Schooling substantially improves intelligence, but neither lessens nor widens the impacts of socioeconomics and genetics.

Nicholas Judd^{12*}, Bruno Sauce³, Torkel Klingberg^{1*}

¹ Department of Neuroscience, Karolinska Institute, Stockholm, Sweden

² Cognitive Neuroscience Department, Donders Institute for Brain, Cognition, and Behavior, Radboud University Medical Center, Nijmegen, The Netherlands

³ Department of Biological Psychology, Vrije Universiteit Amsterdam, Amsterdam, The Netherlands

* nickkjudd@gmail.com; torkel.klingberg@ki.se

Abstract

Schooling, socioeconomic status (SES), and genetics all impact intelligence. However, it is unclear to what extent their contributions are unique and if they interact. Here we used a multi-trait polygenic score for cognition (cogPGS) with a quasi-experimental regression discontinuity design to isolate how months of schooling relate to intelligence in 6,567 children (aged 9-11). We found large, independent effects of schooling ($\beta \sim .15$), cogPGS ($\beta \sim .10$), and SES ($\beta \sim .20$) on working memory, crystallized (cIQ), and fluid intelligence (fIQ). Notably, two years of schooling had a larger effect on intelligence than the lifetime consequences, since birth, of SES or cogPGS based inequalities. However, schooling showed no interaction with cogPGS or SES for the three intelligence domains tested. While schooling had strong main effects on intelligence, it did not lessen, nor widen the impact of these preexisting SES or genetic factors.

Significance Statement

Here we show that schooling, socio-economic status (SES), and cogPGS (a genetic score from thousands of genetic markers associated with cognition) play large, independent roles for intelligence differences in 9 – 11-year-old children. Interestingly, there were no interactions between schooling, SES, and cogPGS. This would suggest schools do not weaken, nor amplify, differences in intelligence due to preexisting genetic or environmental inequality. Notably, two years of schooling had a larger effect on intelligence than these lifetime consequences of inequality.

Introduction

Inter-individual differences in intelligence predict a variety of important life outcomes, such as life satisfaction, mortality, and educational achievement (EA) ¹⁻³, showing correlations higher than 0.7 with achievement ^{4,5}. There has been considerable controversy on the source of these differences. Decades of research have shown intelligence to be highly associated with genetic differences (heritability estimates around 0.6) but also impacted by experiences and context (called here “environmental factors”) ⁶⁻¹².

Schooling is an important environmental factor, having a large impact on intelligence in children ¹³⁻¹⁵. This has been shown in longitudinal studies controlling for prior intelligence ¹⁶ and in studies evaluating the cognitive effects of policy changes regarding compulsory schooling ¹⁷. A third method to evaluate the impact of schooling (called regression discontinuity designs) exploits the fact children are put in a grade based on an arbitrary age cut-off, and allows us to separate the effect of chronological age from months of schooling ¹⁸. Studies using this method also replicate the findings that schooling affects intelligence ^{19,20}. Thus, many lines of research provide converging evidence that schooling can change abilities often thought to be ‘fixed’, such as fluid intelligence and working memory, with estimates of one year of additional schooling benefitting cognitive abilities somewhere between 1 to 5 IQ points, or .07 to .3 SD ^{13,19,21}. What is less clear is how the impact of schooling *interacts* with the environments that children experience and with their genetic predispositions – in other words, do school settings amplify pre-existing differences (i.e., “rich-gets-richer”), or conversely, weaken existing differences between children (i.e., “catch up”).

Much of a child’s environment is captured by socioeconomic status (SES); a summary measure usually comprised of household income, parental education, and neighborhood quality ²². While commonly implicated in initial differences in intelligence, SES has also been found to widen existing differences throughout development ²³⁻²⁵. Recently, research on SES has been criticized for neglecting the role of genetics – as parents not only hand down environments but also genes ^{26,27}. For example, a genetically informed twin study found a strong genetic influence on SES and its association with intelligence ²⁸. While there is a large body of research looking at how preexisting SES differences interplay with years of schooling ²⁹, none of these previous studies have incorporated genetics.

Fortunately, genome-wide association studies (GWAS) with extremely large sample sizes and the viability of polygenic scores, have made it possible to incorporate genetically informative measures into a study. A polygenic score is an index that combines thousands/millions of DNA regions (each with only a tiny effect on the trait of interest) and gives a value to each individual representing their genetic propensity. Relevant to us here, a multi-trait cognitive polygenic score (cogPGS) was recently shown to predict 7-10% of the variance in cognitive performance ³⁰. This and similar polygenic scores correlate moderately ($r \sim .3$) with

SES ^{31,32}, but little is known about their unique contributions to different domains of intelligence. And even less known if, or how, they interplay with schooling.

Gene-by-environment (GE) interplay is often proposed as an explanation of how intelligence can show high heritability alongside malleability ^{33–36}. To date, there are only a few studies on GE interplay using polygenic scores. Of these studies, most have focused on SES as the environmental variable of interest and none have used the environmental variable of schooling, which is particularly relevant to intelligence. Unfortunately, GE-interplay results with SES have been inconsistent for educational achievement/attainment – some positive, negative, or null ^{37–41}. While there is a high correlation between educational achievement and intelligence, educational achievement is a broader concept thought to also include personality characteristics such as consciousness and openness to experience ^{42,43}. Furthermore, we are not aware of any research examining if schooling moderates' genetic effects on intelligence.

Schooling, SES, and genetics thus represent three substantial contributors to intelligence, but it is unclear to what extent their contributions are 1) unique and 2) interact with one another. In a sample of 3rd to 5th-grade children, we estimated the unique contributions of a year of schooling, SES, and cogPGS on crystallized intelligence (cIQ), fluid intelligence (fIQ), and working memory (WM). We chose these domains of intelligence since they are particularly important for educational outcomes ^{4,16,44}. WM was included since WM has shown to be heavily impacted by schooling ²¹, malleable ⁴⁵, and potentially relevant for GE-interplay ⁴⁶. Our main aim was to examine if GE-interplay is present for these domains of cognition. Specifically, we tested if the effect of 1) schooling or 2) SES is moderated by cogPGS, and 3) a 3-way interaction between schooling, SES, and cogPGS. These interactions allowed us to test if schooling enhances or compensates for preexisting genetic and environmental inequity.

Results

We included data from 6,567 children (mean age = 9.88, range 8.92 – 11.00; SI Table 1) recruited by the ABCD consortium to be representative of the United States in sex, race, ethnicity, SES, and urbanicity⁴⁷. SES was defined as the first component of a probabilistic PCA capturing 65% of the variance in total household income, highest parental education, and neighborhood quality. Due to modeling constraints, we had to exclude 1,086 children that were missing DNA data. This group had significantly lower SES (Cohen's $d = -.23$, $p < .001$). SES and cogPGS were positively correlated with each other and each cognitive domain (Figure 1; SI Figure 4).

Figure 1 A correlation plot showing the relationships of our variables of interest, colored values indicate $p < .001$. These values are corrected for genetic PC's (see SI Fig 4 for more variables).

Schooling, SES, and cogPGS effect on cognition

To examine the effect of schooling on clQ, flQ, and WM development, we used a regression discontinuity design over grades 3 to 5, while controlling for age, sex, cogPGS, SES, and 20 ancestry-based principal components (Equation 2, SI Table's 3-5).

We found that schooling had a significant effect (all p 's < .001) for each cognitive domain we examined (cIQ: $\beta = .13$, fIQ: $\beta = .10$, WM: $\beta = .09$). One year of schooling (i.e., 10 months) contributed .22SD, .14SD, and .14SD to the development of cIQ, fIQ & WM respectively (Figure 2). Notably, the ratio of one year of schooling to one year of chronological age differed depending on the domain. As expected, schooling affected cIQ (ratio = 1.1) more than fIQ (ratio = .54). Interestingly, WM, a subtask of fIQ, had the highest ratio of 2.2, indicating for this age range one year of schooling had double the effect of one year of chronological age. There were no significant differences between the schooling coefficients for cIQ, fIQ, or WM ($|Z| < 1.96$).

Sex had a significant effect for each cognitive domain, with females performing better in fIQ ($\beta = .09$, $p < .001$) yet worse in cIQ ($\beta = -.05$, $p = .023$) and WM ($\beta = -.08$, $p < .001$). CogPGS and SES both showed independent significant effects (all p 's < .001) for cIQ, fIQ, and WM. The effect sizes of cogPGS ($\beta = .16$) and SES ($\beta = .29$) were the largest for cIQ. CogPGS showed similarly sized effects for fIQ ($\beta = .09$) and WM ($\beta = .09$), yet SES had a slightly higher effect for WM ($\beta = .22$) than fIQ ($\beta = .18$).

Figure 2 Independent effects of one year of age, one year of schooling, cogPGS, and SES from mixed-effects models predicting cIQ, fIQ, and WM (Equation 2). All results are significant for predicting their respective cognitive domain (SI Table 3 - 5). Bars reflect 95% frequentist confidence intervals.

SES subcomponents

The analysis above showed that our combined measure of SES had effects on cIQ, fIQ, and WM. Since research has shown that different subcomponents of SES could relate differently to intelligence^{48–50} we also performed an analysis of each sub-component. All components were significant ($p_{FDR} < .001$) for each cognitive domain. cIQ showed the largest effects for parental education ($\beta = .26$), family income ($\beta =$

.22) and neighborhood quality ($\beta = .11$). In a similar fashion to the SES composite, WM had slightly larger effect sizes than *flQ* for parental education (WM: $\beta = .19$; *flQ*: $\beta = .17$), family income (WM: $\beta = .17$; *flQ*: $\beta = .14$), and neighborhood quality (WM: $\beta = .08$; *flQ*: $\beta = .06$).

Sibling analysis

Gene-environment correlations can inflate the estimation of cogPGS on phenotypes^{33,51,52}. Therefore, we conducted a posthoc sibling analysis (families = 392, $n = 792$) to estimate within (β_w) and between (β_B) family effects of cogPGS on *clQ*, *flQ* and WM. Within family effects (β_w) are less confounded by the shared environment since the transmission of alleles is random giving each sibling an equal probability of inheriting any given allele. Yet, there is no variance within families for SES and very little for schooling therefore the sibling analysis is limited to genetics (cogPGS). We found *clQ*'s within-family effect ($\beta_w = .08$, $p_{FDR} = .009$) to be roughly half of the between-family effect ($\beta_B = .15$, $p_{FDR} = .009$). For *flQ* we found a significant within-family effect ($\beta_w = .08$, $p_{FDR} = .013$), yet the between-family effect was not significant ($\beta_B = .10$, $p_{FDR} = .074$). For WM, neither the within-family ($\beta_w = .04$, $p_{FDR} = 0.235$) nor the between-family ($\beta_B = .10$, $p_{FDR} = 0.066$) effects were significant.

Gene-by-environment interplay

There were no significant interactions for any of the cognitive domains (Equations 3 & 4; SI Tables 3-5). This included our two-way interaction terms of interest (i.e., schooling-cogPGS, schooling-SES & cogPGS-SES) and the three-way interaction term (i.e., schooling-cogPGS-SES). This null result held when we added principal component interactions with schooling, cogPGS, and SES for each model⁵³. We, therefore, carried out posthoc Bayesian null hypothesis testing using region of practical equivalence (ROPE) boundaries with 95% highest-density intervals (HDI) for the two-way interaction terms of interest (Figure 3, Equation 3). We used weakly informative priors, centered around zero, for the two-way interaction terms (see Methods). Crucially, we used two ROPE boundaries in standard units of 0.05 and 0.02. This was done for two reasons, 1) a lack of consensus in the field on a minimal effect size of interest and 2) schooling representing a cumulative process⁵⁴⁻⁵⁶.

Almost all interaction terms were entirely within a ROPE boundary of .05 (Fig. 3). This means that with 95% probability the interaction effect was less than 0.05 SD, adding evidence for the null hypothesis (SI Table 8). The two exceptions were the schooling-cogPGS interaction (Fig 3b,c), where the 95% were slightly outside the .05 boundary for *flQ* (3%) and WM (5%). However, most of the terms have a substantial part of their distribution overlapping with the ROPE boundaries of 0.02. This means we cannot confirm nor disprove the null hypothesis for a maximal effect size of interest of .02 SDs.

Figure 3 The estimated interaction effects of schooling-SES, schooling-cogPGS and cogPGS-SES on **a)** cIQ, **b)** fIQ and **c)** WM from a hierarchical Bayesian mixed-effects model. All values are in standard units. Dark blue shading indicates the 95% highest density interval's (HDI) of the estimates posterior distribution. The gray band represents a region of practical equivalence (ROPE) of .02 SD's, while the dotted lines indicate a ROPE boundary of .05 SD's. Most of the interaction terms are fully within a .05 SD ROPE boundary providing evidence for the null hypothesis at this boundary, yet none fully lie within a ROPE boundary of .02 SD's (SI Table 8).

Post hoc *g* analysis

A single-factor confirmatory factor analysis fit the cognitive tasks well (RMSEA = .03 & CFI = .987; SI Fig. 2). We then extracted factor scores (*g*) and used them as the dependent variable. The standardized effect of schooling on *g* was .136 SD ($p_{FDR} < .001$) – a similar magnitude as *fIQ* and WM's effects. Mirroring the other cognitive domains, no two- or three-way interactions were significant following FDR correction (SI Table 6).

Post hoc European ancestry analysis

Cog-PGS has less accuracy in non-European populations therefore we conducted a post hoc reanalysis in the full model (equation 4) for each cognitive variable including only those children whose genetic ancestry 4-means clustered on the first two principal components^{57,58}. This subsample was less representative of the United States with substantially higher SES (Cohen's $d = .80$, $p < .001$). The results

from that analysis stayed generally the same as the analysis of the full population (SI Table 7), both in terms of effect sizes on the main results and the lack of significance on the interaction terms. In reference to the full sample, there was a slight increase in the size of the effect from Cog-PGS (β range = .005 – .020), yet this was followed by larger decreases from SES (β range = -.046 – -.080).

Discussion

Schooling showed substantial and independent effects for each intelligence domain tested: cIQ, fIQ, and WM. In line with previous research, we found the raw effect of schooling on cIQ to be larger than for fIQ, though this difference was not significant¹³. This was also true for the relative influence of schooling compared to the effect of chronological age, as that ratio for cIQ was almost double that of fIQ (1.1 vs .54), showing almost near equal influences per year of schooling and age. Surprisingly, WM had the highest ratio (2.2), with the effect of schooling being more than double that of age. While this is in agreement with a previous study in younger children²¹, it should be interpreted with caution as the WM measure comprised of only one task⁵⁹.

As expected, SES and cogPGS were highly correlated with each other, highlighting the need to isolate the independent effects of each. Both had large, independent effects on cIQ, fIQ, and WM. In a follow-up analysis, we estimated the contribution of each SES component separately. Notably, all SES components were significant for each intelligence domain, with the effects from parental education and income being similar in size while neighborhood quality was roughly half.

A child's SES is not independent of their cogPGS³¹, which makes it difficult to support causal inferences of these factors as well as interpret the interaction between them (i.e., the endogeneity problem)⁶⁰. This gene-environment dependence can cause spurious gene-environment interactions^{41,61}. Our sibling analysis sheds light on this issue. We found the within-family effect of cogPGS to be roughly half of the between-family effect for cIQ, in line with the literature^{51,52}. This indicates the presence of passive genotype-environment correlations – whereby parents create family environments consistent with their genotypes, which in turn facilitate the development of their children's intelligence. Since we only had data from 392 families a lack of statistical power is most likely the reason for our null findings for fIQ and WM. While our cogPGS estimate in the full sample should be interpreted with caution, previous research has shown SES to be the major source of these between-family effects^{51,62}.

Predominant theories of GE-interplay imply a positive sign – genetically endowed cognition influences one's proximal environment, and that environment, in turn, influences one's cognition in continuous, reciprocal interactions, such as the multiplier theory³⁴, the transactional model³⁵ and the bioecological model³⁶. In line with this, a meta-analysis on twin research found the heritability of intelligence to increase with higher SES in the United States⁶³. But this effect is far from consistent. The same meta-analysis did not replicate this finding on data collected outside the United States. Furthermore, a large twin study found negative and null results for a heritability by SES interaction regarding mathematics and reading in Florida⁶⁴. Two studies using a similar polygenic marker to ours did not find evidence of GE-interplay for EA^{65,66}, yet a study with 130,000 adults in the UK found a very small negative interaction of

SES with neighborhood quality for flQ and EA ⁴⁰. Crucially, the standardized effect size of this interaction was ($\beta < .02$ SD) – translating to less than a third IQ point throughout one’s entire life – in turn having no practical effect for the individual.

We did not find any significant interaction between schooling and SES or cogPGS. One strength of our design is that schooling is, in principle, independent from cogPGS and SES. We are not aware of any other research looking at GE-interplay with schooling. A recent study did find low PGS children in high-SES schools to continue with mathematics much longer than genetically similar children in low-SES schools ³⁹. However, we see their result as more relevant to inform a cogPGS-SES effect rather than the gene-by-schooling interaction.

We expected our interaction terms to either compensate or accelerate preexisting differences. Schooling, for example, could increase (i.e., Mathew’s effect) economic/genetic inequality or lessen these differences between children (i.e., catch-up effect). The Coleman Report, a seminal study with more than half a million students and over 3000 schools in 1966, controversially concluded schools did not contribute to widening achievement gaps between children ²⁹. Conversely, there is some evidence that schooling might lessen socioeconomic disparities between children (i.e., a catch-up effect) for cognitive skills ⁶⁷.

Our study indicates schooling to not be a major driving force for either increasing or decreasing differences due to SES or cogPGS. Yet, we emphasize caution in interpreting these null effects as our range of schooling (3rd – 5th grade) was limited, and Bayesian analysis showed that an effect of less than 0.02 SD could not be ruled out (Fig. 3). Since any interaction effect with schooling could accumulate – that is, continue to increase each year – a very small ($< .05$ SD) effect size could be of practical relevance ^{54,55}. For example, an interaction with schooling as small as .02 SD could accumulate over five years to .1 SD or roughly 30% of the largest SES main effect (i.e., $\text{clQ} = .29$). This is of course a simplistic scenario assuming no counteracting mechanisms, yet it illustrates how very small effect sizes can become consequential ^{68,69}. In contrast, cogPGS-SES’ interaction is a lifelong effect and does not have the potential to accumulate in the same way. However, our sample had a slightly lower SES (Cohen’s $d = -.23$) than the average for the US, therefore we cannot rule out an interaction at the lower tail of the SES distribution.

One limitation of this study is that the 1.1 million individuals used to estimate the cogPGS are heavily biased towards those of European descent and from higher SES areas ^{30,70}. This means our results regarding genetics should only be generalized to white populations. Furthermore, GWAS methods cannot detect certain types and sizes of GE-interactions since they are intended to detect *additive* effects ⁷¹. Another consideration is how to interpret findings with multitrait GWAS’s – in our case cognitive ability,

mathematics, and educational attainment – since one of the supplementary phenotypes could be driving the results ⁷². The extent of this issue depends on 1) the relative sample size differences between the GWAS included and 2) the genetic correlation of these traits. In our case, there are sample size differences between educational attainment and cognitive ability, yet the very high ($r \sim .75$) genetic correlation between these traits most likely mitigates this issue ⁷³. Lastly, a strength of our study is that we controlled for ancestry-based genetic PCs in the full model, rather than just correcting cogPGS. While this means SES's relationship with cognition is controlled for population stratification, it also brought the limitation that we had to exclude subjects without DNA, resulting in the average level of SES increasing.

We found that schooling causes relatively large increases in children's intelligence. The two years of schooling (3rd to 5th grade) caused a larger difference in intelligence than either SES or cogPGS. However, schooling did not change the rank order of individuals' intelligence. This was shown by the lack of significant two-way interactions between Schooling, SES, and cogPGS, although our power to detect potentially meaningful small effects for schooling was limited. Intriguingly, we did not find any interaction between SES and cogPGS, this means that children's genetic differences do not matter more, or less, for intelligence dependent upon their SES background.

Methods

We used data from the Adolescent Brain Cognitive Development (ABCD) study which was approved by the appropriate institutional review boards (see Acknowledgements). Parental informed consent along with child assent was obtained for all participants. Part of the sample included siblings, along with non-representative amounts of monozygotic and dizygotic twins ^{47,74}. To correct this, we randomly selected one child per family. We also excluded children that reported ever repeating a grade, as this would bias our statistical analysis. This resulted in a total of 6,567 children between grades three and five enrolled in regular private or public schooling.

Behavioral and demographic measures

Since recruitment was continuous throughout the year this allowed us to measure schooling in months. We excluded summer vacation (15th of June until 15th of August) from our schooling variable by coding children recruited during summer as having the last month of schooling from the previous grade. This resulted in a variable with 10 months of schooling per year. Chronological age was also measured in months to preserve anonymity.

Our endogenous variables were working memory (WM), fluid (fIQ), and crystallized intelligence (cIQ) from the NIH toolbox cognition battery ⁷⁵. These tasks have been shown to have good reliability and validity ^{59,76,77}. cIQ consisted of a picture vocabulary task and an oral reading recognition task. fIQ consisted of five tasks; pattern comparison processing speed test, list-sorting WM test, picture sequence memory test, flanker task, and a dimensional change card sort task. One of the fluid tasks, list-sorting WM, was used as our WM measure. We used the sum scores provided by the NIH toolbox, rather than latent factors, to facilitate comparison with other studies. All outliers were brought to the fence (Tukey/Boxplot Method). Variables were then standardized to a mean of zero and a standard deviation of one.

SES was defined as the first principal component from a probabilistic PCA of total household income, highest parental education, and neighborhood quality. We used a probabilistic PCA because of decent amounts of non-overlapping missing data in parental income ($n = 474$, ~7%) and neighborhood quality ($n = 263$, ~4%). Children missing more than one of the three measures were excluded ($n = 45$). Parental education was recoded to reflect middle school or less (1), some high school (2), high school graduate (3), some college/associates degree (4), bachelor's degree (5), a master's degree (6), or professional degree (7). Our measure of neighborhood quality was the area deprivation index calculated from the American Community Survey using the address of primary residency ⁷⁸. The SES composite and each subcomponent were standardized with a mean of zero and a standard deviation of one.

Genetic measures

Genotyping was done by the ABCD study and the data provided to us. Saliva samples were collected at the baseline visit the genotyping was performed using the Smokescreen array ⁷⁹, consisting of 646,247 genetic variants.

Quality control (QC), imputation, and genetic PCA were performed by the National Bioinformatics Infrastructure Sweden (NBIS), as a service contracted by us. Before imputation, SNPs were excluded if they had high levels of missing data (SNP call rate < 98%), departed from Hardy-Weinberg equilibrium as calculated in the lfa R package (sHWE) ($P < 1 \times 10^{-6}$), or had minor allele frequencies (MAF) < 1%. Moreover, individuals with an absolute autosomal heterozygosity > 0.2 or more than 2% missing genotypes were excluded. These filtering steps resulted in a cleaned dataset of 10,069 individuals and 430,622 variants. Subsequently, haplotypes were pre-phased with SHAPEIT2. Genetic markers were imputed using the IMPUTE4 software. As the reference population, we used the 1,000 Genomes haplotypes – Phase 3 integrated variant set release in NCBI build 37 (hg19) coordinates. This is a mixed, multi-ethnic population dataset consisting of 2504 samples and 5008 haplotypes from populations of Europeans, Africans, East Asians, Southern Asians, and Americans (https://mathgen.stats.ox.ac.uk/impute/1000GP_Phase3.html). One of the main advantages of this imputation approach is that it provides better concordance in diverse human populations (for more information, see ⁸⁰ and ⁸¹). After imputation, genotypes with an INFO score < 0.3 or a MAF < 0.001% were excluded. The final number of SNPs after imputation was 40,637,119 in a total of 10,069 individuals.

To check for outliers and to control for population structure, principal components of SNPs were obtained using the Principal Component Analysis (PCA) module as implemented in RICOPILI. First, SNPs were pruned to ensure that there is little linkage disequilibrium between SNPs ($R^2 < 0.2$, 200 SNPs window: plink – indep-pairwise 200 100 0.2). The LD pruning was repeated until 100K SNPs were reached. Then, the resulting SNPs go into the PCA. We used the first 20 principal components (PCs) from that genetic PCA as covariates in our main analyses.

With the SNPs QCed and imputed, our group then created polygenic scores for cognitive performance (here called “cogPGS”) for each participant using PRSice-2 ⁸². This was calculated by the sum of effect sizes of thousands of SNPs (weighted by how many of the effect alleles were present in each individual) that were discovered by a large genome-wide association study on educational attainment, mathematical ability, and general cognitive ability ³⁰. That study has available all effects sizes and p values of their SNPs on the website of the Social Science Genetics Association Consortium (<https://www.thessgac.org/data>). We used the data available by the consortium from a multi-trait analysis of GWAS ⁸³, which, in our case, represents a joint polygenic score focused on a GWAS of cognitive performance and complemented by information from a GWAS on educational attainment, a GWAS on the highest-level math class completed, and a GWAS on self-reported math ability. This joint analysis is ideal

because pairwise genetic correlations of these traits were high³⁰. Furthermore, these GWAS had hundreds of thousands of individuals, and such a large sample size allows new studies to detect effects in samples of a few hundred individuals with 80% statistical power³⁰.

For the creation of cogPGS in our samples, we performed clumping and pruning to remove nearby SNPs that are correlated with one another. We used the SNPs below the original threshold of $P < 5e-5$ from the GWAS as we wanted to use the full GWAS sample (limited SNP release due to anonymity concerns). After adopting a clumping sliding window of 250kb, with the linkage disequilibrium clumping set to $r^2 > 0.25$, this resulted in 5255 SNPs for our dataset. Finally, we normalized the polygenic scores (mean=0, sd=1).

Statistical analysis

We used random intercept mixed-effects models to predict the effect of schooling from our three cognitive variables of interest (i.e., *flQ*, *clQ* and *WM*); *Y* denotes these outcome variables. Every model included a random intercept per collection site (*j*) to account for the clustering of individuals (*i*). Models were fit using maximum likelihood estimation with the R package *lme4* (v. 1.1-27.1)^{84,85}. All results are reported in standard units (mean = 0, SD = 1), unless specified otherwise. P-values on all models were derived using Satterthwaite's degrees of freedom method with the *lmerTest* package (v. 3.1-3)⁸⁶, with an alpha level of .05.

We broke the equation into four steps to more clearly convey the identification assumptions behind our estimands⁸⁷. A fuzzy regression discontinuity design (Equation 1) was used to isolate the effect of one year of schooling from chronological age. This causal inference method is one of the best to isolate the effect of schooling, yet it relies on two critical assumptions: 1) age-based allocation rule and 2) linearity of the within-grade regression. Previous research has shown that, in practice, violation of these assumptions does not substantially bias the schooling or age coefficient^{18,88}. Data collection was continuous throughout the school year therefore we correct for months of schooling rather than grade, yet our instrument (age-based grade allocation) is on the level of grade. We included posthoc sensitivity checks using grades 3-5 and comparing the two most frequent, grades 4 & 5, for Equation 1 (SI Table 9a&b). Lastly, we also compared the schooling coefficients using a z-test on the difference between the coefficients. This method sums the standard error from the coefficients as error variance, assuming no correlation between the coefficients thereby being conservative⁸⁹. We used an absolute z-value of 1.96, corresponding to an alpha level of .05.

$$y_{ij} \sim \alpha_0 + \beta_1(Age_{ij}) + \beta_2(Schooling_{ij}) + \gamma_{0j} + \epsilon_{ij}$$

(1)

We then add a fixed effect for cogPGS and SES, while controlling sex and 20 genetic principal components (Equation 2). β_* represents 20 fixed effects for each principal component. This model allowed us to estimate the causal effect of one year of schooling, along with estimating the independent effects of chronological age, sex, cog-PGS, and SES. Crucially, schooling is the only exogenous variable. It is important to highlight that by adding 20 genetic principal components to the model we are controlling all variables for population stratification, most notably SES's relationship with intelligence.

$$y_{ij} \sim \alpha_0 + \beta_1(Age_{ij}) + \beta_2(Schooling_{ij}) + \beta_3(SES_{ij}) + \beta_4(cogPGS_{ij}) + \beta_5(SexMale_{ij}) + \beta_*(20PC_{ij}) + \gamma_{0j} + \epsilon_{ij}$$

(2)

In equation 3, we were interested in determining if schooling interacted with cogPGS (i.e., β_6) or SES (i.e., β_7). To properly isolate schooling's interaction effects and avoid spurious results, we included interactions of no interest with age (i.e., β_8 & β_9). We were also interested to see if SES interacted with cogPGS (i.e., β_{10}), yet we emphasize caution in interpreting this term as any interaction found could be spurious due to endogeneity between SES & cogPGS ^{41,90}. We refer to these interactions as GE-interplay, highlighting that they could be caused by gene-by-environment interaction (GxE) and/or gene-by-environment correlation (rGE). rGE refers to the fact that genotypes and environments are not randomly distributed while GxE is an interaction in the classical sense whereby the environment (or genotype) interacts with the other ⁹¹. Due to schooling's exogenous nature, a significant interaction would be most likely due to GxE, yet this is not the case for an interaction between SES and cogPGS which could be the result of either GxE or rGE.

$$y_{ij} \sim \alpha_0 + \beta_1(Age_{ij}) + \beta_2(Schooling_{ij}) + \beta_3(SES_{ij}) + \beta_4(cogPGS_{ij}) + \beta_5(SexMale_{ij}) + \beta_6(Schooling \times cogPGS_{ij}) + \beta_7(Schooling \times SES_{ij}) + \beta_8(Age \times cogPGS_{ij}) + \beta_9(Age \times SES_{ij}) + \beta_{10}(cogPGS \times SES_{ij}) + \beta_*(20PC_{ij}) + \gamma_{0j} + \epsilon_{ij}$$

(3)

Lastly, we were interested in the presence of a three-way interaction between schooling, SES, and cogPGS (Equation 4, β_{11}). To accomplish this, we added a 3-way interaction term, which was then compared, using a likelihood-ratio test to Equation 3.

$$\begin{aligned}
y_{ij} \sim & \alpha_0 + \beta_1(\text{Age}_{ij}) + \beta_2(\text{Schooling}_{ij}) \\
& + \beta_3(\text{SES}_{ij}) + \beta_4(\text{cogPGS}_{ij}) + \beta_5(\text{SexMale}_{ij}) + \beta_6(\text{Schooling} \times \text{cogPGS}_{ij}) \\
& + \beta_7(\text{Schooling} \times \text{SES}_{ij}) + \beta_8(\text{Age} \times \text{cogPGS}_{ij}) + \beta_9(\text{Age} \times \text{SES}_{ij}) + \beta_{10}(\text{cogPGS} \times \text{SES}_{ij}) \\
& + \beta_{11}(\text{Schooling} \times \text{cogPGS} \times \text{SES}_{ij}) + \beta_*(20PC_{ij}) + \gamma_{0j} + \epsilon_{ij}
\end{aligned}
\tag{4}$$

SES subcomponents

In cases of significant SES composite findings, we also reported the results for each SES subcomponent separately. This was done for two reasons: 1) research showing specific SES measures to relate to intelligence more than others, and 2) call in the literature to treat SES measures independently^{48–50}. We considered the entire subcomponent analysis a family, therefore p-values were corrected using false discovery rate (FDR) for the number of terms tested.

Post hoc sibling analysis

To estimate the within and between family effect cogPGS on cIQ, fIQ, and WM we conducted a sibling analysis using the procedure described by Selzam and colleagues 2019⁵¹. This allowed us to estimate the within family direct genetic effects (β_w) and the between family genetic effects (β_B). For families to be included in the analysis they needed to have at least two non-identical siblings. We considered the entire sibling analysis a family, therefore p-values were corrected using false discovery rate (FDR) for the number of terms of interest tested. SES has been shown to largely explain between-family effects therefore cogPGS in our main analysis is, to some extent, controlled for these between family effects^{51,62}.

Post hoc g analysis

We fit nine cognitive tasks into a single factor solution using confirmatory factor analysis with the Lavaan package in R (SI Fig. 2)⁹². This included all the tasks from the NIH toolbox cognition battery along with the overall score on a WM nback task and the total raw score from matrix reasoning on the Wechsler Intelligence Scale for Children. A single factor solution fit the data well (RMSEA = .03 & CFI = .987) when correlated covariances were added between the two crystallized tasks, the two WM tasks, and a cluster of three tasks sharing similar attributes (Flanker, Pattern comparison & Card sorting). We then extracted factor scores and fit them to equations 1-4 while using FDR correction for multiple comparisons.

Post hoc European ancestry analysis

Cog-PGS has limited prediction accuracy in non-European samples⁵⁷. We therefore subsetting the data using 4-means clustering on the first two principal components (n = 3751), resulting in the exclusion of 43% of the sample⁵⁸. The proportion is equal to the full ABCD sample which is representative of the

United States. Yet this subsample had significantly higher SES (Cohen's $d = .80.$, $p < .001$). All variables were (re)standardized to this population with a mean of 0 and an SD of 1. We then fit equation 4 on this subset for clQ , flQ , WM , and g and used FDR correction on the p-values (SI Table 7).

Bayesian hierarchical modeling

To have a better understanding of our results we conducted Bayesian mixed-effects models of Equation 3 with the brms package (v. 2.15.0)⁹³ using Markov Chain Monte Carlo sampling with 10,000 iterations (1,000 warmup) in 15 chains. We set weakly informative normally distributed priors for our terms of interest, keeping the default non-informative priors unless otherwise specified. For clQ age (β_1) and schooling (β_2) had normally distributed priors with a mean of .20 and a standard deviation (SD) of .15. CogPGS (β_4) had a prior with a mean of .15 and an SD of .1, while SES (β_3) had a larger mean of .25 and an SD of .2. All two-way interaction terms (β_{6-10}) had two-tailed priors with a mean of zero and an SD of .1. Gender and the 20 PCs had default flat priors. For flQ and WM we set identical priors, these were a mean of .15 and an SD of .15 for age (β_1) and schooling (β_2). CogPGS (β_4) had a prior with a mean of .1 and an SD of .1, while SES (β_3) was double that with a mean of .2 and an SD of .2. All two-way interaction terms (β_{6-10}) had identical priors to clQ , along with flat priors for gender and each principal component. We also fit Equation 4 to test the null of the 3-way interaction term where priors were identical to Equation 3 while the 3-way term (β_{11}) had a mean of 0 and an SD of .1. Notably, our results for the interactions in Equation 3 and 4 did not meaningfully change in comparison to flat priors.

We then computed the 95% highest-density intervals (HDI) of the posterior distributions for our three interaction terms of interest (β_6 , β_7 , β_{10} , β_{11}) for clQ , flQ , and WM . Crucially, we used two ROPE boundaries in standard units of 0.05 and 0.02. This was done for two reasons, 1) a lack of consensus in the field on a minimal effect size of interest, and 2) schooling representing a cumulative process. Since the schooling interaction terms (β_6 , β_7 , β_{11}) are cumulative they could warrant a smaller minimal effect size of interest than the cogPGS-SES' interaction^{54–56}. We then calculated the percentage of the estimates 95% HDI lying within our ROPE boundaries, giving us the probability of the null hypothesis. If 95% of the estimates posterior distribution lies within ROPE boundaries, the null hypothesis can be confirmed as any probable effect is considered too small to be meaningful.

Data and Code Availability

The data to replicate this analysis is on the NIHM data archive (<https://nda.nih.gov>) under release 3.0 'ABCDstudyNDA'. The code to replicate all analysis and figures will be made available upon publication at <https://github.com/njudd/ABCDschooling>.

Competing Interests

Nicholas Judd, Bruno Sauce, and Torkel Klingberg declare no competing interests.

Author Contributions

N.J., B.S., and T.K. contributed equally to all aspects of the study.

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Supplementary information

Schooling project ABCD

Nicholas Judd

01/09/2021

Nickkjudd(at)gmail.com

github.com/njudd/ABCDschooling

*"I do not think demonstrating that they are null warrants publication in this journal.
Despite my negative conclusion, I think this is a strong paper that deserves publication elsewhere,
and as I say I appreciate the authors' responsiveness."* – anonymous PNAS reviewer

Supplementary Table 1

Descriptive table of the full sample.

	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
ciQ	6567	0.00	1.00	-0.01	-0.01	0.91	-2.46	2.44	4.90	0.10	-0.08	0.01
fiQ	6567	0.00	1.00	0.07	0.02	1.02	-2.77	2.72	5.49	-0.23	-0.02	0.01
WM	6567	0.00	1.00	-0.06	0.03	1.05	-2.45	2.34	4.79	-0.29	-0.20	0.01
Age	6567	0.00	1.00	-0.08	-0.02	1.22	-1.59	1.85	3.44	0.10	-1.21	0.01
Age Unscaled	6567	9.88	0.61	9.83	9.87	0.74	8.92	11.00	2.08	0.10	-1.21	0.01
Schooling	6567	0.00	1.00	0.16	-0.02	1.10	-2.37	1.94	4.31	0.08	-0.84	0.01
Schooling Unscaled	6567	1.69	0.67	1.80	1.68	0.74	0.10	3.00	2.90	0.08	-0.84	0.01
SES	6567	0.00	1.00	0.14	0.04	0.97	-2.88	3.19	6.07	-0.32	-0.19	0.01
cogPGS	6567	0.00	1.00	0.03	0.01	1.03	-3.41	3.63	7.04	-0.05	-0.24	0.01
Parental Income	6093	0.00	1.00	0.26	0.14	0.64	-2.75	1.12	3.87	-1.15	0.57	0.01
Max Parental Education	6566	0.00	1.00	0.05	0.04	1.12	-2.97	1.56	4.53	-0.38	-0.25	0.01
Neighborhood Quality	6304	0.00	1.00	-0.23	-0.17	0.61	-1.35	3.63	4.99	1.95	4.13	0.01

Supplementary Table 2

Checks for multicollinearity using the full model for cIQ (i.e., Equation 4). Variance inflation factors (VIF) are all below 5, indicating low correlations. VIFs were almost identical across different dependent variables (i.e., cIQ, fIQ & WM).

Term	VIF	Increased SE
Age	3.14	1.77
Schooling	3.37	1.84
Sex	1.01	1.00
cogPGS	1.45	1.21
SES	1.50	1.23
C1	1.58	1.26
C2	1.08	1.04
C3	1.18	1.08
C4	1.05	1.02
C5	1.02	1.01
C6	1.95	1.40
C7	1.94	1.39
C8	1.04	1.02
C9	1.12	1.06
C10	1.20	1.10
C11	1.13	1.06
C12	1.12	1.06
C13	1.04	1.02
C14	1.02	1.01
C15	1.04	1.02
C16	1.01	1.01
C17	1.02	1.01
C18	1.01	1.00
C19	1.01	1.00
C20	1.04	1.02
cogPGS*SES	1.11	1.05
Schooling*cogPGS	3.56	1.89
Schooling*SES	3.48	1.87
Age*cogPGS	3.51	1.87
Age*SES	3.39	1.84
Schooling*cogPGS*SES	1.23	1.11

Supplementary Table 3

Linear mixed-effects models for crystallized IQ (cIQ) including subjects for subjects with complete data ($n = 6567$).

<i>Predictors</i>	cIQ (Equation 1)			cIQ (Equation 2)			cIQ (Equation 3)			cIQ (Equation 4)		
	<i>Estimates</i>	<i>SE</i>	<i>p</i>	<i>Estimates</i>	<i>SE</i>	<i>p</i>	<i>Estimates</i>	<i>SE</i>	<i>p</i>	<i>Estimates</i>	<i>SE</i>	<i>p</i>
(Intercept)	0.000	0.045	1.000	-0.027	0.026	0.302	-0.018	0.026	0.495	-0.018	0.026	0.491
Age	0.144	0.021	<0.001	0.129	0.018	<0.001	0.131	0.018	<0.001	0.132	0.018	<0.001
Schooling	0.134	0.021	<0.001	0.145	0.018	<0.001	0.142	0.018	<0.001	0.134	0.019	<0.001
Sex [M]				0.046	0.020	0.023	0.045	0.020	0.026	0.045	0.020	0.026
cogPGS				0.159	0.012	<0.001	0.161	0.012	<0.001	0.161	0.012	<0.001
SES				0.291	0.013	<0.001	0.288	0.013	<0.001	0.289	0.013	<0.001
C1				-0.117	0.013	<0.001	-0.111	0.014	<0.001	-0.111	0.014	<0.001
C2				0.057	0.012	<0.001	0.059	0.012	<0.001	0.059	0.012	<0.001
C3				0.103	0.011	<0.001	0.104	0.011	<0.001	0.104	0.011	<0.001
C4				0.014	0.011	0.187	0.014	0.011	0.194	0.014	0.011	0.195
C5				0.002	0.010	0.851	0.002	0.010	0.863	0.002	0.010	0.843
C6				-0.003	0.014	0.846	-0.004	0.014	0.796	-0.004	0.014	0.792
C7				0.007	0.014	0.604	0.008	0.014	0.555	0.008	0.014	0.564

C8	-0.022	0.011	0.040	-0.023	0.011	0.035	-0.022	0.011	0.040
C9	-0.037	0.011	0.001	-0.037	0.011	0.001	-0.037	0.011	0.001
C10	-0.011	0.011	0.347	-0.011	0.011	0.316	-0.011	0.011	0.320
C11	-0.034	0.011	0.002	-0.035	0.011	0.002	-0.035	0.011	0.001
C12	-0.011	0.011	0.324	-0.012	0.011	0.269	-0.012	0.011	0.262
C13	0.001	0.010	0.947	0.000	0.010	0.979	0.000	0.010	0.970
C14	-0.008	0.010	0.435	-0.007	0.010	0.479	-0.008	0.010	0.463
C15	0.005	0.010	0.620	0.005	0.010	0.616	0.005	0.010	0.614
C16	-0.007	0.010	0.521	-0.007	0.010	0.512	-0.007	0.010	0.505
C17	-0.001	0.010	0.914	-0.002	0.010	0.881	-0.001	0.010	0.908
C18	0.010	0.010	0.333	0.010	0.010	0.347	0.009	0.010	0.351
C19	-0.008	0.010	0.433	-0.008	0.010	0.416	-0.008	0.010	0.428
C20	-0.020	0.010	0.051	-0.020	0.010	0.052	-0.021	0.010	0.047
cogPGS * SES				-0.020	0.011	0.063	0.020	-0.011	0.066
Schooling * cogPGS				0.003	0.019	0.877	0.004	0.019	0.828
Schooling * SES				-0.013	0.019	0.487	-0.010	0.019	0.604
Age * cogPGS				0.022	0.019	0.254	0.021	0.019	0.275
Age * SES				0.026	0.019	0.176	0.025	0.019	0.189

Schooling * cogPGS * SES

0.018   0.010   0.092

Random Effects

σ^2	0.89	0.67	0.67	0.67
τ_{00}	0.04 site_id_l	0.01 site_id_l	0.01 site_id_l	0.01 site_id_l
ICC	0.04	0.01	0.01	0.01
N	22 site_id_l	22 site_id_l	22 site_id_l	22 site_id_l
Observations	6567	6567	6567	6567
Marginal R ² / Conditional R ²	0.070 / 0.112	0.330 / 0.340	0.331 / 0.341	0.332 / 0.341
AIC	17934.378	16104.673	16100.450	16099.616
log-Likelihood	-8962.189	-8024.337	-8017.225	-8015.808

Supplementary Table 4

Linear mixed-effects models for fluid IQ (fIQ) including subjects for subjects with complete data ($n = 6567$).

<i>Predictors</i>	<i>fIQ</i> (Equation 1)			<i>fIQ</i> (Equation 2)			<i>fIQ</i> (Equation 3)			<i>fIQ</i> (Equation 4)		
	<i>Estimates</i>	<i>SE</i>	<i>p</i>	<i>Estimates</i>	<i>SE</i>	<i>p</i>	<i>Estimates</i>	<i>SE</i>	<i>p</i>	<i>Estimates</i>	<i>SE</i>	<i>p</i>
(Intercept)	-0.009	0.044	0.845	0.041	0.024	0.088	0.045	0.025	0.070	0.045	0.025	0.070
Age	0.162	0.021	<0.001	0.160	0.020	<0.001	0.162	0.020	<0.001	0.162	0.020	<0.001
Schooling	0.100	0.021	<0.001	0.096	0.020	<0.001	0.095	0.020	<0.001	0.097	0.020	<0.001
Sex [M]				-0.094	0.022	<0.001	-0.095	0.022	<0.001	-0.095	0.022	<0.001
cogPGS				0.088	0.014	<0.001	0.089	0.014	<0.001	0.089	0.014	<0.001
SES				0.182	0.014	<0.001	0.181	0.014	<0.001	0.181	0.014	<0.001
C1				-0.131	0.014	<0.001	-0.130	0.015	<0.001	-0.130	0.015	<0.001
C2				-0.021	0.013	0.105	-0.020	0.013	0.121	-0.020	0.013	0.121
C3				0.079	0.012	<0.001	0.080	0.012	<0.001	0.080	0.012	<0.001
C4				0.016	0.012	0.168	0.016	0.012	0.178	0.016	0.012	0.178
C5				0.003	0.011	0.818	0.003	0.011	0.812	0.003	0.011	0.818
C6				0.009	0.015	0.573	0.008	0.015	0.586	0.008	0.015	0.585
C7				0.053	0.015	0.001	0.054	0.015	<0.001	0.054	0.015	<0.001

C8	-0.020	0.012	0.087	-0.021	0.012	0.078	-0.021	0.012	0.075
C9	0.009	0.012	0.471	0.009	0.012	0.467	0.009	0.012	0.466
C10	0.009	0.012	0.438	0.009	0.012	0.439	0.009	0.012	0.440
C11	-0.017	0.012	0.164	-0.017	0.012	0.153	-0.017	0.012	0.155
C12	-0.008	0.012	0.490	-0.008	0.012	0.480	-0.008	0.012	0.483
C13	-0.006	0.011	0.589	-0.006	0.011	0.586	-0.006	0.011	0.584
C14	-0.013	0.011	0.247	-0.013	0.011	0.253	-0.013	0.011	0.257
C15	0.017	0.011	0.135	0.017	0.011	0.141	0.017	0.011	0.141
C16	-0.002	0.011	0.857	-0.002	0.011	0.872	-0.002	0.011	0.874
C17	0.012	0.011	0.301	0.012	0.011	0.296	0.012	0.011	0.301
C18	0.005	0.011	0.680	0.005	0.011	0.642	0.005	0.011	0.640
C19	-0.005	0.011	0.671	-0.005	0.011	0.666	-0.005	0.011	0.662
C20	-0.007	0.011	0.523	-0.007	0.011	0.530	-0.007	0.011	0.539
cogPGS * SES				-0.006	0.012	0.621	-0.006	0.012	0.618
Schooling * cogPGS				-0.019	0.021	0.362	-0.019	0.021	0.353
Schooling * SES				-0.013	0.020	0.511	-0.014	0.020	0.480
Age * cogPGS				0.015	0.021	0.479	0.015	0.021	0.470

Age * SES	0.007	0.021	0.746	0.007	0.021	0.738
Schooling * cogPGS * SES				-0.006	0.011	0.608

Random Effects

σ^2	0.90	0.80	0.80	0.80
τ_{00}	0.04 site_id_l	0.01 site_id_l	0.01 site_id_l	0.01 site_id_l
ICC	0.04	0.01	0.01	0.01
N	22 site_id_l	22 site_id_l	22 site_id_l	22 site_id_l
Observations	6567	6567	6567	6567
Marginal R ² / Conditional R ²	0.062 / 0.101	0.195 / 0.202	0.195 / 0.202	0.195 / 0.202
AIC	18017.919	17218.323	17225.680	17227.416
log-Likelihood	-9003.960	-8581.162	-8579.840	-8579.708

Supplementary Table 5

Linear mixed-effects models for Working Memory list sorting (WM) including subjects for subjects with complete data ($n = 6567$).

<i>Predictors</i>	WM (Equation 1)			WM (Equation 2)			WM (Equation 3)			WM (Equation 4)		
	<i>Estimates</i>	<i>SE</i>	<i>p</i>	<i>Estimates</i>	<i>SE</i>	<i>p</i>	<i>Estimates</i>	<i>SE</i>	<i>p</i>	<i>Estimates</i>	<i>SE</i>	<i>p</i>
(Intercept)	-0.009	0.034	0.796	-0.046	0.022	0.036	-0.047	0.023	0.038	-0.047	0.023	0.038
Age	0.052	0.021	0.016	0.039	0.020	0.055	0.039	0.020	0.057	0.039	0.020	0.058
Schooling	0.087	0.021	<0.001	0.095	0.020	<0.001	0.095	0.020	<0.001	0.096	0.021	<0.001
Sex [M]				0.078	0.023	0.001	0.078	0.023	0.001	0.078	0.023	0.001
cogPGS				0.086	0.014	<0.001	0.086	0.014	<0.001	0.086	0.014	<0.001
SES				0.215	0.015	<0.001	0.215	0.015	<0.001	0.215	0.015	<0.001
C1				-0.111	0.015	<0.001	-0.111	0.015	<0.001	-0.111	0.015	<0.001
C2				0.023	0.013	0.075	0.022	0.013	0.082	0.022	0.013	0.082
C3				0.041	0.013	0.001	0.041	0.013	0.001	0.041	0.013	0.001
C4				0.023	0.012	0.060	0.022	0.012	0.064	0.022	0.012	0.064
C5				0.002	0.012	0.872	0.002	0.012	0.868	0.002	0.012	0.869
C6				0.020	0.016	0.214	0.020	0.016	0.211	0.020	0.016	0.211
C7				0.052	0.016	0.001	0.052	0.016	0.001	0.052	0.016	0.001

C8	-0.011	0.012	0.342	-0.011	0.012	0.347	-0.011	0.012	0.346
C9	-0.002	0.012	0.848	-0.002	0.012	0.860	-0.002	0.012	0.860
C10	-0.004	0.013	0.779	-0.003	0.013	0.783	-0.003	0.013	0.783
C11	-0.023	0.012	0.059	-0.023	0.012	0.057	-0.023	0.012	0.057
C12	0.000	0.012	0.980	0.000	0.012	0.977	0.000	0.012	0.976
C13	-0.003	0.012	0.819	-0.003	0.012	0.811	-0.003	0.012	0.811
C14	-0.008	0.012	0.471	-0.008	0.012	0.464	-0.008	0.012	0.465
C15	0.006	0.012	0.615	0.006	0.012	0.624	0.006	0.012	0.624
C16	0.003	0.011	0.760	0.004	0.011	0.759	0.004	0.011	0.759
C17	-0.004	0.012	0.740	-0.004	0.012	0.739	-0.004	0.012	0.738
C18	0.018	0.011	0.113	0.019	0.011	0.104	0.019	0.011	0.104
C19	-0.006	0.011	0.600	-0.006	0.011	0.604	-0.006	0.011	0.603
C20	0.005	0.012	0.657	0.005	0.012	0.665	0.005	0.012	0.663
cogPGS * SES				-0.002	0.012	0.887	-0.002	0.012	0.888
Schooling * cogPGS				-0.021	0.022	0.335	-0.021	0.022	0.334
Schooling * SES				-0.012	0.021	0.561	-0.012	0.021	0.570
Age * cogPGS				0.007	0.021	0.756	0.007	0.021	0.754
Age * SES				0.003	0.021	0.892	0.003	0.021	0.894

Schooling * cogPGS * SES

0.001 0.012 0.929

Random Effects

σ^2	0.96	0.85	0.85	0.85
τ_{00}	0.02 site_id_l	0.00 site_id_l	0.00 site_id_l	0.00 site_id_l
ICC	0.02	0.01	0.01	0.01
N	22 site_id_l	22 site_id_l	22 site_id_l	22 site_id_l
Observations	6567	6567	6567	6567
Marginal R ² / Conditional R ²	0.018 / 0.039	0.147 / 0.152	0.148 / 0.152	0.148 / 0.152
AIC	18419.937	17650.254	17658.583	17660.575
log-Likelihood	-9204.968	-8797.127	-8796.291	-8796.287

Supplementary Table 6

Post hoc Linear mixed-effects models for g including subjects for subjects with complete data ($n = 6567$). P -values are FDR corrected.

Predictors	g (Equation 1)			g (Equation 2)			g (Equation 3)			g (Equation 4)		
	Estimates	SE	p	Estimates	SE	p	Estimates	SE	p	Estimates	SE	p
(Intercept)	-0.007	0.049	0.895	-0.004	0.025	0.921	0.003	0.025	0.976	0.003	0.025	0.999
Age	0.146	0.021	<0.001	0.136	0.018	<0.001	0.137	0.018	<0.001	0.137	0.018	<0.001
Schooling	0.129	0.021	<0.001	0.134	0.018	<0.001	0.134	0.018	<0.001	0.133	0.019	<0.001
Sex [M]				-0.009	0.020	0.792	-0.010	0.020	0.829	-0.010	0.020	0.855
cogPGS				0.145	0.012	<0.001	0.146	0.012	<0.001	0.146	0.012	<0.001
SES				0.301	0.013	<0.001	0.299	0.013	<0.001	0.299	0.013	<0.001
C1				-0.146	0.013	<0.001	-0.142	0.013	<0.001	-0.142	0.013	<0.001
C2				0.022	0.012	0.150	0.023	0.012	0.146	0.023	0.012	0.151
C3				0.086	0.011	<0.001	0.087	0.011	<0.001	0.087	0.011	<0.001
C4				0.018	0.011	0.195	0.018	0.011	0.241	0.018	0.011	0.249
C5				0.007	0.010	0.706	0.007	0.010	0.799	0.007	0.010	0.825
C6				0.003	0.014	0.915	0.002	0.014	0.976	0.002	0.014	0.999
C7				0.038	0.014	0.024	0.039	0.014	0.024	0.039	0.014	0.025

C8	-0.023	0.011	0.079	-0.025	0.011	0.074	-0.025	0.011	0.077
C9	-0.006	0.011	0.789	-0.006	0.011	0.823	-0.006	0.011	0.849
C10	0.005	0.011	0.792	0.005	0.011	0.829	0.005	0.011	0.855
C11	-0.027	0.011	0.049	-0.027	0.011	0.052	-0.027	0.011	0.054
C12	-0.009	0.011	0.635	-0.010	0.011	0.662	-0.010	0.011	0.683
C13	-0.003	0.010	0.882	-0.004	0.010	0.907	-0.004	0.010	0.936
C14	-0.013	0.010	0.397	-0.013	0.010	0.460	-0.013	0.010	0.475
C15	0.012	0.010	0.431	0.012	0.010	0.498	0.012	0.010	0.514
C16	0.001	0.010	0.940	0.001	0.010	0.976	0.001	0.010	0.999
C17	0.003	0.010	0.882	0.003	0.010	0.941	0.003	0.010	0.971
C18	0.018	0.010	0.165	0.019	0.010	0.185	0.019	0.010	0.191
C19	-0.007	0.010	0.706	-0.007	0.010	0.791	-0.007	0.010	0.817
C20	-0.010	0.010	0.545	-0.010	0.010	0.600	-0.010	0.010	0.619
cogPGS * SES				-0.015	0.011	0.378	-0.015	0.011	0.390
Schooling * cogPGS				-0.009	0.019	0.829	-0.009	0.019	0.855
Schooling * SES				-0.000	0.018	0.998	0.000	0.019	0.999
Age * cogPGS				0.011	0.019	0.823	0.011	0.019	0.849
Age * SES				0.001	0.019	0.976	0.001	0.019	0.999

Schooling * cogPGS *
SES

0.000 0.010 0.999

Random Effects

σ^2	0.88	0.66	0.66	0.66
τ_{00}	0.05 site_id_l	0.01 site_id_l	0.01 site_id_l	0.01 site_id_l
ICC	0.05	0.01	0.01	0.01
N	22 site_id_l	22 site_id_l	22 site_id_l	22 site_id_l
Observations	6567	6567	6567	6567
Marginal R ² / Conditional R ²	0.069 / 0.119	0.337 / 0.345	0.337 / 0.346	0.337 / 0.346
AIC	17890.653	16004.406	16011.960	16013.959
log-Likelihood	-8940.326	-7974.203	-7972.980	-7972.979

Supplementary Table 7

Post hoc Linear mixed-effects models of Equation 4 for each cognitive variable including European ancestry subjects defined with 4-means clustering on the first two principal components (n =3715). P-values are FDR corrected and variables are restandardized on the population.

<i>Predictors</i>	cIQ (Equation 4)			flQ (Equation 4)			WM (Equation 4)			g (Equation 4)		
	<i>Estimates</i>	<i>SE</i>	<i>p</i>	<i>Estimates</i>	<i>SE</i>	<i>p</i>	<i>Estimates</i>	<i>SE</i>	<i>p</i>	<i>Estimates</i>	<i>SE</i>	<i>p</i>
(Intercept)	-0.031	0.035	0.621	0.039	0.030	0.531	-0.065	0.028	0.134	-0.016	0.033	0.805
Age	0.148	0.027	<0.001	0.177	0.029	<0.001	0.031	0.030	0.804	0.145	0.027	<0.001
Schooling	0.172	0.028	<0.001	0.103	0.029	0.003	0.113	0.030	0.002	0.172	0.028	<0.001
Sex [M]	0.071	0.030	0.087	-0.112	0.031	0.003	0.100	0.032	0.014	0.006	0.030	0.885
cogPGS	0.170	0.015	<0.001	0.094	0.016	<0.001	0.106	0.016	<0.001	0.166	0.015	<0.001
SES	0.208	0.016	<0.001	0.135	0.017	<0.001	0.158	0.017	<0.001	0.228	0.016	<0.001
C1	-0.042	0.026	0.383	0.019	0.027	0.761	-0.017	0.028	0.851	-0.017	0.026	0.805
C2	-0.030	0.019	0.383	-0.010	0.020	0.801	-0.014	0.020	0.851	-0.032	0.019	0.535
C3	0.018	0.017	0.588	0.022	0.018	0.531	0.007	0.019	0.851	0.018	0.017	0.781
C4	0.008	0.028	0.856	0.042	0.030	0.531	0.016	0.030	0.851	0.019	0.028	0.805
C5	0.013	0.018	0.653	0.014	0.019	0.760	0.002	0.020	0.928	0.011	0.018	0.805
C6	-0.010	0.015	0.666	-0.008	0.016	0.801	0.007	0.017	0.851	-0.003	0.015	0.885

C7	0.002	0.017	0.894	0.032	0.018	0.374	0.026	0.018	0.711	0.008	0.017	0.805
C8	-0.031	0.020	0.383	-0.007	0.021	0.803	-0.015	0.021	0.851	-0.029	0.020	0.640
C9	-0.051	0.017	0.015	0.006	0.018	0.803	-0.006	0.018	0.851	-0.014	0.017	0.805
C10	-0.014	0.017	0.621	0.008	0.018	0.803	-0.022	0.018	0.804	-0.004	0.017	0.885
C11	-0.024	0.017	0.422	-0.014	0.018	0.760	0.006	0.018	0.851	-0.007	0.017	0.812
C12	-0.010	0.016	0.666	-0.014	0.017	0.760	0.009	0.017	0.851	-0.007	0.016	0.805
C13	0.009	0.016	0.670	0.010	0.017	0.801	0.017	0.017	0.804	0.020	0.016	0.753
C14	-0.016	0.015	0.588	-0.022	0.016	0.531	0.003	0.016	0.909	-0.017	0.015	0.763
C15	0.011	0.015	0.653	0.026	0.016	0.495	0.016	0.017	0.804	0.022	0.015	0.640
C16	-0.012	0.015	0.637	-0.006	0.016	0.803	-0.009	0.016	0.851	-0.008	0.015	0.805
C17	-0.003	0.015	0.888	0.018	0.016	0.531	-0.002	0.016	0.909	0.001	0.015	0.950
C18	0.008	0.015	0.670	0.002	0.015	0.944	0.023	0.016	0.711	0.021	0.015	0.640
C19	-0.013	0.015	0.621	-0.000	0.016	0.985	-0.005	0.016	0.851	-0.003	0.015	0.885
C20	-0.020	0.015	0.422	-0.018	0.016	0.531	0.006	0.017	0.851	-0.015	0.015	0.781
cogPGS * SES	-0.027	0.015	0.306	0.018	0.016	0.531	0.019	0.016	0.804	-0.007	0.015	0.805
Schooling * cogPGS	-0.005	0.027	0.888	-0.014	0.029	0.801	-0.014	0.029	0.851	-0.014	0.027	0.805
Schooling * SES	-0.026	0.027	0.621	-0.044	0.028	0.495	-0.004	0.029	0.909	-0.030	0.027	0.763
Age * cogPGS	0.037	0.027	0.422	0.020	0.028	0.761	0.023	0.029	0.851	0.026	0.027	0.781

Age * SES	0.023	0.027	0.622	0.036	0.029	0.531	0.013	0.029	0.851	0.021	0.027	0.805
Schooling * cogPGS * SES	0.019	0.014	0.422	-0.005	0.015	0.803	0.016	0.015	0.804	0.009	0.014	0.805
Random Effects												
σ^2	0.79			0.88			0.93			0.79		
τ_{00}	0.01 _{site_id_1}			0.01 _{site_id_1}			0.00 _{site_id_1}			0.01 _{site_id_1}		
ICC	0.02			0.01			0.00			0.01		
N	22 _{site_id_1}			22 _{site_id_1}			22 _{site_id_1}			22 _{site_id_1}		
Observations	3715			3715			3715			3715		
Marginal R ² / Conditional R ²	0.203 / 0.217			0.117 / 0.124			0.072 / 0.077			0.203 / 0.214		
AIC	9778.428			10141.305			10337.290			9775.487		
log-Likelihood	-4855.214			-5036.653			-5134.645			-4853.744		

Supplementary Table 8

Region of practical equivalence (ROPE) boundary table from a Bayesian mixed effects model of Equation 3 with boundaries .05 SD and .02 SD on 95% highest density intervals (HDI). Values indicate the percentage of the 95 HDI within the ROPE boundary. See methods for more information on weakly informative priors (results were similar with the default flat priors). The 3-way interaction term comes from Equation 4 with an addition prior with a mean of 0 and an SD of .1.

Parameter	HDI	ciQ ROPE (.05 sd)	fiQ ROPE (.05 sd)	WM ROPE (.05 sd)	ciQ ROPE (.02 sd)	fiQ ROPE (.02 sd)	WM ROPE (.02 sd)
cogPGS * SES	0.95	100%	100%	100%	51%	91%	94%
Schooling * cogPGS	0.95	100%	97%	95%	75%	53%	50%
Schooling * SES	0.95	100%	100%	100%	67%	63%	64%
Schooling * cogPGS * SES	0.95	100%	100%	100%	61%	92%	96%

Supplementary Table 9a

Recruitment was throughout the year in ABCD, this makes controlling for the month of schooling a better option than grade (as there is within-grade months of schooling variance). We carried out two supplementary sensitivity analyses where we recoded schooling a) coding grade as ordinal (i.e., 3, 4, 5) and another b) where we excluded the grade with the least subjects (3rd grade) and added a dummy coded categorical variable for fifth grade. P-values are uncorrected.

	cIQ ordinal coding			fIQ ordinal coding			WM ordinal coding		
<i>Predictors</i>	<i>Estimates</i>	<i>SE</i>	<i>p</i>	<i>Estimates</i>	<i>SE</i>	<i>p</i>	<i>Estimates</i>	<i>SE</i>	<i>p</i>
(Intercept)	-3.453	0.237	<0.001	-3.616	0.239	<0.001	-1.504	0.244	<0.001
Age Unscaled	0.288	0.031	<0.001	0.333	0.032	<0.001	0.106	0.033	0.001
Grade Ordinal	0.146	0.027	<0.001	0.077	0.027	0.005	0.106	0.028	<0.001
Random Effects									
σ^2	0.89			0.90			0.96		
τ_{00}	0.04 _{site_id_1}			0.04 _{site_id_1}			0.02 _{site_id_1}		
ICC	0.05			0.04			0.02		
N	22 _{site_id_1}			22 _{site_id_1}			22 _{site_id_1}		
Observations	6567			6567			6567		
Marginal R ² / Conditional R ²	0.068 / 0.111			0.060 / 0.100			0.017 / 0.039		
AIC	17947.668			18032.967			18421.990		
log-Likelihood	-8968.834			-9011.484			-9205.995		

Supplementary Table 9b

Recruitment was throughout the year in ABCD, this makes controlling for the month of schooling a better option than grade (as there is within-grade months of schooling variance). We carried out two supplementary sensitivity analyses where we recoded schooling a) coding grade as ordinal (i.e., 3, 4, 5) and another b) where we excluded the grade with the least subjects (3rd grade) and added a dummy coded categorical variable for fifth grade. P-values are uncorrected.

Predictors	cIQ dummy coding			fIQ dummy coding			WM dummy coding		
	Estimates	std. Error	p	Estimates	std. Error	p	Estimates	std. Error	p
(Intercept)	-2.926	0.327	<0.001	-3.374	0.325	<0.001	-1.152	0.332	0.001
Age Unscaled	0.293	0.033	<0.001	0.338	0.033	<0.001	0.113	0.034	0.001
5 th grade TRUE	0.159	0.037	<0.001	0.092	0.037	0.014	0.114	0.038	0.003
Random Effects									
σ^2	0.91			0.90			0.95		
τ_{00}	0.04 site_id_1			0.03 site_id_1			0.02 site_id_1		
ICC	0.04			0.04			0.02		
N	22 site_id_1			22 site_id_1			22 site_id_1		
Observations	5458			5458			5458		
Marginal R ² / Conditional R ²	0.051 / 0.091			0.051 / 0.085			0.012 / 0.031		
AIC	15023.598			14970.674			15245.739		
log-Likelihood	-7506.799			-7480.337			-7617.869		

SI Figure 4: A partial residual plot for a) years of schooling and b) Schooling in standard units for cIQ, flQ and WM.

SI Figure 5: A single factor CFA was fit to estimate *g* with maximum likelihood estimation with robust (Huber-White) standard errors and FIML imputation (RMSEA = .032 & CFI = .987). Abbreviations are as follows; PCVCB = Picture vocabulary, RDNG = Oral reading recognition, FLNKR = Flanker task, PTTRN = Pattern comparison processing speed, CRDSRT = Card sorting task, LST = List sorting WM task, PCTR = Picture sequence memory test, WM = Overall nback accuracy, PEA = matrix reasoning total raw score.

SI Figure 6: Sample selection flow chart, missing data is mainly genetic. Inclusion of those repeating grades bias the schooling coefficient upwards.

SI Figure 7 Correlation plot uncorrected for genetic PC's. All correlations are significant ($<.0001$) using Holm's multiple comparison correction.