

Study	**Country**	**Data**	**Main design**	**SES measure**	**PGI version**	**Stronger in high-SES**	**Stronger in low-SES**	**No interaction**
Conley et al., 2015	US	Framingham Heart Study (FHS), Health and Retirement Study (HRS)	Between-family and within-family	Family's SES: mothers' education	PGI EA2			X For years of education
Trejo et al., 2018	US	The Wisconsin Longitudinal Study (WLS) National Longitudinal Study of Adolescent to Adult Health (Add Health)	Between-family	School SES: % of students in school with mother graduated high school and Gini coefficient	PGI EA3	X For college completion		
de Zeeuw et al., 2019	NL	Netherlands Twin Register (NTR)	Between-family and within-family	Family's SES: parental job status, occupational and education level	PGI EA3			X For educational achievement (scholastic knowledge, including language and mathematical skills)
Harden et al., 2020	US	National Longitudinal Study of Adolescent to Adult Health (Add Health)	Between-family	School SES: % of students in school with mother graduated high school	PGI EA3		X For persistency in mathematics across the 4 years of high-school	X For mathematics tracking at grade 9th

Papageorge and Thom, 2020	US	The Health and Retirement Study (HRS)	Between-family	Family's SES: fathers' income, family well off, father's unemployment, moved asked for help	PGI EA3	X For college completion	X For high-school completion	X For labour market outcomes
Lin, 2020	US	Health and Retirement Study (HRS)	Between-family	Family's SES: highest years of education attained by father or mother	PGI EA3		X For educational attainment (in the following categories: No degree, GED/High school diploma, 2-year college degree/Some college, 4-year college degree, MA, PhD)	
Uchikoshi and Conley, 2021	US	National Longitudinal Study of Adolescent to Adult Health (Add Health)	Between-family	Family's SES: parental education, occupation, household income, receipt of public assistance	PGI EA3	X For tracking in mathematics in the 10th grade		
Isungset et al., 2021	NO	Norwegian Mother, Father and Child Cohort Study (MoBa)	Trio-design	Parents' education when parents are 30 years old	PGI EA3			X For children's academic test scores in Reading, English and Mathematics, taken in the 5th, 8th and 9th grades

Judd et al., 2021	US	Adolescent Brain Cognitive Development (ABCD) study	Between-family and within-family	Family's SES: total household income, highest parental education, and neighborhood quality	PGI Cognitive skills (Lee et al., 2018)			X For cognitive skills (crystallised intelligence, fluid intelligence, and working memory)
Arold et al., 2022	US	National Longitudinal Study of Adolescent to Adult Health (Add Health)	Between-family	School investment (teacher quality and teacher quantity)	PGI EA3		X Education attainment (years of education, high school, 2-year college degree, 4-year college degree, or completed a post-graduate degree) for the interaction with teacher quality	
Cheesman et al., 2022	NO	Norwegian Mother, Father and Child Cohort Study (MoBa)	Between-family, within-family and trio desing	Schools and residential areas	PGI EA3		X Standardised national test results for maths and reading at grades 5, 8, and 9, and English at grades 5	

							and 8 for the interaction with school	
Ronda et al. 2022	DK	Integrative Psychiatric Research (iPSYCH) study	Between-family and within-family	Family's SES: Parental human capital, family resources, family stability, and parental mental health	PGI EA3	X Years of education (only in the between-family), post-secondary education, Danish (only in the between-family), Mathematics		
Malanchini et al., 2022	UK	Twins Early Development Study (TEDS)	Twin analysis, Between-family and within-family	Family's SES: Index taking parents educational qualifications, employment, and mothers' age at first birth	PGI Cognitive and PGI Non-cognitive skills (Demange et al., 2020)			X Cognitive abilities (age 7, 9, 12, 16), Academic achievement (age 7, 9, 12, 16), Education specific non-cognitive abilities (age 9, 12, 16), Self-regulation
Breinholt et al., 2023	US (African ancestries and Latinx ancestries)	Future of Families and Child Wellbeing Study (FFCWS)	Between-family analysis	Family SES: Maternal education (0 = high school or less, 1 = more education than high school) and household income	PGI EA3			X Cognitive skills (age 9)

Note: PGI EA3: Polygenic index for educational attainment release 3 (Lee et al., 2018). PGI EA2: Polygenic index for educational attainment release 2 (Rietveld et al., 2013). Previous studies are ordered in chronological order.

2 Differences between pre-registered study and final version

Here we list and motivate a few differences between the pre-registered version of this paper and its final version:

1. Regarding adult educational attainment, we restrict the analysis to those born from 1980 instead of taking the overall available sample while conducting robustness checks on the subsample born before 1980 (see below). This decision was motivated to have comparable samples of the historical period and educational system between the young and adult *Netherlands Twin Study* cohorts since the latter has a year of birth distribution ranging from 1914 to 1991. We did not realise it at the time of the pre-registration and amended it accordingly.
2. We do not look at teachers' recommendations for the type of secondary school attended (at age 12) as an additional outcome due to its many missing observations. We thus decided to exclude it since we already included the actual academic track attended by the child.
3. We also added the number of children in the family as a control variable in the between-family and trio design models and the genetic testing platform in all models, as these variables can be potential confounders.
4. In the pre-registration we state the intention to perform a power analysis prior to data analyses to discard those underpowered outcomes/analytical samples and avoid the likelihood of observing false positives or not detecting true positives. However, to time constraints we do not perform a power analysis prior to data analysis.
5. We estimated models accounting for *the prediction hypothesis* in the pre-registration (i.e., the impact of the PGI for cognitive and non-cognitive skills on educational outcomes). However, for the sake of brevity in the final version of the paper, we decided to focus mainly on the Scarr-Rowe and compensatory advantaged hypotheses.
6. Still regarding the theoretical expectations, although we discussed and speculated about the implications of the outcomes' timing for the main findings and how future research might address it, we did not specify or test any hypotheses about the timing of the outcomes. More specifically, in the preregistration, we expect that:
    - The association between cognitive and noncognitive PGI would increase with age
    - The GxE would be stronger for school grades than CITO
    - The GxE would be stronger for tracking than cito
    - The GxE would be stronger for later outcomes than earlier

3 Samples characteristics

The following are the main criteria used to select our sample of interest and the size of the analytical samples. We selected all children or adult participants in the NTR with the available:

1. Genotypic data, and
2. Information on at least one of the following educational outcomes in all birth cohorts: school grades in numeracy and literacy, CITO at age 12, type of secondary school attended from age 12, educational attainment and

3. Information on parental SES (i.e., parent's education)

In the additional supplementary materials (Excel file), we report the summary statistics of all independent and dependent variables of the analysis by outcome and research design subsamples.

4 Main analyses tables

4.1 Between-family analysis

Table S2: OLS (mathematics, reading achievement and CITO) and LPM (academic tracking and educational attainment) regressions to test the association between children's cognitive and non-cognitive PGI and educational outcomes without including family SES.

	Mathematics (age 7)	Reading (age 7)	Mathematics (age 10)	Reading (age 10)	Test scores CITO (age 12)	Upper secondary track (age 12-18)	Educational Attainment (age ≥ 25)
Cognitive PGI	0.161***	0.155***	0.210***	0.179***	0.271***	0.114***	0.106***
	(0.015)	(0.015)	(0.016)	(0.016)	(0.020)	(0.009)	(0.013)
Non-Cognitive PGI	0.0791***	0.0868***	0.106***	0.0966***	0.184***	0.0851***	0.0688***
	(0.015)	(0.015)	(0.016)	(0.016)	(0.020)	(0.009)	(0.014)
Sex (ref: Female)	-0.0897**	0.140***	-0.246***	0.184***	-0.0905*	0.0158	0.0142
	(0.028)	(0.030)	(0.031)	(0.031)	(0.038)	(0.017)	(0.028)
Year of birth	0.00811*	-0.000592	0.00309	0.00282	-0.00503	-0.000717	-0.0196***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.003)	(0.004)
Mother age at birth	0.00725+	0.0115**	0.00820+	0.00424	0.0223***	0.0127***	0.0111**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)	(0.003)	(0.003)
Number of children	0.00856	-0.0404+	0.0226	-0.0425+	-0.0292	0.0114	-0.0180
	(0.022)	(0.023)	(0.024)	(0.024)	(0.032)	(0.013)	(0.016)
Observations	3728	3756	3829	3875	2690	3318	1224
Adjusted R2	0.0537	0.0497	0.0750	0.0473	0.116	0.105	0.0789

Note: Robust standard errors in parentheses. Two-tailed t-test: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.000$ Controls included but not reported above: first 10 PCs and Platform.

Table S3: OLS (mathematics, reading and CITO) and LPM (academic tracking and educational attainment) regressions to test the association between children's cognitive and non-cognitive PGI and educational outcomes including family SES.

	Mathematics (age 7)	Reading (age 7)	Mathematics (age 10)	Reading (age 10)	Test scores CITO (age 12)	Upper secondary track (age 12-18)	Educational Attainment (age ≥ 25)
Cognitive PGI	0.150***	0.145***	0.193***	0.161***	0.247***	0.103***	0.0942***
	(0.015)	(0.016)	(0.017)	(0.017)	(0.020)	(0.009)	(0.013)
Non-Cognitive PGI	0.0703***	0.0779***	0.0927***	0.0825***	0.164***	0.0764***	0.0604***
	(0.015)	(0.015)	(0.016)	(0.016)	(0.020)	(0.009)	(0.014)
SES (ref: Low-SES)	0.158***	0.159***	0.228***	0.241***	0.388***	0.173***	0.175***
	(0.038)	(0.040)	(0.041)	(0.041)	(0.047)	(0.020)	(0.027)
Sex (ref: Female)	-0.0881**	0.142***	-0.244***	0.185***	-0.0861*	0.0167	0.0224
	(0.028)	(0.030)	(0.031)	(0.031)	(0.037)	(0.017)	(0.027)
Year of birth	0.00753*	-0.00111	0.00166	0.00129	-0.00564	-0.000441	-0.0177***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.003)	(0.004)
Mother age at birth	0.00490	0.00920*	0.00533	0.00120	0.0154**	0.00978***	0.00828*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)	(0.003)	(0.003)
Number of children	0.00813	-0.0410+	0.0233	-0.0415+	-0.0277	0.00913	-0.0176
	(0.022)	(0.023)	(0.024)	(0.024)	(0.031)	(0.012)	(0.016)
Observations	3728	3756	3829	3875	2690	3318	1224
Adjusted R2	0.0586	0.0541	0.0834	0.0567	0.138	0.123	0.0992

Note: Robust standard errors in parentheses. Two-tailed t-test: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.000$. Controls included but not reported above: first 10 PCs and Platform.

Table S4: OLS and LPM (academic tracking and educational attainment) regressions to test the interaction between children's cognitive and non-cognitive PGI and family SES on educational outcomes.

	Mathematics (age 7)	Reading (age 7)	Mathematics (age 10)	Reading (age 10)	Test scores CITO (age 12)	Upper secondary track (age 12-18)	Educational Attainment (age ≥ 25)
SES x PGI Cognitive	-0.0378	-0.0132	-0.0736^{+}	0.00177	-0.0580	-0.0564**	-0.108***
	(0.038)	(0.042)	(0.042)	(0.040)	(0.050)	(0.019)	(0.028)
Observations	3728	3756	3829	3875	2690	3318	1224
Adjusted R2	0.0605	0.0553	0.0835	0.0573	0.139	0.124	0.106
SES x PGI Non-Cognitive	-0.00397	-0.00160	-0.00976	-0.00987	-0.0626	-0.0383*	-0.0867**
	(0.038)	(0.042)	(0.039)	(0.040)	(0.045)	(0.019)	(0.028)
Observations	3728	3756	3829	3875	2690	3318	1224
Adjusted R2	0.0607	0.0530	0.0840	0.0576	0.137	0.126	0.110

Note: Robust standard errors in parentheses. Two-tailed t-test: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.000$. Controls included but not reported above: first 10 PCs and Platform. And all controls in table A2. We also include covariates-environment (family's' SES) and covariates-gene (PGI) interaction (Keller, 2014).

4.2 Within-family analysis

Table S5: Family-fixed effect regressions to test the association between children's cognitive and non-cognitive PGI and educational outcomes.

	Mathematics (age 7)	Reading (age 7)	Mathematics (age 10)	Reading (age 10)	Test scores CITO (age 12)	Upper secondary track (age 12-18)	Educational Attainment (age ≥ 25)
Cognitive PGI	0.126***	0.139***	0.193***	0.168***	0.214***	0.0999***	0.0669
	(0.032)	(0.032)	(0.037)	(0.033)	(0.042)	(0.017)	(0.042)
Non-Cognitive PGI	0.0763*	0.0791*	0.0897**	0.0601^{+}	0.174***	0.0658***	0.0894^{+}
	(0.031)	(0.032)	(0.034)	(0.034)	(0.042)	(0.018)	(0.047)
Year of birth					-0.0155	-0.00576	-0.0441^{+}
					(0.039)	(0.009)	(0.025)
Sex (ref: Female)	-0.217***	0.133*	-0.354***	0.203***	-0.109^{+}	0.000889	0.0258
	(0.047)	(0.052)	(0.052)	(0.056)	(0.060)	(0.027)	(0.059)
Observations	2124	2130	2212	2236	1500	2004	426
Adjusted R2	0.0389	0.0221	0.0753	0.0310	0.0552	0.0317	0.0673

Note: Robust standard errors in parentheses. Two-tailed t-test: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.000$. Controls included but not reported above: first 10 PCs and Platform.

Table S6: Family-fixed effect regressions to test the interaction between children's cognitive and non-cognitive PGI and family SES on educational outcomes.

	Mathematics (age 7)	Reading (age 7)	Mathematics (age 10)	Reading (age 10)	Test scores CITO (age 12)	Upper secondary track (age 12-18)	Educational Attainment (age ≥ 25)
SES x PGI Cognitive	-0.0113	-0.102	-0.161^{+}	-0.0510	-0.134	-0.0835^{*}	-0.0451
	(0.088)	(0.089)	(0.086)	(0.091)	(0.087)	(0.037)	(0.100)
Observations	2124	2130	2212	2236	1500	2004	426
Adjusted R2	0.0683	0.0435	0.108	0.0455	0.0683	0.0461	0.138
SES x PGI Non-Cognitive	-0.0389	0.167^{+}	-0.112	0.0197	0.0364	-0.0369	-0.0341
	(0.089)	(0.085)	(0.092)	(0.099)	(0.099)	(0.043)	(0.086)
Observations	2124	2130	2212	2236	1500	2004	426
Adjusted R2	0.0592	0.0466	0.0964	0.0421	0.0619	0.0512	0.178

Note: Robust standard errors in parentheses. Two-tailed t-test: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.000$. Controls included but not reported above: first 10 PCs and Platform. We also include covariates-environment (family's' SES) and covariates-gene (PGI) interaction (Keller, 2014).

4.3 Trio-design

Table S7: OLS (mathematics, reading and CITO) and LPM (academic tracking and educational attainment) regressions to test the association between children's cognitive and non-cognitive PGI and educational outcomes using the sample of the trio-design, without controlling for family SES and parents cognitive and non-cognitive PGI.

	Mathematics (age 7)	Reading (age 7)	Mathematics (age 10)	Reading (age 10)	Test scores CITO (age 12)	Upper secondary track (age 12-18)	Educational Attainment (age ≥ 25)
Cognitive PGI	0.170***	0.165***	0.196***	0.182***	0.250***	0.117***	0.0982***
	(0.022)	(0.023)	(0.023)	(0.023)	(0.030)	(0.012)	(0.020)
Non-Cognitive PGI	0.0873***	0.0966***	0.116***	0.100***	0.148***	0.0770***	0.0624**
	(0.021)	(0.022)	(0.023)	(0.022)	(0.029)	(0.013)	(0.020)
Sex (ref: Female)	-0.116**	0.140**	-0.294***	0.169***	-0.127*	-0.00141	-0.00379
	(0.041)	(0.043)	(0.043)	(0.044)	(0.056)	(0.024)	(0.039)
Year of birth	0.0119*	-0.00145	0.00400	0.00228	-0.00760	-0.00399	-0.0240***
	(0.005)	(0.005)	(0.005)	(0.004)	(0.007)	(0.004)	(0.006)
Mother age at birth	0.00706	0.0119+	0.00201	-0.00256	0.00782	0.00964*	0.00626
	(0.006)	(0.006)	(0.007)	(0.007)	(0.009)	(0.004)	(0.005)
Number of children	0.0312	-0.0466	0.0538+	-0.0463	-0.0318	0.00635	-0.0507*
	(0.031)	(0.032)	(0.031)	(0.033)	(0.046)	(0.018)	(0.022)
Observations	1861	1869	2022	2051	1254	1500	576
Adjusted R2	0.0577	0.0501	0.0679	0.0440	0.0864	0.105	0.0657

Note: Robust standard errors in parentheses. Two-tailed t-test: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.000$. Controls included but not reported above: first 10 PCs and Platform.

Table S8: OLS (mathematics, reading and CITO) and LPM (academic tracking and educational attainment) regressions to test the association between children's cognitive and non-cognitive PGI and educational outcomes using the sample of the trio-design, controlling for family SES and not for parents cognitive and non-cognitive PGI.

	Mathematics (age 7)	Reading (age 7)	Mathematics (age 10)	Reading (age 10)	Test scores CITO (age 12)	Upper secondary track (age 12-18)	Educational Attainment (age ≥ 25)
Cognitive PGI	0.153***	0.150***	0.173***	0.159***	0.215***	0.101***	0.0798***
	(0.022)	(0.024)	(0.024)	(0.024)	(0.030)	(0.012)	(0.020)
Non-Cognitive PGI	0.0742***	0.0850***	0.0989***	0.0838***	0.126***	0.0656***	0.0512**
	(0.022)	(0.023)	(0.023)	(0.022)	(0.029)	(0.013)	(0.019)
SES (ref: Low-SES)	0.216***	0.188**	0.257***	0.252***	0.430***	0.203***	0.212***
	(0.055)	(0.059)	(0.056)	(0.057)	(0.066)	(0.028)	(0.038)
Sex (ref: Female)	-0.116**	0.140**	-0.291***	0.170***	-0.123*	-0.00110	0.00422
	(0.040)	(0.043)	(0.043)	(0.043)	(0.055)	(0.024)	(0.038)
Year of birth	0.0116*	-0.00164	0.00295	0.00130	-0.00581	-0.00307	-0.0209***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.007)	(0.004)	(0.006)
Mother age at birth	0.00395	0.00925	-0.000961	-0.00555	0.0000989	0.00588	0.00168
	(0.006)	(0.006)	(0.007)	(0.007)	(0.009)	(0.004)	(0.005)
Number of children	0.0292	-0.0487	0.0512	-0.0482	-0.0370	0.000380	-0.0449*
	(0.031)	(0.032)	(0.031)	(0.033)	(0.045)	(0.018)	(0.022)
Observations	1861	1869	2022	2051	1254	1500	576
Adjusted R2	0.0667	0.0561	0.0788	0.0546	0.115	0.132	0.0993

Note: Robust standard errors in parentheses. Two-tailed t-test: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.000$. Controls included but not reported above: first 10 PCs and Platform.

Table S9: OLS (mathematics, reading and CITO) and LPM (academic tracking and educational attainment) regressions to test the association between children's cognitive and non-cognitive PGI and educational outcomes using the sample of the trio-design, controlling for family SES and for parents cognitive and non-cognitive PGI.

	Mathematics (age 7)	Reading (age 7)	Mathematics (age 10)	Reading (age 10)	Test scores CITO (age 12)	Upper secondary track (age 12-18)	Educational Attainment (age ≥ 25)
Cognitive PGI	0.133***	0.158***	0.217***	0.195***	0.197***	0.0869***	0.0716**
	(0.029)	(0.032)	(0.032)	(0.033)	(0.042)	(0.017)	(0.027)
Non-Cognitive PGI	0.0770**	0.0835**	0.0724*	0.0728*	0.0911*	0.0504**	0.0571+
	(0.029)	(0.031)	(0.032)	(0.032)	(0.041)	(0.017)	(0.029)
Sex (ref: Female)	-0.118**	0.140**	-0.289***	0.173***	-0.128*	-0.00300	0.00355
	(0.041)	(0.044)	(0.043)	(0.044)	(0.056)	(0.024)	(0.038)
Year of birth	0.0118*	-0.00172	0.00307	0.00133	-0.00545	-0.00296	-0.0210***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.007)	(0.004)	(0.006)
Mother age at birth	0.00393	0.00919	-0.00165	-0.00580	-0.000460	0.00611	0.00153
	(0.006)	(0.006)	(0.007)	(0.007)	(0.009)	(0.004)	(0.005)
Number of children	0.0274	-0.0486	0.0523+	-0.0475	-0.0395	0.000935	-0.0431+
	(0.031)	(0.032)	(0.031)	(0.033)	(0.045)	(0.018)	(0.022)
Cognitive PGS Mother	0.0120	-0.00844	-0.0606*	-0.0452	0.0370	0.00125	0.00606
	(0.027)	(0.029)	(0.029)	(0.030)	(0.036)	(0.016)	(0.024)
Cognitive PGS Father	0.0259	-0.00736	-0.0290	-0.0275	-0.00107	0.0249	0.0129
	(0.028)	(0.029)	(0.031)	(0.031)	(0.038)	(0.017)	(0.025)
Non-Cognitive PGS Father	-0.00274	-0.0123	0.0306	-0.00106	0.0302	0.0348*	0.00320
	(0.026)	(0.028)	(0.030)	(0.031)	(0.036)	(0.016)	(0.026)
Non-Cognitive PGS Mother	-0.00540	0.0155	0.0219	0.0243	0.0393	-0.00898	-0.0161
	(0.026)	(0.028)	(0.030)	(0.029)	(0.039)	(0.016)	(0.026)
Adjusted R2	0.0653	0.0546	0.0808	0.0551	0.114	0.134	0.0943
Observations	1861	1869	2022	2051	1254	1500	576

Note: Robust standard errors in parentheses. Two-tailed t-test: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.000$. Controls included but not reported above: first 10 PCs and Platform.

Table S10: OLS and LPM (academic tracking and educational attainment) regressions to test the interaction between children's PGI for cognitive and non-cognitive skills and family SES on educational outcomes.

	Mathematics (age 7)	Reading (age 7)	Mathematics (age 10)	Reading (age 10)	Test scores CITO (age 12)	Upper secondary track (age 12-18)	Educational Attainment (age ≥ 25)
SES x PGI Cognitive	-0.0308	-0.0451	-0.162*	-0.0513	-0.115	-0.0823*	-0.0448
	(0.070)	(0.081)	(0.079)	(0.081)	(0.097)	(0.036)	(0.054)
Observations	1861	1869	2022	2051	1254	1500	576
Adjusted R2	0.0722	0.0613	0.0897	0.0614	0.111	0.130	0.106
SES x PGI Non-Cognitive	-0.0250	-0.110	-0.0342	-0.0744	-0.244*	-0.0686^{+}	-0.121^{+}
	(0.072)	(0.082)	(0.078)	(0.079)	(0.096)	(0.039)	(0.064)
Observations	1861	1869	2022	2051	1254	1500	576
Adjusted R2	0.0721	0.0564	0.0865	0.0627	0.104	0.127	0.0786

Note: Robust standard errors in parentheses. Two-tailed t-test: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.000$. Controls included but not reported above: first 10 PCs and Platform. We also include covariates-environment (family's' SES) and covariates-gene (PGI) interaction (Keller, 2014).

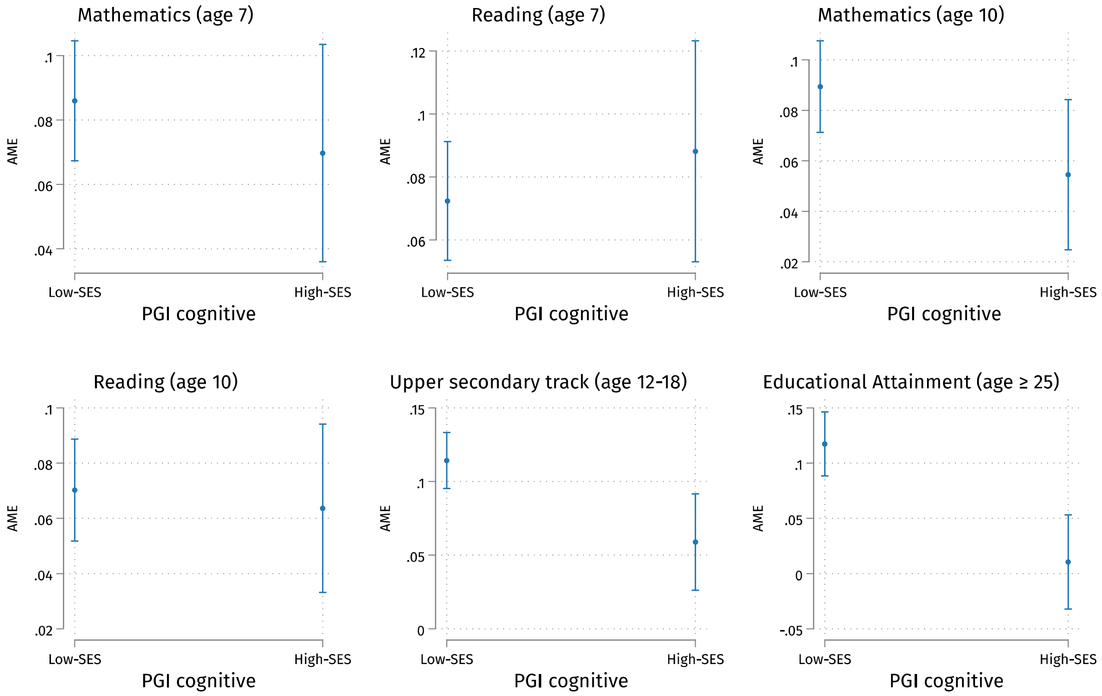
5 Robustness checks

5.1 Alternative model specifications

5.1.1 Logistic regression models

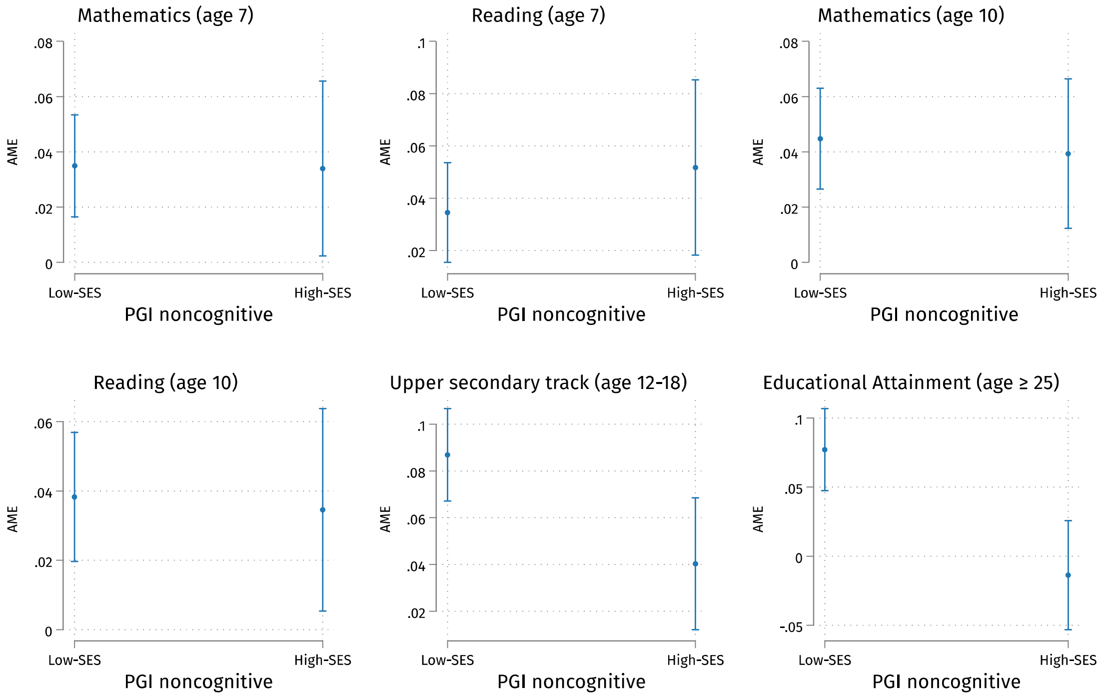
5.1.1.1 Between-family design

Figure S1: Logistic regression models for dichotomous outcomes variables in the between-family samples (without controlling for parents' PGI) for the interaction between family's SES and PGI for cognitive skills (average marginal effect, at 95 percent confidence interval)



Note: Average marginal effect (AME). Controls are included. We also include covariates-environment (family SES) and covariates-gene (PGI) interaction (Keller, 2014). For this robustness check, school grades are dichotomized.

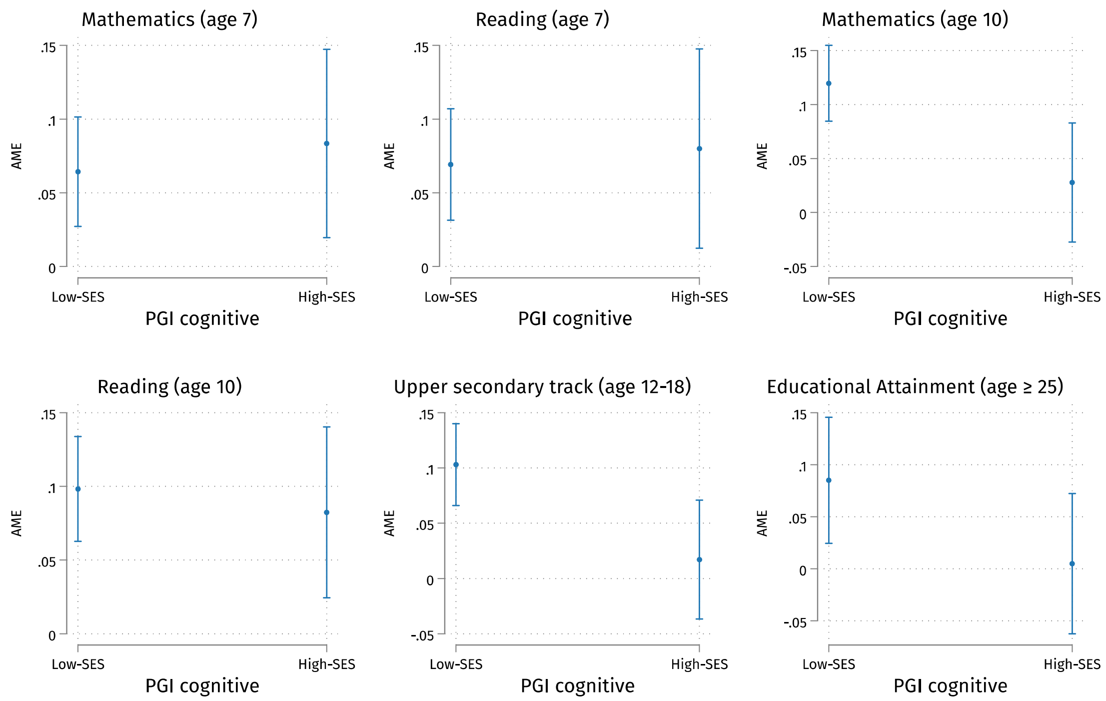
Figure S2: Logistic regression models for dichotomous outcomes variables in the between-family samples (without controlling for parents' PGI) for the interaction between family's SES and PGI for noncognitive skills (average marginal effect, at 95 percent confidence interval)



Note: Average marginal effect (AME). Controls are included. We also include covariates-environment (family SES) and covariates-gene (PGI) interaction (Keller, 2014). For this robustness check, school grades are dichotomized.

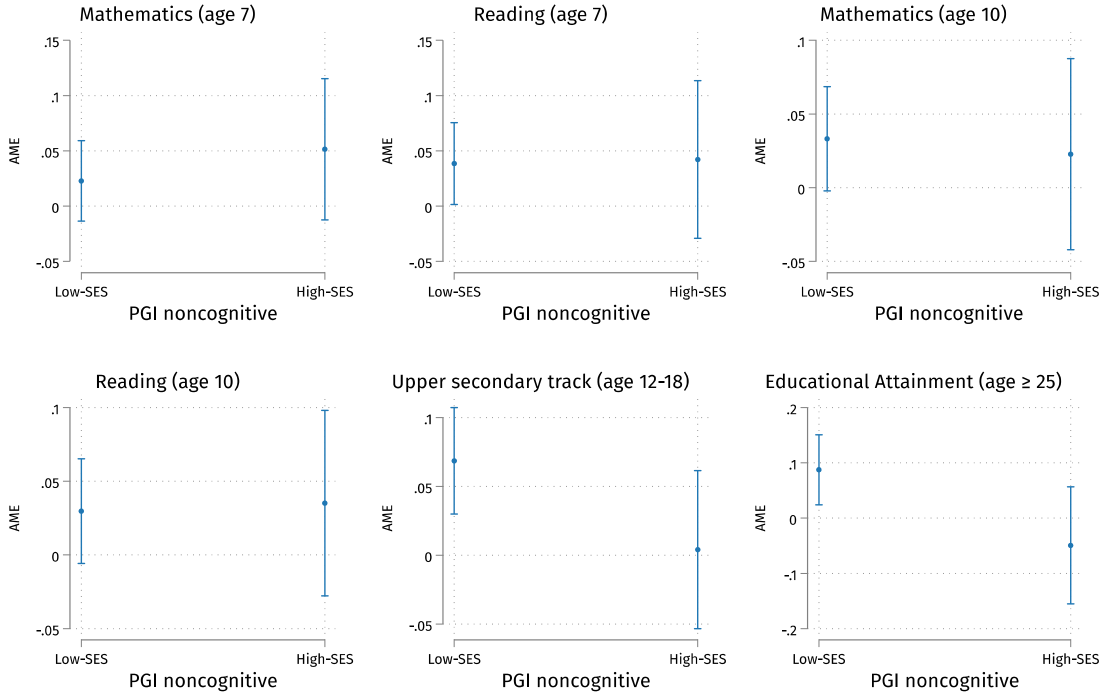
5.1.1.2 Trio design

Figure S3: Logistic regression models for dichotomous outcomes variables in the trio samples (controlling for parents' PGI) for the interaction between family SES and PGI for cognitive skills (average marginal effect, at 95 percent confidence interval)



Note: Average marginal effect (AME). Controls are included. We also include covariates-environment (family SES) and covariates-gene (PGI) interaction (Keller, 2014). For this robustness check, school grades are dichotomised.

Figure S4: Logistic regression models for dichotomous outcomes variables in the trio samples (controlling for parents' PGI) for the interaction between family's SES and PGI for noncognitive skills (average marginal effect, at 95 percent confidence interval)



Note: Average marginal effect (AME). Controls are included. We also include covariates-environment (family SES) and covariates-gene (PGI) interaction (Keller, 2014). For this robustness check, school grades are dichotomised.

5.1.2 Non-linear PGIs models for continuous outcomes

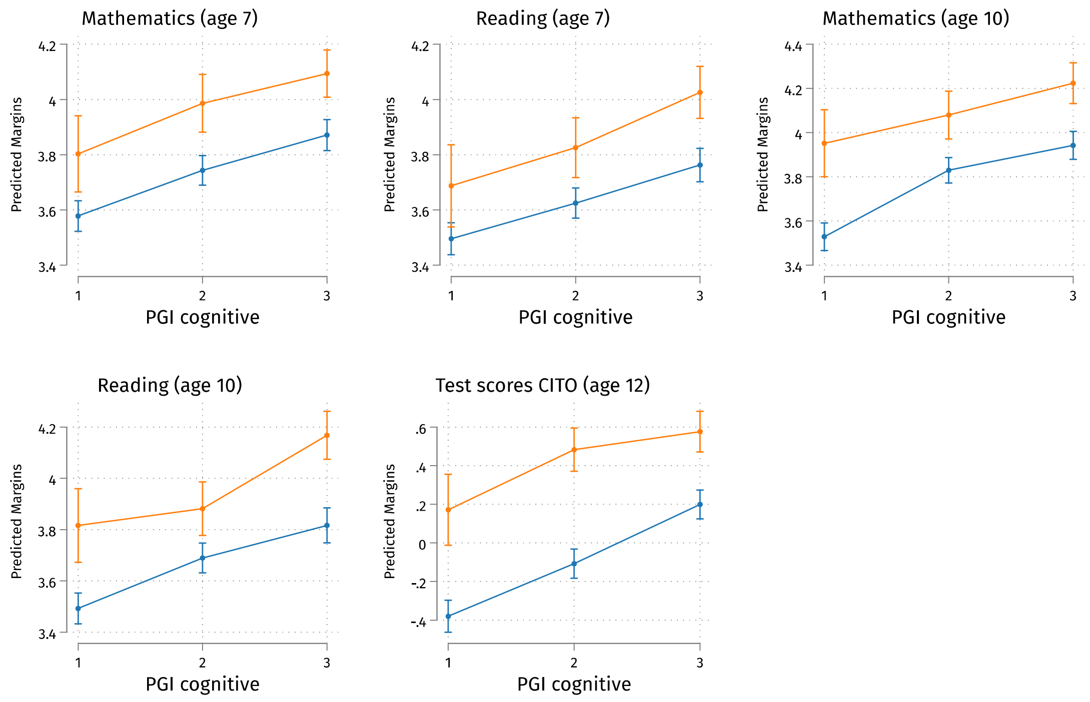
5.1.2.1 Between-family design

Table S11: OLS regression models with PGI in terciles in the *between-family samples* (without controlling for parents' PGI) for the interaction between family's SES and PGI for cognitive skills on our not dichotomous variables (i.e., CITO and school grades).

	Mathematics (age 7)	Reading (age 7)	Mathematics (age 10)	Reading (age 10)	Test scores CITO (age 12)
SES x PGI Cognitive (2nd tercile)	0.00892	0.0334	-0.199^{+}	-0.163^{+}	0.0428
	(0.095)	(0.101)	(0.103)	(0.099)	(0.125)
SES x PGI PGI Cognitive (3rd tercile)	-0.0189	0.0578	-0.138	0.0392	-0.125
	(0.095)	(0.102)	(0.105)	(0.102)	(0.129)
Observations	3728	3756	3829	3875	2690
Adjusted R2	0.0501	0.0485	0.0773	0.0531	0.120

Note: Robust standard errors in parentheses. Two-tailed t-test: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.000$. Controls included but not reported above: first 10 PCs and Platform. We also include covariates-environment (family SES) and covariates-gene (PGI) interaction (Keller, 2014).

Figure S5: OLS regression models with PGI in terciles in the between-family samples (without controlling for parents' PGI) for the interaction between family's SES and PGI for cognitive skills on our not dichotomous variables (i.e., CITO and school grades).



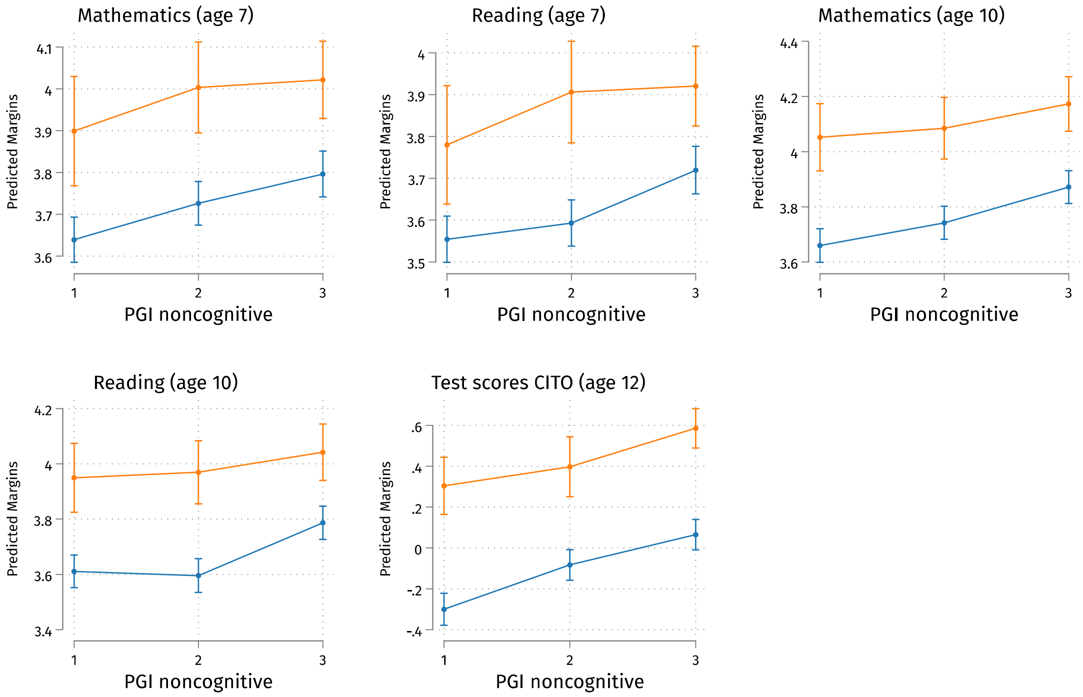
Controls are included. We also include covariates-environment (family SES) and covariates-gene (PGI) interaction (Keller, 2014).

Table S12: OLS regression models with PGI in terciles in the between-family samples (without controlling for parents' PGI) for the interaction between family's SES and PGI for non-cognitive skills on our not dichotomous variables (i.e., CITO and school grades).

	Mathematics (age 7)	Reading (age 7)	Mathematics (age 10)	Reading (age 10)	Test scores CITO (age 12)
SES x PGI Non-Cognitive (2nd tercile)	0.00704	0.0546	-0.0445	0.00859	-0.149
	(0.099)	(0.105)	(0.095)	(0.100)	(0.118)
SES x PGI Non-Cognitive (3rd tercile)	-0.0278	-0.0288	-0.0841	-0.0759	-0.124
	(0.093)	(0.101)	(0.096)	(0.097)	(0.107)
Observations	3728	3756	3829	3875	2690
Adjusted R2	0.0523	0.0454	0.0767	0.0563	0.120

Note: Robust standard errors in parentheses. Two-tailed t-test: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.000$. Controls included but not reported above: first 10 PCs and Platform. We also include covariates-environment (family SES) and covariates-gene (PGI) interaction (Keller, 2014).

Figure S6: OLS regression models with PGI in terciles in the between-family samples (without controlling for parents' PGI) for the interaction between family's SES and PGI for non-cognitive skills on our not dichotomous variables (i.e., CITO and school grades).



Controls are included. We also include covariates-environment (family SES) and covariates-gene (PGI) interaction (Keller, 2014).

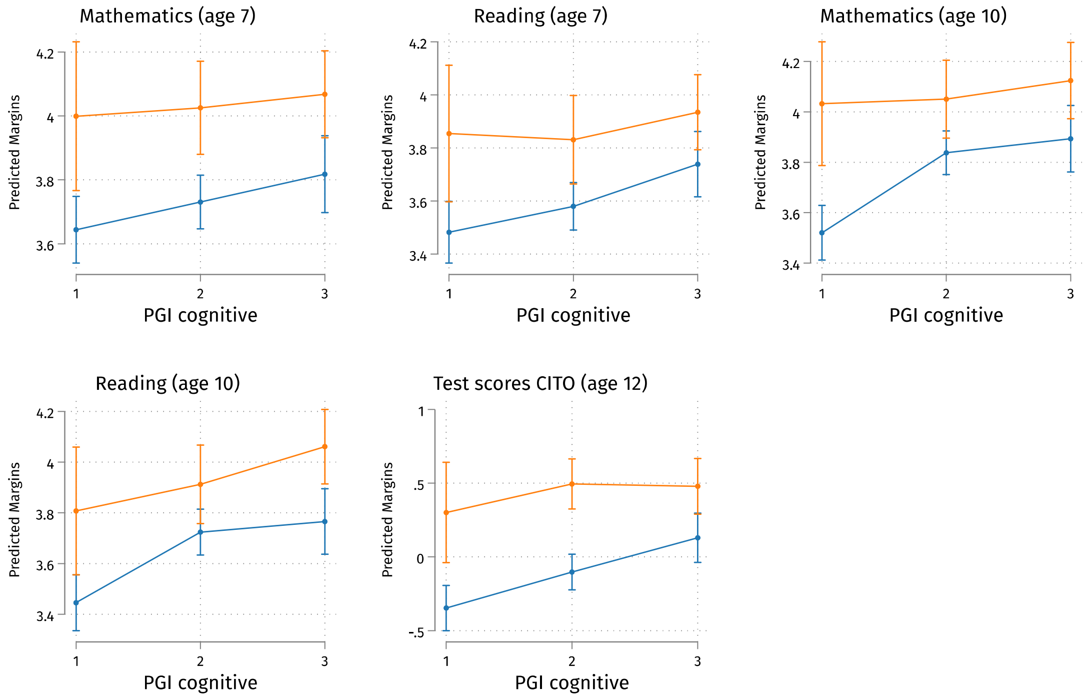
5.1.2.2 Trio design

Table S13: OLS regression models with PGI in terciles in the trio samples for the interaction between family's SES and PGI for cognitive skills on our not dichotomous variables (i.e., CITO and school grades).

	Mathematics (age 7)	Reading (age 7)	Mathematics (age 10)	Reading (age 10)	Test scores CITO (age 12)
SES x PGI Cognitive (2nd tercile)	-0.0356	-0.0375	-0.273^{+}	-0.139	-0.0435
	(0.137)	(0.152)	(0.141)	(0.142)	(0.200)
SES x PGI Cognitive (3rd tercile)	-0.0468	-0.0942	-0.234	-0.0127	-0.249
	(0.162)	(0.174)	(0.173)	(0.173)	(0.236)
Observations	1776	1781	1919	1948	1212
Adjusted R2	0.0630	0.0561	0.0808	0.0539	0.108

Note: Robust standard errors in parentheses. Two-tailed t-test: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.000$. Controls included but not reported above: first 10 PCs and Platform. We also include covariates-environment (family SES) and covariates-gene (PGI) interaction (Keller, 2014).

Figure S7: OLS regression models with PGI in terciles in the trio samples for the interaction between family's SES and PGI for cognitive skills on our not dichotomous variables (i.e., CITO and school grades).



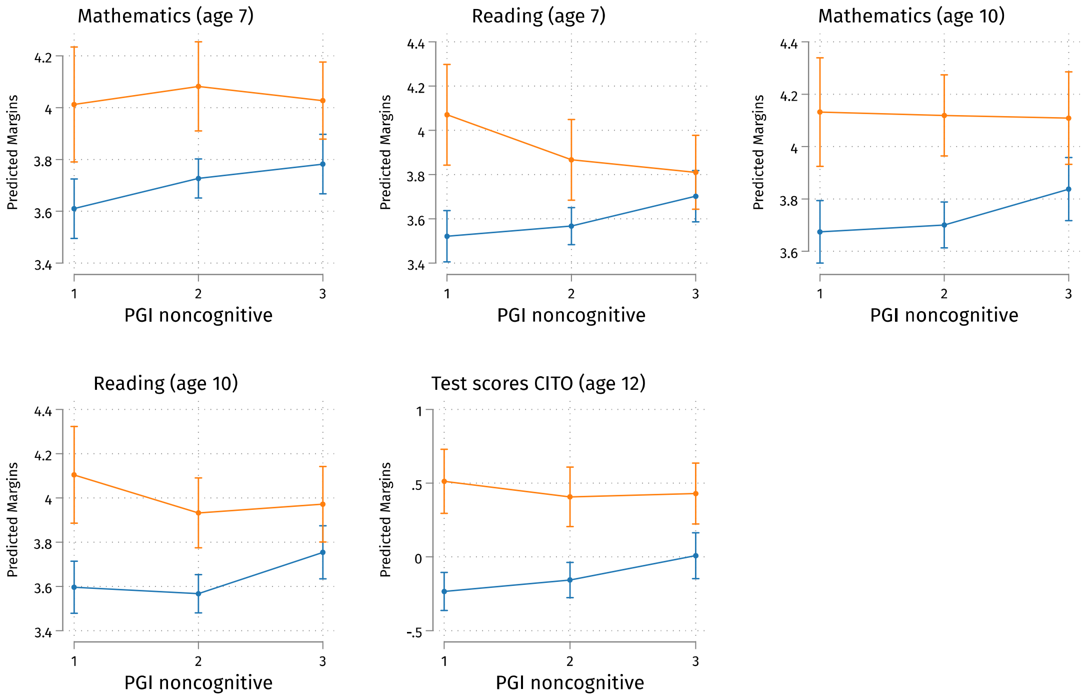
Controls are included. We also include covariates-environment (family's' SES) and covariates-gene (PGI) interaction (Keller, 2014).

Table S14: OLS regression models with PGI in terciles in the trio samples for the interaction between family's SES and PGI for non-cognitive skills on our not dichotomous variables (i.e., CITO and school grades).

	Mathematics (age 7)	Reading (age 7)	Mathematics (age 10)	Reading (age 10)	Test scores CITO (age 12)
SES x PGI Non-Cognitive (2nd tercile)	-0.102	-0.258	-0.0666	-0.148	-0.304^{+}
	(0.149)	(0.158)	(0.139)	(0.145)	(0.183)
SES x PGI Non-Cognitive (3rd tercile)	-0.187	-0.431*	-0.188	-0.279	-0.415*
	(0.167)	(0.175)	(0.169)	(0.171)	(0.192)
Observations	1861	1869	2022	2051	1254
Adjusted R2	0.0705	0.0490	0.0778	0.0658	0.0987

Note: Robust standard errors in parentheses. Two-tailed t-test: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.000$. Controls included but not reported above: first 10 PCs and Platform. We also include covariates-environment (family SES) and covariates-gene (PGI) interaction (Keller, 2014).

Figure S8: OLS regression models with PGI in terciles in the trio samples for the interaction between family's SES and PGI for non-cognitive skills on our not dichotomous variables (i.e., CITO and school grades).

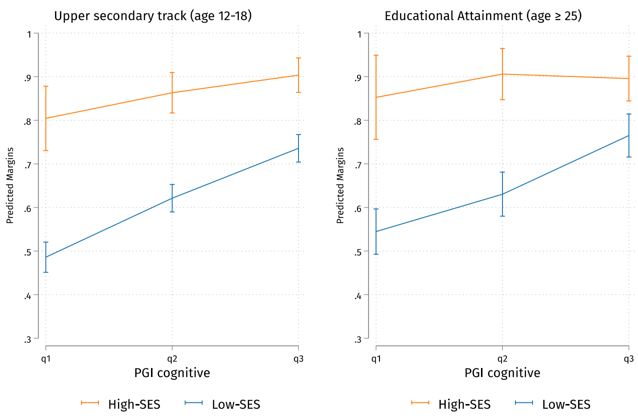


Controls are included. We also include covariates-environment (family SES) and covariates-gene (PGI) interaction (Keller, 2014).

5.1.3. Logistic regression models and non-linearities in the PGI

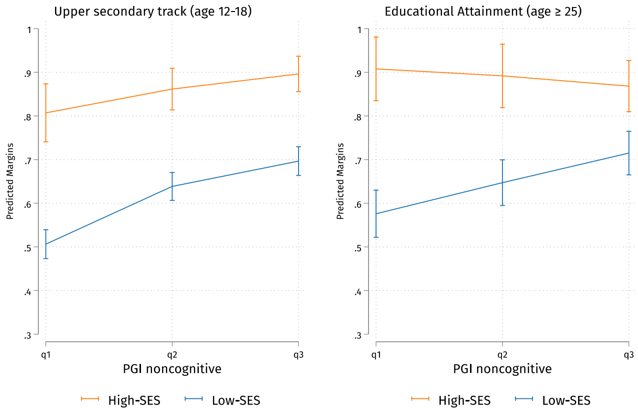
5.1.3.1. Between-family design

Figure S9: Logistic regression models for dichotomous outcomes variables and with the PGI in terciles in the between family samples (without controlling for parents' PGI) for the interaction between family's SES and PGI for cognitive skills (average marginal effect, at 95 percent confidence interval)



Controls are included. We also include covariates-environment (family SES) and covariates-gene (PGI) interaction (Keller, 2014).

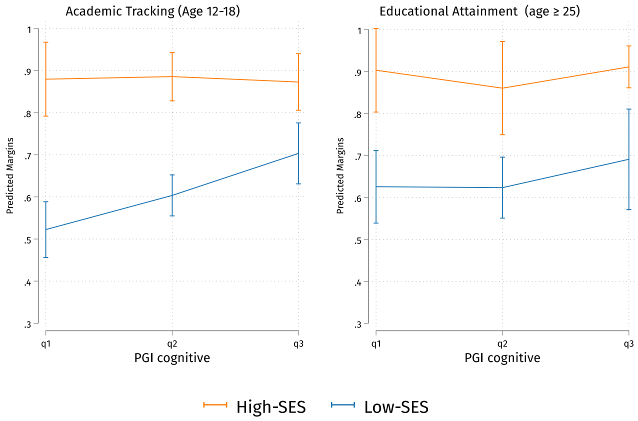
Figure S10: Logistic regression models for dichotomous outcomes variables and with the PGI in terciles in the between family samples (without controlling for parents' PGI) for the interaction between family's SES and PGI for non-cognitive skills (average marginal effect, at 95 percent confidence interval)



Controls are included. We also include covariates-environment (family SES) and covariates-gene (PGI) interaction (Keller, 2014).

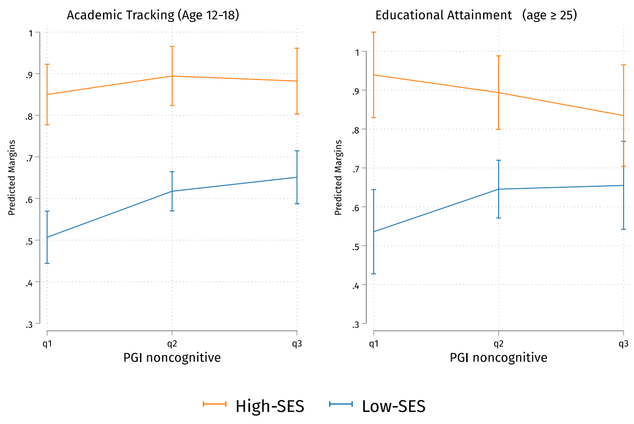
5.1.3.2 Trio design

Figure S11: Logistic regression models for dichotomous outcomes variables (i.e., academic tracking and educational attainment) and with the PGI in terciles in the trio samples (controlling for parents' PGI) for the interaction between family's SES and PGI for cognitive skills (average marginal effect, at 95 percent confidence interval)



Controls are included. We also include covariates-environment (family SES) and covariates-gene (PGI) interaction (Keller, 2014).

Figure S12: Logistic regression models for dichotomous outcomes variables (i.e., academic tracking and educational attainment) and with the PGI in terciles in the trio samples (controlling for parents' PGI) for the interaction between family's SES and PGI for non-cognitive skills (average marginal effect, at 95 percent confidence interval)



Controls are included. We also include covariates-environment (family SES) and covariates-gene (PGI) interaction (Keller, 2014).

5.2. Alternative samples

5.2.1. Between-family with all MZ twins

Table S15: OLS (mathematics, reading and CITO) and LPM (academic tracking and educational attainment) regressions to test the association between children's cognitive and non-cognitive PGI and educational outcomes without including family SES.

	Mathematics (age 7)	Reading (age 7)	Mathematics (age 10)	Reading (age 10)	Test scores CITO (age 12)	Upper secondary track (age 12-18)	Educational Attainment (age ≥ 25)
Cognitive PGI	0.153^{***}	0.152^{***}	0.208^{***}	0.179^{***}	0.261^{***}	0.111^{***}	0.103^{***}
	(0.014)	(0.015)	(0.016)	(0.016)	(0.020)	(0.008)	(0.012)
Non-Cognitive PGI	0.0732^{***}	0.0779^{***}	0.0952^{***}	0.0960^{***}	0.184^{***}	0.0855^{***}	0.0802^{***}
	(0.014)	(0.015)	(0.016)	(0.016)	(0.020)	(0.009)	(0.012)
Sex (ref: Female)	-0.0934^{***}	0.126^{***}	-0.255^{***}	0.173^{***}	-0.118^{**}	0.00952	0.00562
	(0.028)	(0.029)	(0.031)	(0.031)	(0.036)	(0.017)	(0.026)
Year of birth	0.00837^{**}	-0.00190	0.00322	0.00247	-0.00357	-0.000641	-0.0203^{***}
	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.003)	(0.004)
Mother age at birth	0.00760^{*}	0.00963^{*}	0.00736^{+}	0.00370	0.0206^{***}	0.0106^{***}	0.0116^{***}
	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)	(0.002)	(0.003)
Number of children	0.0107	-0.0270	0.00887	-0.0457^{*}	-0.0249	0.000913	-0.0313^{*}
	(0.021)	(0.022)	(0.024)	(0.023)	(0.031)	(0.013)	(0.016)
Observations	5088	5134	5240	5303	3611	4377	1648
Adjusted R2	0.0527	0.0451	0.0713	0.0466	0.109	0.0961	0.0892

Note: Robust standard errors in parentheses. Two-tailed t-test: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.000$. Controls included but not reported above: first 10 PCs and Platform.

Table S16: OLS (mathematics, reading and CITO) and LPM (academic tracking and educational attainment) regressions to test the association between children's cognitive and non-cognitive PGI and educational outcomes including family SES.

	Mathematics (age 7)	Reading (age 7)	Mathematics (age 10)	Reading (age 10)	Test scores CITO (age 12)	Upper secondary track (age 12-18)	Educational Attainment (age ≥ 25)
Cognitive PGI	0.142***	0.141***	0.191***	0.160***	0.238***	0.100***	0.0931***
	(0.014)	(0.016)	(0.016)	(0.017)	(0.020)	(0.008)	(0.012)
Non-Cognitive PGI	0.0629***	0.0673***	0.0793***	0.0794***	0.162***	0.0758***	0.0729***
	(0.014)	(0.015)	(0.016)	(0.016)	(0.020)	(0.009)	(0.012)
SES (ref: Low-SES)	0.172***	0.177***	0.252***	0.263***	0.406***	0.184***	0.153***
	(0.037)	(0.039)	(0.040)	(0.040)	(0.046)	(0.019)	(0.027)
Sex (ref: Female)	-0.0906***	0.129***	-0.251***	0.176***	-0.112**	0.0109	0.0125
	(0.027)	(0.029)	(0.031)	(0.031)	(0.036)	(0.016)	(0.026)
Year of birth	0.00777*	-0.00244	0.00183	0.00101	-0.00445	-0.000255	-0.0190***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.003)	(0.004)
Mother age at birth	0.00516	0.00711+	0.00398	0.000198	0.0135*	0.00737**	0.00905**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)	(0.002)	(0.003)
Number of children	0.0108	-0.0274	0.00975	-0.0450*	-0.0231	-0.00172	-0.0314*
	(0.021)	(0.022)	(0.023)	(0.023)	(0.030)	(0.013)	(0.015)
Observations	5088	5134	5240	5303	3611	4377	1648
Adjusted R2	0.0586	0.0508	0.0814	0.0578	0.133	0.116	0.104

Note: Robust standard errors in parentheses. Two-tailed t-test: $^{+}$ p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.000. Controls included but not reported above: first 10 PCs and Platform.

Table S17: OLS (mathematics, reading and CITO) and LPM (academic tracking and educational attainment) regressions to test the interaction between children's cognitive and non-cognitive PGI and family SES

	Mathematics (age 7)	Reading (age 7)	Mathematics (age 10)	Reading (age 10)	Test scores CITO (age 12)	Upper secondary track (age 12-18)	Educational Attainment (age ≥ 25)
SES x PGI Cognitive	-0.0258	0.0209	-0.0493	0.0275	-0.0158	-0.0472^{*}	-0.0931^{**}
	(0.037)	(0.041)	(0.041)	(0.041)	(0.048)	(0.019)	(0.028)
Observations	5088	5134	5240	5303	3611	4377	1648
Adjusted R2	0.0610	0.0545	0.0826	0.0612	0.137	0.118	0.112
SES x PGI Non-Cognitive	-0.00352	0.00796	-0.00419	0.00513	-0.0789^{+}	-0.0395^{*}	-0.0734^{**}
	(0.037)	(0.041)	(0.038)	(0.039)	(0.044)	(0.019)	(0.028)
Observations	5088	5134	5240	5303	3611	4377	1648
Adjusted R2	0.0624	0.0526	0.0851	0.0612	0.135	0.120	0.115

Note: Robust standard errors in parentheses. Two-tailed t-test: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.000$. Controls included but not reported above: first 10 PCs and Platform.

5.2.2. Trio analysis with all MZ twins

Table S18: OLS (mathematics, reading and CITO) and LPM (academic tracking and educational attainment) regressions to test the association between children's cognitive and non-cognitive PGI and educational outcomes using the sample of the trio-design, controlling for family SES but without parents cognitive and non-cognitive PGI.

	Mathematics (age 7)	Reading (age 7)	Mathematics (age 10)	Reading (age 10)	Test scores CITO (age 12)	Upper secondary track (age 12-18)	Educational Attainment (age ≥ 25)
Cognitive PGI	0.144***	0.147***	0.170***	0.153***	0.201***	0.0962***	0.0644***
	(0.021)	(0.024)	(0.023)	(0.023)	(0.028)	(0.012)	(0.019)
Non-Cognitive PGI	0.0686**	0.0762***	0.0823***	0.0842***	0.120***	0.0651***	0.0545**
	(0.021)	(0.022)	(0.022)	(0.022)	(0.029)	(0.013)	(0.017)
SES (ref: Low-SES)	0.233***	0.218***	0.291***	0.279***	0.473***	0.213***	0.199***
	(0.052)	(0.056)	(0.053)	(0.054)	(0.063)	(0.026)	(0.036)
Sex (ref: Female)	-0.106**	0.136**	-0.284***	0.160***	-0.119*	0.00220	-0.0111
	(0.040)	(0.042)	(0.043)	(0.043)	(0.053)	(0.024)	(0.035)
Year of birth	0.0120**	-0.00141	0.00463	0.00327	-0.00333	-0.00302	-0.0210***
	(0.004)	(0.005)	(0.005)	(0.004)	(0.007)	(0.004)	(0.005)
Mother age at birth	0.00708	0.00752	-0.000348	-0.00407	0.00244	0.00505	0.00639
	(0.006)	(0.006)	(0.006)	(0.006)	(0.008)	(0.004)	(0.005)
Number of children	0.0189	-0.0508+	0.0390	-0.0514	-0.0303	-0.00827	-0.0489*
	(0.029)	(0.030)	(0.031)	(0.031)	(0.042)	(0.017)	(0.023)
Observations	2570	2586	2798	2835	1683	1984	776
Adjusted R2	0.0675	0.0590	0.0792	0.0552	0.114	0.127	0.104

Note: Robust standard errors in parentheses. Two-tailed t-test: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.000$. Controls included but not reported above: first 10 PCs and Platform.

Table S19: OLS (mathematics, reading and CITO) and LPM (academic tracking and educational attainment) regressions to test the association between children's cognitive and non-cognitive PGI and educational outcomes using the sample of the trio-design, controlling for family SES and parents cognitive and non-cognitive PGI.

	Mathematics (age 7)	Reading (age 7)	Mathematics (age 10)	Reading (age 10)	Test scores CITO (age 12)	Upper secondary track (age 12-18)	Educational Attainment (age ≥ 25)
Cognitive PGI	0.130***	0.160***	0.208***	0.193***	0.173***	0.0801***	0.0541*
	(0.030)	(0.032)	(0.032)	(0.032)	(0.041)	(0.017)	(0.026)
Non-Cognitive PGI	0.0636*	0.0589+	0.0373	0.0607+	0.0699+	0.0380*	0.0507*
	(0.030)	(0.032)	(0.033)	(0.034)	(0.041)	(0.017)	(0.025)
SES (ref: Low-SES)	0.227***	0.219***	0.293***	0.287***	0.456***	0.204***	0.197***
	(0.053)	(0.057)	(0.054)	(0.054)	(0.063)	(0.027)	(0.037)
Sex (ref: Female)	-0.107**	0.137**	-0.284***	0.163***	-0.127*	-0.00129	-0.0110
	(0.040)	(0.043)	(0.044)	(0.043)	(0.053)	(0.024)	(0.035)
Year of birth	0.0121**	-0.00157	0.00453	0.00304	-0.00270	-0.00276	-0.0211***
	(0.004)	(0.005)	(0.005)	(0.004)	(0.007)	(0.004)	(0.005)
Mother age at birth	0.00703	0.00737	-0.00116	-0.00419	0.00170	0.00494	0.00614
	(0.006)	(0.006)	(0.006)	(0.006)	(0.008)	(0.004)	(0.005)
Number of children	0.0179	-0.0500+	0.0401	-0.0504	-0.0329	-0.00882	-0.0498*
	(0.029)	(0.030)	(0.031)	(0.032)	(0.042)	(0.017)	(0.023)
Cognitive PGS Mother	0.0172	-0.00589	-0.0451	-0.0397	0.0462	0.00392	0.0166
	(0.026)	(0.029)	(0.028)	(0.029)	(0.036)	(0.016)	(0.021)
Cognitive PGS Father	0.0106	-0.0189	-0.0324	-0.0410	0.00922	0.0253	0.00590
	(0.028)	(0.028)	(0.031)	(0.029)	(0.036)	(0.016)	(0.023)
NonCognitive PGI Father	0.0111	0.00269	0.0501+	0.00533	0.0514	0.0419**	0.00739
	(0.026)	(0.028)	(0.030)	(0.030)	(0.034)	(0.015)	(0.023)
NonCognitive PGI Mother	-0.00146	0.0317	0.0388	0.0425	0.0465	0.00871	0.00147
	(0.026)	(0.028)	(0.029)	(0.029)	(0.037)	(0.016)	(0.024)
Observations	2570	2586	2798	2835	1683	1984	776
Adjusted R2	0.0665	0.0586	0.0822	0.0573	0.115	0.131	0.100

Note: Robust standard errors in parentheses. Two-tailed t-test: + p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.000. Controls included but not reported above: first 10 PCs and Platform.

Table S20: OLS (mathematics, reading and CITO) and LPM (academic tracking and educational attainment) regressions to test the interaction between children's cognitive and non-cognitive PGI and family's SES using the sample of the trio-design, controlling for family SES and parents cognitive and non-cognitive PGI.

	Mathematics (age 7)	Reading (age 7)	Mathematics (age 10)	Reading (age 10)	Test scores CITO (age 12)	Upper secondary track (age 12-18)	Educational Attainment (age ≥ 25)
SES x PGI Cognitive	-0.0274	0.000251	-0.147^{+}	-0.0342	-0.0380	-0.0623^{+}	-0.0177
	(0.070)	(0.078)	(0.076)	(0.079)	(0.092)	(0.034)	(0.049)
Observations	2570	2586	2798	2835	1683	1984	776
Adjusted R2	0.0756	0.0699	0.0918	0.0633	0.112	0.130	0.121
SES x PGI Non-Cognitive	-0.0221	-0.0988	-0.0199	-0.0157	-0.205*	-0.0653^{+}	-0.113*
	(0.071)	(0.082)	(0.075)	(0.076)	(0.093)	(0.036)	(0.053)
Observations	2570	2586	2798	2835	1683	1984	776
Adjusted R2	0.0773	0.0663	0.0894	0.0650	0.113	0.130	0.0959

Note: Robust standard errors in parentheses. Two-tailed t-test: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.000$. Controls included but not reported above: first 10 PCs and Platform.

5.2.3 Educational attainment: all participants, those born before 1980, those born after 1980

In this section, we first repeat the analysis for educational attainment using different samples. Specifically, we compare the main results (those born after 1980) with the results obtained looking also at those born before 1980 and then only to those born before 1980.

5.2.3.1 Between-family design

Table S21: LPM regressions to test the association between children's cognitive and non-cognitive PGI and educational attainment controlling for family SES in the between-family design in the three different samples

	Educational Attainment (age ≥ 25) Overall sample	Educational Attainment (age ≥ 25) Prior to 1980	Educational Attainment (age ≥ 25) After 1980
SES (ref: Low-SES)	0.257***	0.298***	0.175***
	(0.018)	(0.023)	(0.027)
Cognitive PGS	0.0927***	0.0923***	0.0945***
	(0.007)	(0.009)	(0.013)
Non-Cognitive PGS	0.0905***	0.0964***	0.0632***
	(0.007)	(0.009)	(0.014)
Sex (ref: Female)	-0.0479**	-0.0753***	0.0224
	(0.015)	(0.018)	(0.027)
Year of birth	0.00847***	0.00846***	-0.0177***
	(0.001)	(0.001)	(0.004)
Mother age at birth	0.00619***	0.00683***	0.00828*
	(0.002)	(0.002)	(0.003)
Number of children	-0.0188*	-0.0209**	-0.0176
	(0.008)	(0.008)	(0.016)
Observations	4541	3317	1224

Note: Robust standard errors in parentheses. Two-tailed t-test: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.000$. Controls included but not reported above: first 10 PCs and Platform.

Table S22: LPM regressions to test the interaction between children's cognitive and non-cognitive PGI and family SES in the between-family design in the three different samples

	Educational Attainment (age ≥ 25) Overall sample	Educational Attainment (age ≥ 25) Prior to 1980	Educational Attainment (age ≥ 25) After 1980
SES x PGI Cognitive	-0.0416*	-0.0129	-0.108***
	(0.018)	(0.022)	(0.028)
Adjusted R2	0.162	0.149	0.106
SES x PGI Non-Cognitive	-0.0730***	-0.0525*	-0.0908**
	(0.020)	(0.025)	(0.030)
Observations	4541	3317	1224
Adjusted R2	0.161	0.147	0.110

Note: Robust standard errors in parentheses. Two-tailed t-test: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.000$. Controls included but not reported above: first 10 PCs and Platform. We also include covariates-environment (family SES) and covariates-gene (PGI) interaction (Keller, 2014).

5.2.3.2 Within-family design

Table S23: Family-fixed effect regressions to test the association between children's cognitive and non-cognitive PGI on educational attainment in the within-family design in the three different samples

	Educational Attainment (age ≥ 25) Overall sample	Educational Attainment (age ≥ 25) Prior to 1980	Educational Attainment (age ≥ 25) After 1980
Cognitive PGS	0.0711***	0.0717***	0.0669
	(0.018)	(0.021)	(0.042)
Non-Cognitive PGS	0.0590**	0.0555**	0.0894^{+}
	(0.019)	(0.021)	(0.047)
Year of birth	-0.00936^{+}	-0.00506	-0.0441^{+}
	(0.005)	(0.006)	(0.025)
Sex (ref: Female)	-0.0169	-0.0312	0.0258
	(0.027)	(0.032)	(0.059)
Observations	2030	1566	426

Note: Robust standard errors in parentheses. Two-tailed t-test: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.000$. Controls included but not reported above: first 10 PCs and Platform.

Table S24: Family-fixed effect regressions to test the interaction between children's cognitive and non-cognitive PGI and family SES in the within-family design in the three different samples

	Educational Attainment (age ≥ 25) Overall sample	Educational Attainment (age ≥ 25) Prior to 1980	Educational Attainment (age ≥ 25) After 1980
SES x PGI Cognitive	0.0436	0.0771	-0.0451
	(0.048)	(0.059)	(0.100)
Adjusted R2	0.0220	0.0308	0.138
SES x PGI Non-Cognitive	0.0478	0.167*	-0.0341
	(0.059)	(0.069)	(0.086)
Observations	2030	1566	426
Adjusted R2	0.0220	0.0269	0.178

Note: Robust standard errors in parentheses. Two-tailed t-test: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.000$. Controls included but not reported above: first 10 PCs and Platform. We also include covariates-environment (family SES) and covariates-gene (PGI) interaction (Keller, 2014).

5.2.3.3 Trio design

Table S25: LPM regressions to test the interaction between children's cognitive and non-cognitive PGI and family SES in the trio design in the three different samples

	Educational Attainment (age ≥ 25) Overall sample	Educational Attainment (age ≥ 25) Prior to 1980	Educational Attainment (age ≥ 25) After 1980
Cognitive PGS	0.0391*	0.0258	0.0740**
	(0.016)	(0.020)	(0.028)
Non-Cognitive PGS	0.0201	0.00389	0.0613+
	(0.017)	(0.020)	(0.032)
SES (ref: Low-SES)	0.246***	0.269***	0.210***
	(0.025)	(0.032)	(0.039)
Sex (ref: Female)	-0.0373+	-0.0643*	0.00355
	(0.023)	(0.028)	(0.038)
Year of birth	0.00630***	0.00695*	-0.0210***
	(0.002)	(0.003)	(0.006)
Mother age at birth	0.00870**	0.0113**	0.00153
	(0.003)	(0.004)	(0.005)
Number of children	-0.0326**	-0.0339**	-0.0431+
	(0.012)	(0.013)	(0.022)
Cognitive PGS Mother	0.0408**	0.0510**	0.00630
	(0.014)	(0.018)	(0.025)
Cognitive PGS Father	0.0385*	0.0534**	0.0128
	(0.016)	(0.020)	(0.025)
Non-Cognitive PGS Father	0.0637***	0.0836***	0.00329
	(0.015)	(0.018)	(0.026)
Non-Cognitive PGS Mother	0.0432**	0.0643***	-0.0163
	(0.015)	(0.018)	(0.026)
Observations	1783	1207	576

Note: Robust standard errors in parentheses. Two-tailed t-test: + p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.000. Controls included but not reported above: first 10 PCs and Platform.

Table S26: LPM regressions to test the interaction between children's cognitive and non-cognitive PGI and family SES in the trio design in the three different samples

	Educational Attainment (age ≥ 25) Overall sample	Educational Attainment (age ≥ 25) Prior to 1980	Educational Attainment (age ≥ 25) After 1980
SES x PGI Cognitive	0.0386	0.0958*	-0.0463
	(0.036)	(0.048)	(0.056)
Adjusted R2	0.161	0.166	0.106
SES x PGI Non-Cognitive	0.00726	0.0861	-0.130+
	(0.046)	(0.064)	(0.069)
Observations	1783	1207	576
Adjusted R2	0.151	0.164	0.0786

Note: Robust standard errors in parentheses. Two-tailed t-test: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.000$. Controls included but not reported above: first 10 PCs and Platform. We also include covariates-environment (family SES) and covariates-gene (PGI) interaction (Keller, 2014).

5.3 Alternative measure of SES: Parents' occupation

5.3.1 Between-family design

Table S27: OLS and LPM (academic tracking and educational attainment) regressions to test the interaction between children's cognitive and non-cognitive PGI and family SES on educational outcomes in the between-family analysis.

	Mathematics (age 7)	Reading (age 7)	Mathematics (age 10)	Reading (age 10)	Test scores CITO (age 12)	Upper secondary track (age 12-18)	Educational Attainment (age ≥ 25)
SES x PGI Cognitive	-0.0357	-0.0194	-0.0822+	-0.0263	-0.0512	-0.0581**	-0.115*
	(0.043)	(0.050)	(0.047)	(0.047)	(0.053)	(0.020)	(0.047)
Observations	3728	3756	3829	3875	2647	3225	900
Adjusted R2	0.0562	0.0511	0.0789	0.0534	0.137	0.124	0.0950
SES x PGI Non-Cognitive	0.0350	0.0502	-0.0365	-0.00544	-0.0465	-0.0472*	-0.114**
	(0.044)	(0.047)	(0.043)	(0.046)	(0.044)	(0.018)	(0.039)
Observations	3728	3756	3829	3875	2647	3225	900
Adjusted R2	0.0558	0.0493	0.0790	0.0545	0.135	0.126	0.0969

Note: Robust standard errors in parentheses. Two-tailed t-test: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.000$. Controls included but not reported above: first 10 PCs and Platform. We also include covariates-environment (family SES) and covariates-gene (PGI) interaction (Keller, 2014).

5.3.2 Within-family design

Table S28: Family-fixed effect regressions to test the interaction between children's cognitive and non-cognitive PGI and family SES on educational outcomes in the within-family analysis.

	Mathematics (age 7)	Reading (age 7)	Mathematics (age 10)	Reading (age 10)	Test scores CITO (age 12)	Upper secondary track (age 12-18)	Educational Attainment (age ≥ 25)
SES x PGI Cognitive	0.0547	0.0350	-0.174^{+}	0.0261	-0.124	-0.0887*	-0.0106
	(0.093)	(0.085)	(0.092)	(0.096)	(0.086)	(0.035)	(0.162)
Observations	2124	2130	2212	2236	1494	1976	342
Adjusted R2	0.0647	0.0376	0.0979	0.0397	0.0705	0.0359	0.221
SES x PGI Non-Cognitive	0.0251	0.113	-0.179^{+}	-0.0747	0.0118	-0.0132	-0.0399
	(0.108)	(0.089)	(0.097)	(0.094)	(0.107)	(0.039)	(0.094)
Observations	2124	2130	2212	2236	1494	1976	342
Adjusted R2	0.0561	0.0415	0.0930	0.0385	0.0636	0.0428	0.243

Note: Robust standard errors in parentheses. Two-tailed t-test: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.000$. Controls included but not reported above: first 10 PCs and Platform. We also include covariates-environment (family SES) and covariates-gene (PGI) interaction (Keller, 2014).

5.3.3 Trio design

Table S29: OLS and LPM (academic tracking and educational attainment) regressions to test the interaction between children's cognitive PGI and family SES on educational outcomes in the *trio analysis*.

	Mathematics (age 7)	Reading (age 7)	Mathematics (age 10)	Reading (age 10)	Test scores CITO (age 12)	Upper secondary track (age 12-18)	Educational Attainment (age ≥ 25)
SES x PGI Cognitive	-0.0549	-0.0254	-0.0122	-0.0341	-0.123	-0.103**	-0.116
	(0.077)	(0.082)	(0.081)	(0.086)	(0.108)	(0.039)	(0.087)
Observations	1861	1869	2022	2051	1248	1475	452
Adjusted R2	0.0575	0.0520	0.0809	0.0524	0.100	0.122	0.0690
SES x PGI Non-Cognitive	0.0203	-0.00785	-0.0201	-0.0114	-0.0857	-0.00877	-0.207**
	(0.084)	(0.088)	(0.080)	(0.078)	(0.096)	(0.035)	(0.076)
Observations	1861	1869	2022	2051	1248	1475	452
Adjusted R2	0.0555	0.0505	0.0761	0.0565	0.0952	0.119	0.0590

Note: Robust standard errors in parentheses. Two-tailed t-test: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.000$. Controls included but not reported above: first 10 PCs and Platform. We also include covariates-environment (family SES) and covariates-gene (PGI) interaction (Keller, 2014).

5.4 Educational attainment as continuous outcome

We repeat the analysis without dichotomising educational attainment by using it in four categories as originally provided by NTR (1: primary school only, lower vocational school and lower secondary school, intermediate vocational school and intermediate or higher secondary school, higher vocational school and university).

5.4.1 Between-family design

Table S30: LPM regression models to test the interaction between children's cognitive and non-cognitive PGI and family SES in the between design in the three different samples and using educational attainment not dichotomised

	Educational Attainment (age ≥ 25) Overall sample	Educational Attainment (age ≥ 25) Prior to 1980	Educational Attainment (age ≥ 25) After 1980
SES x PGI Cognitive	-0.0710**	-0.0385	-0.145***
	(0.024)	(0.031)	(0.036)
Observations	4541	3317	1224
Adjusted R2	0.196	0.190	0.117
SES x PGI Non-Cognitive	-0.115***	-0.0899**	-0.129***
	(0.024)	(0.030)	(0.036)
Observations	4541	3317	1224
Adjusted R2	0.198	0.191	0.120

Note: Robust standard errors in parentheses. Two-tailed t-test: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.000$. Controls included but not reported above: first 10 PCs and Platform. We also include covariates-environment (family SES) and covariates-gene (PGI) interaction (Keller, 2014).

5.4.2 Within-family design

Table S31: Family-fixed effect regressions to test the interaction between children's non-cognitive PGI and family SES in the within-family design in the three different samples and using educational attainment not dichotomised

	Educational Attainment (age ≥ 25) Overall sample	Educational Attainment (age ≥ 25) Prior to 1980	Educational Attainment (age ≥ 25) After 1980
SES x PGI Cognitive	0.0436	0.0771	-0.0451
	(0.048)	(0.059)	(0.100)
Observations	2030	1566	426
Adjusted R2	0.0237	0.0308	0.138
SES x PGI Non-Cognitive	0.0478	0.167*	-0.0341
	(0.059)	(0.069)	(0.086)
Observations	2030	1566	426
Adjusted R2	0.0220	0.0269	0.178

Note: Robust standard errors in parentheses. Two-tailed t-test: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.000$. Controls included but not reported above: first 10 PCs and Platform. We also include covariates-environment (family SES) and covariates-gene (PGI) interaction (Keller, 2014).

5.4.3 Trio design

Table S32: LPM regression models to test the interaction between children's cognitive and non-cognitive PGI and family SES in the trio design in the three different samples and using educational attainment not dichotomised

	Educational Attainment (age ≥ 25) Overall sample	Educational Attainment (age ≥ 25) Prior to 1980	Educational Attainment (age ≥ 25) After 1980
SES x PGI Cognitive	0.0386	0.0958*	-0.0463
	(0.036)	(0.048)	(0.056)
Observations	1783	1207	576
Adjusted R2	0.161	0.166	0.106
SES x PGI Non-Cognitive	0.00726	0.0861	-0.130+
	(0.046)	(0.064)	(0.069)
Observations	1783	1207	576
Adjusted R2	0.151	0.164	0.0786

Note: Robust standard errors in parentheses. Two-tailed t-test: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.000$. Controls included but not reported above: first 10 PCs and Platform. We also include covariates-environment (family SES) and covariates-gene (PGI) interaction (Keller, 2014).

The portal data.europa.eu provides access to open datasets from the EU institutions, bodies and agencies. These can be downloaded and reused for free, for both commercial and non-commercial purposes. The portal also provides access to a wealth of datasets from European countries.

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