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CHILD-DRIVEN PARENTING:
DIFFERENTIAL EARLY CHILDHOOD INVESTMENT BY OFFSPRING GENOTYPE

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ABSTRACT

A growing literature points to children's influence on parents' behavior, including parental investments in children. Further, previous research has shown differential parental response by socioeconomic status to children's birth weight, cognitive ability, and school outcomes – all early life predictors of later socioeconomic success. This study considers an even earlier, more exogenous predictor of parental investments: offspring genotype. Specifically, we analyze (1) whether children's genetic propensity towards educational success affects parenting during early childhood; and (2) whether parenting in response to children's genetic propensity towards educational success is socially stratified. Using data from the Avon Longitudinal Survey of Parents and Children (N=7,738), we construct polygenic scores for educational attainment and regress cognitively stimulating parenting behavior during early childhood on these polygenic scores. We use a range of modeling strategies to address the concern that child's genotype may be proxying unmeasured parent characteristics. Results show that parents provide more cognitive stimulation to children with higher education polygenic scores. This pattern varies by socioeconomic status with college-educated parents responding less to children's genetic propensity towards educational success than non-college-educated parents do.

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Introduction

Cognitively stimulating parenting during early childhood is important for children's skill development and adult well-being: parent-child activities like shared book reading and play appear to increase children's cognitive and socioemotional skills and adult socioeconomic attainment (Attanasio et al. 2014; Cano, Perales, and Baxter 2019; Doyle et al. 2016; Fiorini and Keane 2014; Gertler et al. 2014; Heckman and Mosso 2014; Hsin and Felfe 2014). Sociological studies often focus on how socioeconomic status affects parenting, but a growing body of evidence suggests that parenting may also be influenced by child characteristics and behaviors (Bell 1968; Feinstein, Duckworth, and Sabates 2008; Melhuish et al. 2008). Normal birth weight, early cognitive skills, and school performance have all been linked to cognitively stimulating parenting (Aizer and Cunha 2012; Grätz and Torche 2016; Hsin 2012; Lugo-Gil and Tamis-LeMonda 2008; Quadlin 2015; Restrepo 2016; Tucker-Drob and Harden 2012). For instance, toddlers' with higher cognitive skills receive more cognitively stimulating parenting (Grätz and Torche 2016; Lugo-Gil and Tamis-LeMonda 2008; Tucker-Drob and Harden 2012), and qualitative studies of shared book reading show that toddlers very much drive and shape this parenting practice (Hall, Levy, and Preece 2018; Luo and Tamis-LeMonda 2017). Together, these studies show that children play a crucial role in determining the amount and type of cognitively stimulating parenting they receive.

While birth weight, early cognitive skills, and school performance are all predictors of later socioeconomic attainment, an even earlier predictor would be child's genotype. This predictor is randomly assigned at conception (conditional on parental genotype), not readily observable (as birth weight is), not subject to reverse causation (as early cognitive skills and school performance might be), and not subject to concern and advice from health professionals and educators (as birth weight and school performance may be). Genome-wide association studies (GWAS) show that multiple genes indexed via single nucleotide polymorphisms (SNPs) across the genome are related to educational attainment (Lee et al. 2018; Okbay et al. 2016; Rietveld et al. 2013, 2014). Using GWAS results to construct a measure of genetic propensity for educational attainment, a so-called polygenic score (PGS), recent studies show that parents provide a better home environment to school-age children and adolescent siblings with higher PGS for educational attainment (Sanz-de-Galdeano and Terskaya n.d.; Wertz et al. 2020). However, since socioeconomic and genetic differences in cognitive skills show up well before school age (Belsky et al. 2016; Ermisch 2008; Feinstein 2003; von Hippel and Hamrock 2019), and learning during early childhood is crucial for later achievement (Cunha et al. 2006), we examine whether children's genetic propensity towards educational success affects parenting during early childhood.

Moreover, theories on social stratification suggest that parents' response to children's genetic propensity towards educational success may differ by socioeconomic status. Drawing on the theories of relative risk aversion and effectively maintain inequality (Breen and Goldthorpe 1997; Lucas 2001), one may expect that socioeconomically advantaged parents will invest heavily in their children's development regardless of their genetic propensity towards educational success. Related to these theories, the concept of compensatory advantage (Bernardi 2014) suggests that socioeconomically advantaged parents will go further by actively compensating with more investment directed to those offspring with lower genetic propensities towards educational success—*ceteris paribus*. Testing these hypotheses, we examine whether parenting in response to children's genetic propensity towards educational success is socially stratified.

Specifically, we analyze whether cognitively stimulating parenting during early childhood (18-57 months) is influenced by children's PGS for educational attainment, and whether this influence is socially stratified. In order to answer these questions, we deploy data from the Avon

Longitudinal Study of Parents and Children (ALSPAC) (Boyd et al. 2013; Fraser et al. 2013). ALSPAC provides data on the genotypes of children (n=8,801), mothers (n=9,260), and fathers (n=1,745), as well as measures of cognitively stimulating parenting from infancy through preschool age. In our main analysis (n=7,738), we use several modeling strategies and placebo tests to address the concern that child's genotype may be proxying unmeasured parental characteristics. Further, a subset of the sample with genotype data on children and both parents (n=1,426) allows us to perform an innovative robustness check: controlling for both the mother's and father's education PGSs plausibly renders the variation in the child' education PGS exogenous, in a so-called trio design. We employ this trio design to validate patterns from the main analysis.

Our study makes three contributions to the literature. First, we focus on early childhood where skills develop rapidly, but children are yet to be evaluated by tests or teachers' evaluations. Any influence of children's PGS on cognitively stimulating parenting that we may detect might therefore more directly be related to child behavior as compared to previous studies focusing on school-age children and adolescents. Second, we analyze whether the relationship between child's education PGS and cognitively stimulating parenting is socially stratified and thereby place parenting response in the context of social stratification. Third, we contribute with a methodological advancement by validating our results using a trio design, where controlling for mothers' and fathers' genotype plausibly renders the variation in child genotype exogeneous.

We find that parents provide more cognitively stimulating parenting to children with higher PGSs for educational attainment. This pattern varies by socioeconomic status: College-educated parents do not appear to respond to children's education PGSs, while non-college educated parents do respond. Our findings are robust to a variety of ways to control for the potential endogeneity of child PGS to overall parenting activities, and the direction of the association replicates in the trio design. These findings suggest that the child is an active agent of socialization of parental behavior in the family and that there is a social patterning in how parents respond to child characteristics.

Theoretical Framework

In the following section we combine perspectives from sociology and psychology to outline the argument that genetic effects on educational success may in part be mediated by cognitively stimulating parenting evoked by the genotype of the child. Based on a framework of genotype-environment correlations, we propose a hypothesis for the relationship between children's genetic propensity towards educational success and cognitive stimulating parenting in early childhood. In the latter part of the section, we hypothesize how socioeconomic resources may shape how parents' respond to children's genetic propensity towards educational success based on theories about social inequality in skill formation.

Educational Success and Genotype

Research employing a broad range of methods shows that genetic variation is related to educational success. A meta-analysis of twin studies shows that genetic variation explains, on average, 40 % of the variation in educational attainment across western societies, although this estimate varies substantially across national context and birth cohorts (Branigan, McCallum, and Freese 2013). Studies comparing intergenerational associations of education of adopted and biological children draw similar conclusions (see e.g., Sacerdote, 2007; Scheeren, Das, & Liefbroer, 2017). Exploiting the recent availability of molecular genetic data, genome-wide association studies (GWAS) have found over thousand genetic variants associated with educational attainment (Lee et al. 2018; Okbay et al. 2016; Rietveld et al. 2013, 2014). Summarizing GWAS results into PGSs for educational attainment, studies have found that in independent samples these genetic variants are associated with early cognitive and socioemotional skills, school performance in adolescence, and educational attainment in adulthood (Belsky et al. 2016, 2018; Conley et al. 2015; Liu 2018; Smith-Woolley, Selzam, and Plomin 2019; Ward et al. 2014; Zhu et al. 2015). This result holds up in sibling fixed effect design, showing that part of the association is causal (Belsky et al. 2018; Conley et al. 2015; Domingue et al. 2015; Selzam et al. 2019). While there is evidence that genetic variation affects educational success across the life course, little is known about which mechanisms cause this relationship.

Arguing against the understanding of genetic effects as purely physical and biological, Jencks (1972, 1980) suggests that genetic effects could operate through the environment by evoking differential responses from the people with whom we interact. Genetic variation affecting characteristics of the individual such as appearance, aptitude, temper, etc. leads society to treat individuals differently, resulting in different long-term outcomes. In this way, the social environment mediates the genetic effect. In early childhood, parents are often the focal persons in children's lives and hence could be likely to respond to characteristics stemming from children's genotype. Within behavioral genetics this type of mechanism is called a reactive or evocative genotype-environment correlation (Plomin, DeFries, and Loehlin 1977). In the following, we describe the theoretical framework of genotype-environment correlations.

Genotype-Environment Correlation and Child Development

Evocative genotype-environment correlations are one out of at least three types of genotype-environment correlations. *Passive genotype-environment correlations* occur when biological parents pass on genes to their child and those same genes possessed by the parents affect the environment the parents provide to the child (Plomin et al. 1977). This process has also been termed genetic nurture or social genetic effects in the recent literature (Kong et al. 2018). *Active genotype-environment correlations* occur when the genotype of the child makes the child select activities, environment, and peer groups. *Evocative genotype-environment correlations* occur when the genotype of the child evokes responses from the parents, teachers, or peers (Plomin et al. 1977). Although labelled as ‘correlations’ as opposed to ‘effects’, genotype-environment correlations can describe mechanisms linking genetic variation to outcomes through the social environment.

Passive genotype-environment correlations may have the biggest impact during early childhood when children are highly dependent on their parents (Scarr and McCartney 1983), while the importance of evocative genotype-environment correlations may increase as the child takes on a more active role in the family (Avinun and Knafo 2014). One set of behaviors children may elicit from their parents is activities like play, shared book reading, games etc. typically described as cognitively stimulating parenting. In the next section, we review the empirical evidence on the effect of cognitively stimulating parenting on children’s skill development.

Parenting and Skill Development

In early childhood, cognitively stimulating activities like play, shared book reading, cuddling, imitation games etc. are theorized to increase the development of children’s cognitive and socioemotional skills. Through these activities children gain language skills, learn about the world, and perhaps build an interest in learning in general (Feinstein et al. 2008; Melhuish et al. 2008). Studies applying different methodologies on various study populaitons in general find evidence of an effect of cognitive stimulation in early childhood on children’s development of cognitive and socioemotional skills (Attanasio et al. 2014; Bono et al. 2016; Cano et al. 2019; Doyle et al. 2016, 2017; Fiorini and Keane 2014; Hsin and Felfe 2014; Lugo-Gil and Tamis-LeMonda 2008; Tucker-Drob and Harden 2012) (for exceptions see Andrew et al. 2018; Grätz and Torche 2016). Since cognitive stimulation affects children's skill development, it is particularly interesting to examine whether this aspect of parenting is affected by child characteristics. In the next section, we review studies on how child characteristics affect the cognitive stimulation provided by their parents.

Child Effects on Parenting

The child development literature on bidirectional socialization suggests that parenting is a function of both cultural demands and characteristics of the child (Bell 1968). Children's behaviors and personality evoke and reinforce parenting practices and the intensity of these practices (Bell 1968). In support of this perspective, qualitative studies find that toddlers initiate and shape shared book reading stressing how young children play an active role in this type of cognitive stimulation (Hall et al. 2018; Luo and Tamis-LeMonda 2017). A large scale quantitative study finds positive cross-lagged associations between children's cognitive skills and parents' cognitive stimulation between the ages of 14, 24, and 36 months (Lugo-Gil and Tamis-LeMonda 2008). These cross-lagged associations also show up once genetic variation is taken into account: a study following twins from age two to four finds that children's cognitive skills predict their parents' future behavior as strongly as parents' behaviors predict their children's future skills (Tucker-Drob and Harden 2012). While these studies support the notion of child behavior, personality and skills as central to parenting, they do not point directly towards children's genetic variation as the initial source. In the next section, we review studies that explicitly test whether children's genetic variation affects parenting.

Parenting Evoked by Child Genotype

Empirical studies find support for evocative genotype-environment correlations in various aspect of parenting and employing different research methodologies. Narrative reviews and systematic meta-studies of the twin literature find that children's genotype affects relational aspects of parenting (e.g., warm, accepting, responsive parenting versus hostile, angry and rejecting behavior) and regulatory aspects of parenting (e.g., behavioral control through praise and explanations, autonomy support, setting limits, providing structures, and teaching versus control through power assertiveness such as verbal and physical punishments and intrusiveness) (Avinun and Knafo 2014; Kendler and Baker 2007; Plomin and Bergeman 1991). The most recent meta-study estimates that genetic variation explains 23 % of the variation in these aspects of parenting (Avinun and Knafo 2014). Findings from adoption studies also suggest evocative genotype-environment correlations in regulatory parenting (Klahr et al. 2016). Most recently, studies have begun to use PGSs derived from GWAS to study evocative genotype-environment correlations. A study found that children's PGS for body mass index is associated with parents' regulation of children's food intake (Selzam et al. 2018). More relevant to our study, recent research suggests that children's PGS for educational attainment is positively associated with cognitive stimulation in middle childhood (Wertz et al. 2020) and parental investment in adolescence (Sanz-de-Galdeano and Terskaya n.d.). Based on this body of research we formulate our first hypothesis:

> *Hypothesis 1: Genetic propensity towards educational success increases cognitively stimulating parenting in early childhood.*

Theoretically, evocative genotype-environment correlations include the surroundings responding to a genetic test of the child (i.e., for a hereditable disease like phenylketonuria (PKU)). In the case of genetic propensity towards educational success, we do not think that this type of evocative genotype-environment correlation is at play. Based on the literature on bidirectional socialization, we speculate that genetic propensity towards educational success affects child behavior, personality, and skills, and that these characteristics elicit responses from the parents.

Relative Risk Aversion

Parenting practices are contingent on the social context and vary with families' socioeconomic resources, and as a result, evocative genotype-environment correlations may differ between advantaged and less advantaged families. The theory of relative risk aversion suggests that parents want to avoid that their children end up in a worse position in life than the position of the parents (Breen and Goldthorpe 1997). Basically, the theory claims that parents have a fear of downward social mobility. The more socioeconomically advantaged the parents are, the further down the social ladder their children can potentially fall, and hence the greater the concern. This fear of downward social mobility causes socioeconomically advantaged families to place a greater emphasis on educational success than less advantaged families (Breen and Goldthorpe 1997). Regardless of children's abilities, socioeconomically advantaged parents will maximize the effort to ensure children's success and thereby effectively maintain the family's advantage (Lucas 2001). This process may result in a different pattern of genotype-environment correlations in the most advantaged families: To avoid downward social mobility, socioeconomically advantaged parents may make large parental investments in terms of cognitive stimulation regardless of whether the child has a high or low genetic propensity towards educational success. As a result, the evocative genotype-environment correlation, *Corr(genotype, parenting),* may be lower among socioeconomically advantaged families than among less socioeconomically advantaged families:

Hypothesis 2: $Corr(genotype, parenting)_{High\_SES} < Corr(genotype, parenting)_{Low\_SES}$

Building on relative risk aversion and effectively maintained inequality, the concept of compensatory advantage suggests that socioeconomically advantaged parents compensate for negative child development risks by increasing investments (Bernardi 2014; Bernardi and Grätz 2015). In the context of evocative genotype-environment correlations, compensatory advantage suggests that socioeconomically advantaged parents will direct more cognitively stimulating parenting to children with lower genetic propensity towards educational success. This scenario gives rise to a negative genotype-environment correlation, $Corr(genotype, parenting)_{High\_SES} < 0$, which would support Hypothesis 2 as long the genotype-environment correlation among less advantaged families is larger.

Data

We analyze data from the Avon Longitudinal Study of Children and Parents (ALSPAC) (Boyd et al. 2013; Fraser et al. 2013). ALSPAC is a birth-cohort study that sampled 14,541 pregnancies with expected delivery dates between April 1, 1991, and December 31, 1992, in the former Avon County around Bristol, United Kingdom. Of these initial pregnancies, there was a total of 14,676 fetuses, resulting in 14,062 live births and 13,988 children who were alive at 1 year of age. ALSPAC is ideal for the purpose of our study because a sizable subsample of the children (n=8,801), mothers (n=9,260), and fathers (n=1,745) are genotyped[1], and because ALSPAC contains information on parenting and socioeconomic status throughout early childhood.[2] We define our analytic sample as children with no missing values on parenting measures and child's genotype. These restrictions give us a sample of 7,738 children. Table 1 provides means and standard deviations for the variables in our analysis.

Outcome: Parenting

Our outcome variable is cognitively stimulating parenting reported by the mother when the child was 18, 24, 38, and 57 months old. This age range captures the early childhood before children start formal schooling, where parents have yet to receive evaluations of their children's academic abilities. At these ages ALSPAC asked the mother how frequently she engaged in a series of activities with the child (reading stories, singing songs, cuddling, etc.). Table 2 shows the items for each survey wave. To obtain a measure of parenting with the least possible amount of measurement error, we combine all available items from all available waves. We first create summative scores within each wave, standardize these scores within each wave, and then calculate an average of the standardized scores. Finally, we standardize this variable to have a mean of zero and a standard deviation of one. However, analyzing each wave separately reveals the same pattern of results (results available upon request).

[1]There are many missing cases on father's genotype, since DNA from fathers was collected as a separate study (the Focus on Fathers 1) when children were 20 years old. This was a clinical study involving a two-hour visit. Invitations to participate in the study were sent to 3,663 fathers. 2,001 men attended the clinic of whom 1,401 consented to have their DNA analyzed.

[2]Please note that the study website contains details of all the data that is available through a fully searchable data dictionary and variable search tool (University of Bristol 2020).

Table 1 Means and Standard Deviations

	Mean	St. Dev.
Parenting Score[a]	-1.66E-09	1.00
Education PGS[b] child	6.47E-05	3.92E-06
Education PGS[b] mother[c]	6.48E-05	3.87E-06
Education PGS[b] father[d]	6.56E-05	3.60E-06
Missing only mother’s genotype	0.03	0.16
Missing only father’s genotype	0.59	0.49
Missing both parents’ genotypes	0.20	0.40
Highest parental educational attainment is university degree	0.24	0.43
Mother's educational attainment		
CSE or vocational	0.23	0.42
O Level	0.34	0.48
A Level	0.24	0.43
Degree	0.15	0.35
Missing education	0.03	0.18
Father's educational attainment		
CSE or vocational	0.28	0.45
O Level	0.21	0.41
A Level	0.26	0.44
Degree	0.19	0.40
Missing education	0.06	0.24
Mother's occupational class		
V - Unskilled	0.03	0.18
IV - Semi-skilled	0.15	0.36
III - Manual	0.05	0.21
III - Non-manual	0.41	0.49
II - Managerial and technical	0.30	0.46
I - Professional	0.04	0.19
Missing occupation	0.03	0.16
Father's occupational class		
V - Unskilled	0.03	0.17
IV - Semi-skilled	0.07	0.25
III - Manual	0.34	0.47
III - Non-manual	0.12	0.33
II - Managerial and technical	0.30	0.46
I - Professional	0.09	0.29
Missing occupation	0.05	0.22
Standardized family income	2.40E-09	0.94
Missing family income	0.12	0.33
Female child	0.49	0.50
N		7,738

Note: [a]The parenting score is standardized to have mean zero and standard deviation 1. [b]PGSs are not standardized in this table. When used in analyses, the PGSs are standardized to mean zero and standard deviation. [c]N=6,008. [d]N=1,641.

Table 2 Parenting Items

"How often do you do these activities with your baby/toddler?"	Age in months				
	6	18	24	38	57
Sing to child	x	x	x	x	x
Show child pictures in books	x	.	.	x	.
Read stories or show child pictures in books	.	x	.	.	.
Read child stories	.	.	x	.	x
Play with toys	x	x	.	x	x
Cuddle child	x	x	x	x	x
Physical play (e.g. clapping, rolling over)	x	x	.	x	.
Take child for walks	x	x	.	x	.
Imitation games (pat-a-cake, peek-a-boo)	.	x	.	.	.
Go out to a park or playground with child	.	.	x	.	x
Active play (eg. ball games, hide and seek)	.	.	.	.	x
Take child swimming	.	.	.	.	x
Draw or paint with child	.	.	.	.	x
Cronbach's alpha	0.52	0.68	0.45	0.66	0.73

Predictor: The Polygenic Score for Educational Attainment

Our variable of interest is the polygenic score (PGS) for educational attainment. The PGS is calculated as a weighted sum score:

$$PGS_i = \sum_{j=1}^{J} b_j G_{ij}$$

where b_j is the association between SNP j and educational attainment, G_{ij} is the number of alleles on SNP j possessed by individual i. We use b_j weights and SNPs from the most recent GWAS on educational attainment (Lee et al. 2018). Only SNPs on the autosomal chromosomes are included in the GWAS, so the PGS is by construction orthogonal to sex. Following the recommendations by Ware and colleagues (2017), we do not prune SNPs in linkage disequilibrium. The mean and the standard deviation of the raw score for children, mothers, and father are displayed in Table 1. For the purpose of regression analysis, we standardize the education PGS to have mean zero and standard deviation 1 within each analytic sample. In the Appendix A, we show that the education PGS predicts the educational attainment of mothers in the ALSPAC very well, with an incremental R^2 of 14 % (Table A2). This incremental R^2 is similar to incremental R^2s in other datasets (Lee et al. 2018).

Moderator: Parental Socioeconomic Resources

For the purpose of testing our hypotheses 2, 3 and 3A on whether socioeconomic status moderates the effect of children's education PGS on parenting, we operationalize high socioeconomic status as having at least one parent with a university degree and low socioeconomic status as both parents having less education than a university degree. We focus on education, as an individual's educational attainment predicts other aspects of socioeconomic status. We get similar results for occupational class and family income (see Table S8 in the Appendix A).

Control variables

Education. Mother's and father's education are measured indicator variables for (1) certificate of secondary education or vocational, (2) O level, (3) A level, and (4) university degree. For each parent, we also include an indicator for missing information on education.

Occupational class. Mother's and father's occupational class are measured as (1) V - unskilled, (2) IV - semi-skilled, (3) III - manual, (4) III - non-manual, (5) II - managerial or technical, (6) I - professional. For fathers, we use their own report if available, and the mother's report when the father's own report is missing. For each parent, we also include an indicator for missing information on occupation.

Family income. Mothers were asked to report their weekly take-home family income on a five-point ordinal scale when the child was 33 and 47 months old. In order to get a robust measure of household income, we combine these two variables into a mean of the standardized items. We standardize this combined household income variable to have mean zero and standard deviation one. The Cronbach's alpha for this combined measure is 0.88.

Principal Components of Genetic Variation. To account for the possibility of population stratification in the genetic data, we control for the first eight principal components (PCs) of the variation in the SNPs. Since the participants in ALSPAC were recruited from a limited geographical area it is likely that there are unrecorded family ties. These family ties might distort the principal component analysis. For this reason, we follow the procedure used by The UK Biobank (Bycroft et al. 2018) and identify a set of unrelated individuals among the children and mothers, from whom we calculate the PCs. We estimated the kinship relations using the software KING and used Igraph in R to find a set of unrelated individuals. For this sample of unrelated individuals, we linkage disequilibrium (LD) pruned the SNPs and calculated the top 8 PCs using PLINK2.0. Based on this first principal component analysis, we selected a set of SNPs that contributed very little to the first three PCs. Using this set of SNPs, we re-estimated the kinship and once again found a set of unrelated individuals. We LD pruned the original set of SNPs for this unrelated sample and calculated the 20 PCs. Finally, we projected the full sample on to the PCs. Using PC 1 and PC 2 we detected 12 outliers. We removed the 12 outliers from the second sample of unrelated individuals, LD pruned the original set of SNPs for this sample, recalculated the top 20 PCs, and projected them on to the rest of the sample. We use this final set of the first eight PCS as control variables.

Analytical Strategy

The purpose of the analysis is to estimate the effect of genetic propensity towards educational success on cognitively stimulating parenting and whether this effect varies across socioeconomic status.

The ideal research design in terms preventing confounding (omitted variable bias) is the trio design, where the education PGS of both parents are included as control variables. Half of the child's genetic variants stems from the mother and the other half from the father, and a random process governs which genetic variants each parent passes on to the child. As a result, conditioning on both parents' education PGSs renders the variation in the child's education PGS exogenous. Therefore, there are no bias from environmental variation or genetic nurture. Hence, our ideal model specification is the following:

$$Y_i = \alpha_0 + \alpha_1 PGS_i + \alpha_2 PGS\_m_i + \alpha_3 PGS\_f_i + \varepsilon_i \quad (1)$$

Where for the *i* indexes children, Y_i is the parenting score, PGS_i is the education PGS of the child, PGS_m_i is the education PGS of the mother, and PGS_f_i is the education PGS of the father. α_1 captures the effect of genetic propensity towards educational success on parenting.

In ALSPAC a model specification like equation (1) is possible with a subsample of 1,426 children. However, this empirical strategy has two drawbacks. First, this sample size implies a low statistical power. The incremental R^2 would have to be 0.006 to yield a power over 80%. Second, data on parents' genotypes in ALSPAC is not missing at random: the mean parenting score and the mean child education PGS are higher in the subsample than in full sample (see Table 1). In addition, 24% in the full sample has at least one parent with a university degree, while this figure is 36% among the subsample with both parents genotyped (see Table 1).

To achieve greater statistical power and reduce sample selection, we estimate three alternative model specifications on the full sample (N=7,738). With this sample size the incremental R^2 can be as low as 0.001 to achieve a statistical power of 80%. We compare these estimates to the estimate from the trio design on the subsample with both parents genotyped as a tentative test of whether the direction and magnitude of the coefficients are the same.

The first model specification in the full sample uses social proxies for parental genotypes. This strategy assumes that the effect of parental genotype on parenting are completely mediated by social proxies. These proxies include parents' education, occupational class and income (as described in the section on control variables):

$$Y_i = \beta_0 + \beta_1 PGS_i + \boldsymbol{\beta_2 SES\_m_i} + \boldsymbol{\beta_3 SES\_f_i} + \beta_4 Sex_i + \boldsymbol{\beta_5 PC_i} + \nu_i \quad (2)$$

For the i^{th} child, Sex_i is the sex of the child, $\boldsymbol{SES\_m_i}$ and $\boldsymbol{SES\_f_i}$ are vectors of the mother's and father's education, household income, and occupational class, and $\boldsymbol{PC_i}$ is a vector of children's first eight principal components of SNP variation. We include PCs to control for population stratification. As the PGS by construction are orthogonal to the sex of the child, we only include this variable to reduce overall variation and decrease standard errors. Assuming that this set of control variables captures the relevant confounders, β_1 is the estimated effect of the child's genetic propensity towards educational success on the amount of cognitively stimulating parenting the child receives.

In the second model specification in the full sample, we include the education PGS of the mother. This allows us to control directly for confounding by the mother's genetic propensity towards educational success by way of the 50 % shared genes between offspring and parents. We drop the social proxies of mother's genotype to avoid collider bias, but we keep the social proxies for the genotype of the father to rule out confounding. Hence, we specify the following model:

$$Y_i = \gamma_0 + \gamma_1 PGS_i + \gamma_2 PGS\_m_i + \gamma_3 \boldsymbol{SES\_f}_i + \gamma_4 miss_i + \gamma_5 Sex_i + \boldsymbol{\gamma_6 PC}_i + \boldsymbol{\gamma_7 PC\_m}_i + \mu_i \quad (3)$$

where PGS_m_i is the education PGS of the mother, $\boldsymbol{SES\_f_i}$ is a vector of variables for father's education and occupational class, $miss_i$ is an indicator for missing the mother's genotype, $\boldsymbol{PC}_i$ are the child's first eight PCs of SNP variation, an $\boldsymbol{PC\_m}_i$ is a vector of the mother's first eight PCs of SNP variation. If we have controlled for all relevant confounders, γ_1 captures the effect of children's genetic propensity towards educational success on cognitively stimulating parenting.

In the third model specification in the full sample, we include the education PGS of the father while keeping the social proxies for the father's genotype as only 20% of the sample has a genotyped father:

$$Y_i = \eta_0 + \eta_1 PGS_i + \eta_2 PGS\_m_i + \eta_3 PGS\_f_i + \boldsymbol{\eta_4 miss}_i + \boldsymbol{\eta_5 SES\_f}_i + \eta_6 Sex_i + \xi_i \quad (4)$$

where PGS_f_i is the father's education PGS. $\boldsymbol{miss}_i$ is a vector of an indicator for missing information on the genotype of the mother, an indicator of missing information on the genotype of the father, and an indicator of missing information on both parents' genotypes. η_1 captures the effect of children's genetic propensity towards educational success on cognitively stimulating parenting.

In the final step of our analysis we examine whether the effect of genetic propensity towards educational success on cognitively stimulating parenting varies across socioeconomic status. For this purpose, we specify a model with an interaction terms between the education PGS of the child, PGS_i, and an indicator of having a least one parent with a university, D_i: $PGS_i \times D_i$. We do not include any variable that might mediate the effect of parental education on parenting, which limits our set of control variables to the mother's education PGS, father's education PGS, and the indicators of missing information on parents' genotypes:

$$Y_i = \delta_0 + \delta_1 PGS_i + \delta_2 D_i + \delta_3 PGS_i \times D_i + \delta_4 PGS\_m_i + \delta_5 PGS\_f_i + \boldsymbol{\delta_6 miss_i} + \delta_7 Sex_i + \omega_i \quad (5)$$

δ_3 captures variation across socioeconomic status in parenting response to children's genetic make-up. Hypothesis 2 states that genetic propensity towards educational success is unrelated to cognitively stimulating parenting in socioeconomically advantaged families, which corresponds to $\delta_1 + \delta_3 = 0$. Hypothesis 3 states that genetic propensity towards educational success is negatively related to cognitively stimulating parenting among socioeconomically advantaged families, which corresponds to $\delta_1 + \delta_3 < 0$. Hypothesis 3A states that genetic propensity towards educational success is unrelated to cognitively stimulating parenting among socioeconomically disadvantaged families, which corresponds to $\delta_1 = 0$. However, for the interaction term δ_3 to be unbiased we need exogenous variation both in the child's education PGS and in parental education. Unfortunately, we do not have exogenous variation in parental education, so this part of the analysis represents a tentative test. ALSPAC data has been used to estimate the casual effect of parental education on children's educational performance using the 1972 schooling reform that increased minimum schooling age (Dickson, Gregg, and Robinson 2016). However, a well-powered genotype-environment interaction analysis relying on the 1972 reform needs a much larger sample than ALSPAC (Barcellos, Carvalho, and Turley 2018). Future research may follow up with analyses on large-scale data sets including both parents' and children's genotypes and exogenous variation in educational attainment.

Results

Children's Education PGS and Parenting during Toddlerhood and Preschool Years

We start by testing hypothesis 1 that genetic propensity towards educational success increases cognitively stimulating parenting in early childhood. We regress parenting at the ages 18-57 months on child's education PGS.

The zero-order correlation between the parenting score and children's education PGS is 0.087*** (s.e.= 0.011). Table 3 shows results from our three model specifications on the full sample, all with the goal of reducing upward bias in this estimate (for full regression tables see Table A4). The three model specifications deliver similar results. In Model 1 that controls for social proxies of parental genotypes and children's PCs of SNP variation the estimate is 0.033** (s.e.=0.012). In Model 2 that controls for mothers' education PGS, social proxies of the father's genotype, and the children's and mother's PCs for SNP variation, the estimate is 0.042** (0.014). In Model 3 that controls both parents' education PGS and social proxies for the father's genotype, the estimate is 0.046** (0.014). These estimates suggest that one standard deviation increase in the child's education PGS leads to about 3-5% of a standard deviation increase in cognitively stimulating parenting.[3]

Table 3 Parenting during Early Childhood Regressed on Child's Education Polygenic Score

	Model 1		Model 2		Model 3	
	coef.	s.e.	coef.	s.e.	coef.	s.e.
Child's polygenic score	0.033**	(0.012)	0.042**	(0.014)	0.046**	(0.014)
Female child	yes		yes		yes	
Mother's education	yes					
Father's education	yes		yes		yes	
Mother's occupation	yes					
Father's occupation	yes					
Family income	yes					
Child's principal components	yes		yes			
Mother's principal components	yes		yes			
Mother's polygenic score			yes		yes	
Father's polygenic score					yes	
Mother's polygenic score missing			yes		yes	
Father's polygenic score missing					yes	
Both polygenic scores missing					yes	
N	7,738		7,738		7,738	
R^2	0.047		0.035		0.032	

Note: Cluster robust standard errors. *** p<0.001; ** p<0.01; * p<0.05; (two-tailed tests).

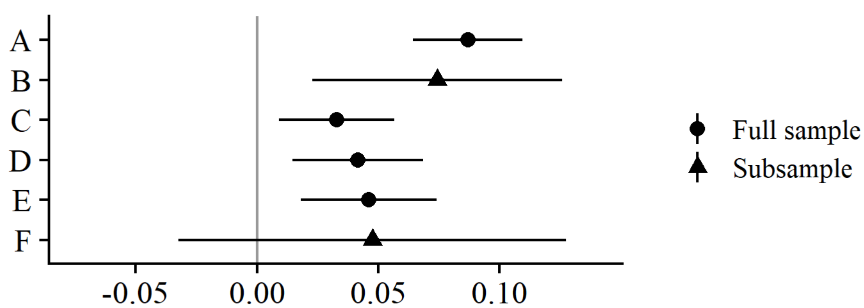
In addition, we regress the parenting score on child education PGS in in the subsample with both parents genotyped, which allow us to control for both the mother's and the father's education PGS. As explained in the Analytical Strategy section, this design ensures exogenous variation in the child's education PGS. With the ALSPAC data, however, the design results in sample selection and low statistical power. The zero-order correlation between the parenting score and the child's education PGS in the subsample is 0.074** (s.e.=0.026), which is lower but not too far from the

[3] We find similar results in analyses using a PGS based on a GWAS of performance in cognitive tests (available upon request).

zero-order correlation in the full sample (0.087***, s.e.= 0.011). The post-hoc statistical power for the child's education PGS is only 21 % as opposed to 76-81 % for models in the full sample (see Table A3 in Appendix A). A statistical power of 21% gives us too slim of a change to discover a true effect. Bearing these limitations in mind, we discuss the result from the ideal estimation strategy on the subsample to assess whether the coefficients are comparable in direction and magnitude. In the fully controlled Model 1 (Table A5 in Appendix A), the coefficient it 0.048 (s.e.=0.041) which closely resembles the results from the full sample although not statistically significant. Figure 1 provides an overview of the results from the subsample and full sample.

In sum the regression results suggest that parents reinforce children's genetic propensity towards educational success by providing more cognitively stimulating activities to children with higher education PGS. This finding supports our first hypothesis that genetic propensity towards educational success increases cognitively stimulating parenting in early childhood.

Figure 1 Comparison of Estimates of Parenting during Early Childhood Regressed on Child's Education Polygenic Scores for Full Sample and Subsample with Both Parents Genotypes



Note: 95 % confidence intervals are calculated from cluster robust standard errors. Estimate A and B are the zero-order estimates from the full sample (n=7,738) and the subsample with both parents genotyped (n=1,426). Estimate C, D, and E are from Model 1, 2, and 3 in Table 3, respectively, all estimated on the full sample. Estimate F is estimated on the subsample (n=1,426) and is controlled for education polygenic scores of the mother and the father (Model 1, Table A5).

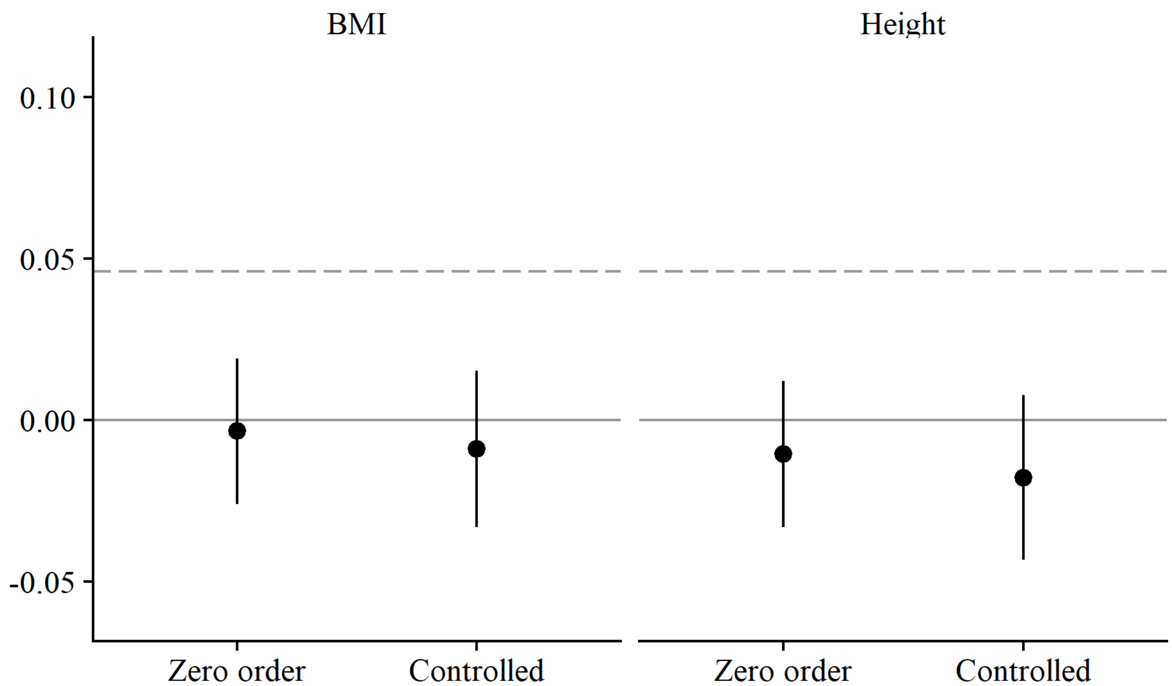
Placebo Tests

We conduct two placebo tests, one for the outcome, cognitively stimulating parenting during early childhood, and one for the variable of interest, the education PGS.

As a placebo test for the variable of interest, we regress cognitively stimulating parenting on children's PGS for height and PGS for body mass index (BMI) (Yengo et al. 2018). We do not expect that SNPs associated with height and BMI will predict cognitively stimulating parenting. Hence, if the PGS for height and the PGS for BMI predicts cognitively stimulating parenting this would suggest that the association between the education PGS and cognitively stimulating parenting is spurious.

Figure 2 shows the zero order correlations and estimates from a model specification like equation (4) (for the full regression tables see Table A6 in Appendix A). The dashed line in Figure 2 represents the estimate of cognitively stimulating parenting regressed on children's education PGS from the same model specification (Model 3, Table 3). Both zero order correlations and estimates controlled for confounding are not statistically significant different from zero, and as compared to the magnitude of the education PGS estimate, also substantially closer to zero.

Figure 2 Parenting Regressed on Child's BMI Polygenic Score and Height Polygenic Score

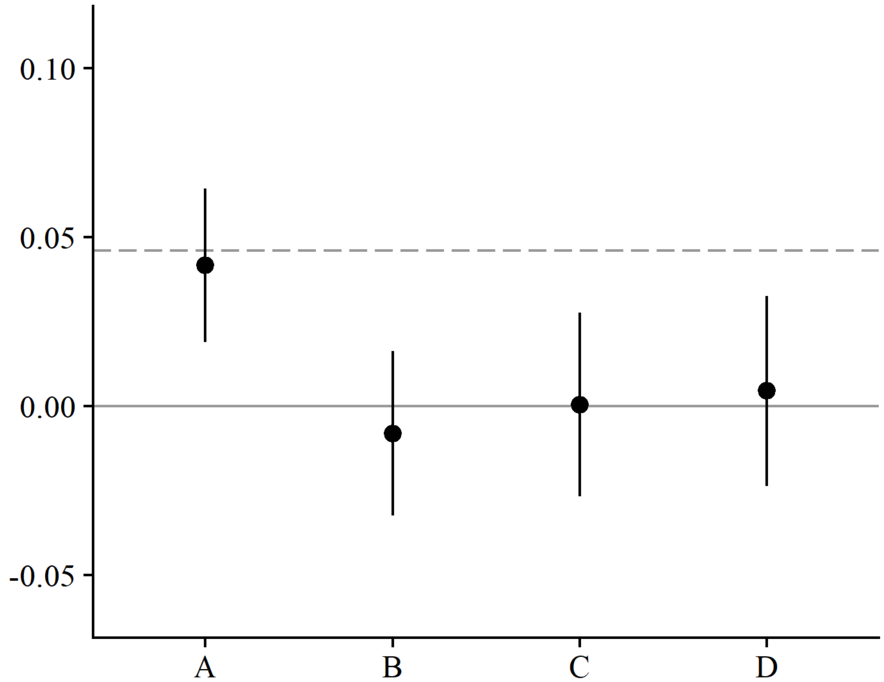


Note: The dashed line represents the estimate of parenting regressed on children's education PGS from Model 3, Table 3 (0.046**, s.e.=0.014). 95% confidence intervals are calculated from cluster robust standard errors. Full sample N=7,738. For full regression tables see Table A6.

As another placebo test for the outcome, we regress cognitively stimulating parenting at age six months on the child's education PGS. As we mentioned in the theoretical framework, we speculate that genetic propensity towards educational success leads to child behavior that evokes cognitively stimulating parenting. Such child behaviors may include intentionally communicating for shared attention with the parent (e.g., when the child with coordinated eye contact points to something exciting to share enjoyment) (Salley et al. 2020). At the age of six months, children are yet to exhibit such communication skills. While children at this age may communicate via eye-gazing, vocalizing (e.g., babbling and crying), and gesturing (e.g., reaching), the combination of these three elements into intentional communication takes off between 8 months and 12 months (Ramenzoni and Liszkowski 2016; Reilly et al. 2006; Salley et al. 2020). Further, there is no research showing that motor skills at this age is associated with later outcomes (Oster 2019). Thus, at this developmental stage, it is too early for children's genetic propensity towards educational success to be expressed via child behavior. At age six months, parents' educational achievement predicts cognitively stimulating parenting (see Table A9). If the child's education PGS merely reflects social class or associated background characteristics, then the child's education PGS will predict parenting at age six months. Hence, we expect not to find any effect of children's education PGS on cognitively stimulating parenting at age six months.

Figure 3 shows the results (for the full regression results see Table A7 in Appendix A). Except for the upwardly biased zero-order correlation in the full sample (estimate A), none of the estimates are statistically different from zero, and their magnitudes range from 0-1% of a standard deviation. The largest coefficient is only a fifth of the size of the coefficient from a regression on cognitively stimulating parenting at age 18-57 months in Model 3, Table 3 (represented in Figure 3 by the dashed line). These results corroborate the results from the main analysis.

Figure 3 Parenting at Age Six Months Regressed on Child's Education Polygenic Score



Note: The dashed line represents the estimate of parenting age 18-57 months regressed on children's education polygenic scores from Model 3, Table 3 (0.046**, s.e.=0.014). 95% confidence intervals are calculated from cluster robust standard errors. Estimate A is the zero-order estimate from the full sample (n=7,291). Estimate B, C, and D are from Model 1, 2, and 3 in Table A7, respectively, all estimated on the full sample.

Socioeconomic Differences in Parenting Response to Children's Education PGS

We now turn to our second research question, whether the effect of genetic propensity towards educational success varies by socioeconomic status. To answer this research question we test hypothesis 2 stating that the correlation between children's genetic propensity towards educational success and cognitively stimulating parenting is lower among socioeconomically advantaged families than among less advantaged families.

We test hypothesis 2 by regressing the parenting score on an interaction terms between the child's education PGS and university degree as highest parental education. Table 4 shows the result.

The main term for children's education PGS is 0.074*** (s.e.=0.016), the main term for college-educated parents is 0.204*** (s.e.=0.027), and the interaction term between children's education PGS and college-educated parents is -0.063* (s.e.=0.025) (Model 5, Table 4).[4] In Appendix A, Table A5, we show that, although attenuated and not statistically significant, this pattern is replicated in the subsample with both parents genotyped. These results suggest that the correlation between children's education PGS and parenting could be lower among socioeconomically advantaged families than among disadvantaged families. Figure 4 illustrates this finding. While a standard deviation increase in children's education PGS is associated with a 7% increase of a standard deviation in parenting among children of parents without university degrees, this is only 1% for children of parents with university degrees and not statistically different from zero. This finding supports hypothesis 2 that genetic propensity towards educational success is less correlated with cognitively stimulating parenting in socioeconomically advantaged families than in less advantaged families. It should be noted, that having college-educated parents is associated with a 20% increase of a standard deviation in the parenting score. Perhaps the high baseline investment among socioeconomically advantaged families means that evoked genotype-environment correlations in cognitively stimulating parenting during early childhood matter less.[5,6]

As we mentioned in the analytical strategy section, we do not have exogenous variation in parental education. Consequently, the association between parental education and parenting and the

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[4] The results are similar for interactions between child education PGS and occupational class and family income (available upon request).

[5] We have also tested for interactions between the child's education PGS and (1) the mother's education PGS, (2) birth order/sibship size, and (3) sex of the child among firstborns (results available upon request). Only the interaction with birth order/sibship size is statically different from zero. This interaction is negative, perhaps, indicating that less time per child leaves less room for parents to pick up on child behaviors stemming from the genetic propensity towards educational success.

[6] During the early 1990s, preschool in the UK was not publicly subsidized. Some of the ALSPAC cohort may have been affected by a reform in 1996 providing vouchers for daycare to 3-year olds, but for the majority of the period we study, there was no public support of child care (West and Noden 2016). While there is an educational gradient in the use of preschools, controlling for age of preschool enrollment does not change the interaction results (available upon request).

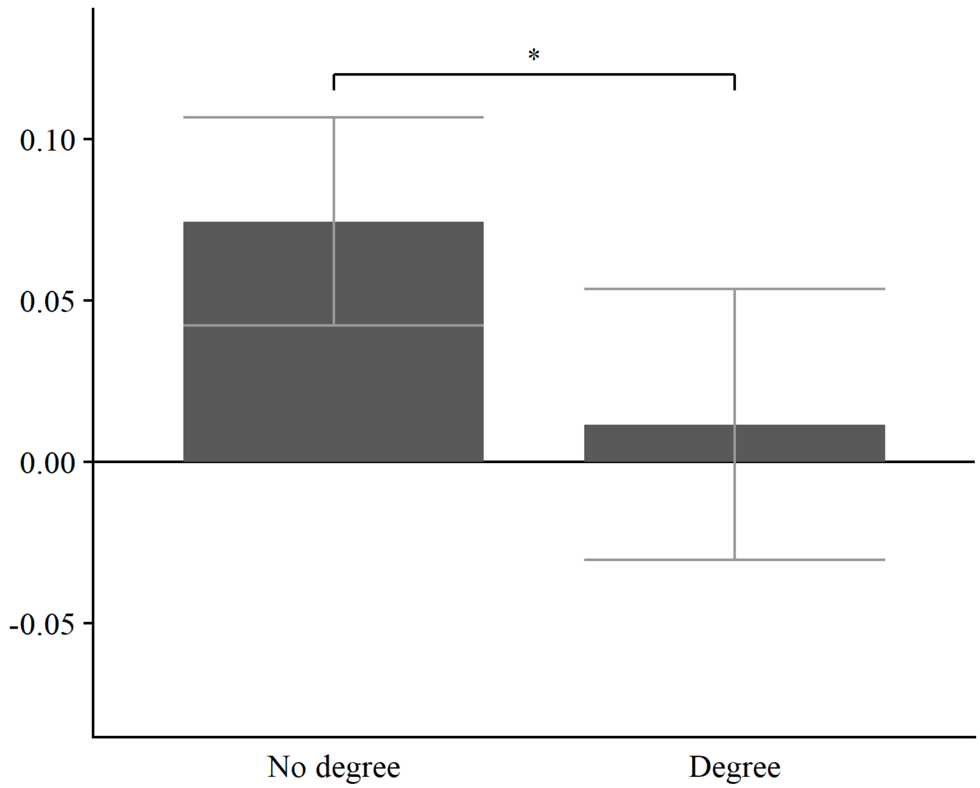
interaction term between children's education PGS and parental university degree may be confounded.

Table 4 Parenting during Early Childhood Regressed on Child's Polygenic Score by Education

	Model 4	
	coef.	s.e.
Child's polygenic score	0.074***	(0.016)
Degree	0.204***	(0.027)
Child's polygenic score x degree	-0.063*	(0.025)
Parental education missing	0.010	(0.086)
Child's polygenic score x parental education missing	0.051	(0.083)
Female child	0.136***	(0.023)
Mother's polygenic score	0.004	(0.015)
Father's polygenic score	-0.008	(0.024)
Mother's polygenic score missing	-0.120	(0.072)
Father's polygenic score missing	-0.006	(0.028)
Both polygenic scores missing	-0.107**	(0.037)
Constant	-0.079**	(0.028)
N	7,738	
R^2	0.021	

Note: Cluster robust standard errors. *** p<0.001; ** p<0.01; * p<0.05; (two-tailed tests).

Figure 4 The Association between Child's Education Polygenic Score and Cognitively Stimulating Parenting by Highest Parental Education

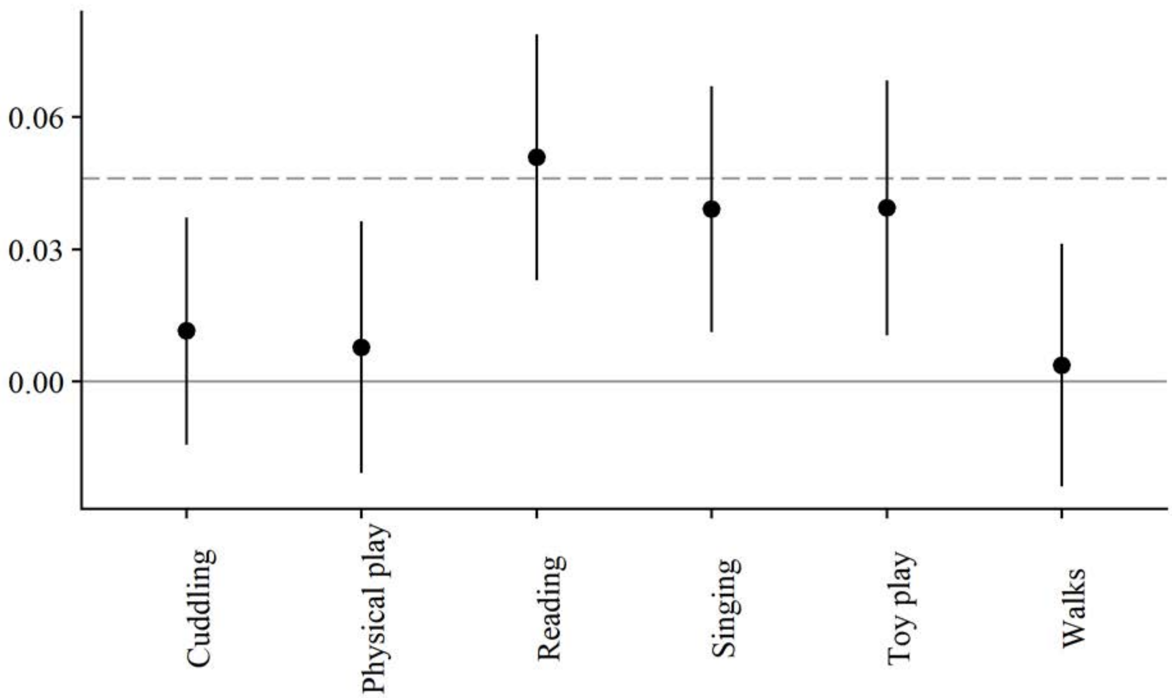


Note: 95% confidence intervals are calculated from cluster robust standard errors. N=7,738.

Specific Parenting Activities

Finally, we analyze whether specific parent-child activities drive the overall effect on cognitively stimulating parenting. For activities that are reported at least three times, we calculate an average across early childhood (18-57 months). As for the overall score for cognitively stimulating parenting, we choose this strategy to minimize measurement error. A series of items involves shared parent-child book reading, but the items change phrasing as the child ages ("show child pictures in books", "read stories or show child pictures in books", and "read child stories"). We group these items under the heading "reading". Figure 5 shows the results (full regression results are presented in Table A8 in the Appendix A) with the dashed line representing the effect of the summary score for cognitively stimulating parenting in Model 3, Table 3. The effect appears to be driven by reading (0.051***, s.e.=0.014), singing (0.039**, s.e.=0.014), and playing with toy (0.039**, s.e.=0.015), while cuddling (0.011, s.e.=0.013), physical play (0.008, s.e.=0.015), and going for walks (0.004, s.e.=0.014) appear much less affected. Given that success in the educational system (as in getting many years of education) is highly dependent on language proficiency, it is not surprising that children's genetic propensity towards educational success evokes activities involving language stimulation.

Figure 5 Specific Parenting Activities Regressed on Child's Education Polygenic Score



Note: All models are estimated like the model specification of equation (4). 95 % confidence intervals are calculated from cluster robust standard errors. Full sample, sample size varies between 7,583 and 7,738 (see Table A8 in Appendix A). The dashed line represents the estimate of parenting regressed on children's education PGS from Model 3, Table 3 (0.046**, s.e.=0.014).

Discussion

Parenting is often conceptualized as a uni-directional socialization process. But parenting is a dynamic process, where parents respond to children's interests and skills (Bell 1968; Feinstein et al. 2008; Melhuish et al. 2008). As an example, children are active agents in initiating and shaping shared book reading (Hall et al. 2018; Luo and Tamis-LeMonda 2017). The previous literature has considered parenting responses to birthweight, early cognitive skills, and school performance (Abufhele, Behrman, and Bravo 2017; Aizer and Cunha 2012; Grätz and Torche 2016; Hsin 2012; Quadlin 2015; Restrepo 2016). Most recently children's genetic propensity towards educational success has been shown to influence parenting during middle childhood and adolescence (Sanz-de-Galdeano and Terskaya n.d.; Wertz et al. 2020). While parents matter throughout children's lives, the early years are especially critical to child development: Both socioeconomic and genetic disparities in cognitive skills show up before school age (Belsky et al. 2016; Ermisch 2008; Feinstein 2003; von Hippel and Hamrock 2019), and parental investments in this period can have effects well into adulthood (Gertler et al. 2014). Furthermore, parenting responses to other child characteristics are often dependent on family socioeconomic status (Aizer and Cunha 2012; Grätz and Torche 2016; Hsin 2012; Restrepo 2016). There has been no investigation of whether socioeconomic status affects the parenting response to children's genetic makeup. In this study, we considered the effect of children's genetic propensity towards educational success on cognitively stimulating parenting during early childhood (age 18 months to 4 years and 9 months), and whether this effect varied across family socioeconomic status.

Our study advances prior work in several ways. First, we draw on molecular genetic data to construct education polygenic scores (PGS) using the newest GWAS results (Lee et al. 2018), which gives us a direct measure of children's and parents' genotypes. The advantages of genotype over past measures of child endowment are that unlike test scores, genotype is fixed and causally prior to any investments on the part of the parents. Unlike birthweight – which is a visible, culturally-encoded signal at birth to parents, medical professionals and others – it is only revealed through the relevant behavior of the child over the course of development. Second, our large sample size (N=7,738) allows for a statistically well-powered analysis (post-hoc power ~ 80%). Third, in a sensitivity analysis for a subsample we control for both the mother's and father's education PGS. This trio design plausibly renders the variation in the child' education PGS completely exogenous to family characteristics. Finally, pooling observation from across early childhood (age 18-57 months), we construct a robust measure of cognitively stimulating parenting less prone to measurement errors.

We find that children's education PGS has a positive effect on cognitively stimulating parenting. An increase of one standard deviation in the children's education PGS increases cognitively stimulating parenting with 3-5% of a standard deviation. This effect varies across family socioeconomic status: College-educated parents do not respond, while non-college-educated parents do respond (7%). To put these findings in perspective, having a least one college-educated parent is associated with a 20% increase in the standard deviation of cognitively stimulating parenting. An interpretation of the variation across socioeconomic status may be that college-educated parents are already investing so heavily in children's cognitive development that the child's genetic make-up makes less of a difference.

Our study is subject to at least three limitations. First, 79% of our analytic sample lacks information on fathers' genotype as less than a third of the ALSPAC fathers were invited to provide DNA. In order to achieve enough statistical power, we utilize the full sample and estimate models that in addition to controlling for father's education PGS controls for social proxies for father's genotype and indicators of missing. If this strategy does not sufficiently control for father's genotype, the effect of children's education PGS on parenting may be exaggerated via passive genotype-environment correlations. We address this issue by analyzing the direction and magnitude of the coefficients in a smaller subsample (N=1,426) with both parents' genotyped. Results from this trio design support our main findings. We also address the issues of confounding from passive genotype-environment correlations by conducting several placebo tests. PGSs for traits unrelated to educational success – BMI and height – show no effect on parenting. Meanwhile, parenting at age six months—a developmental stage before genetic signature would have displayed a clear behavioral signature in the child—is unaffected.

Second, our analysis of variation across socioeconomic status is limited in its ability to provide causal evidence as we do not have exogenous variation in parental education, our indicator of socioeconomic status. Further, this part of the analysis is less statistically powered than the analysis of the main effect. However, to our knowledge ALSPAC is the largest data set available with information on both genotype and cognitively stimulating parenting during early childhood.

Third, we only analyze children with European ancestries which contributes to the increasing inequality in sociogenetic information between different ancestral populations. PGSs predict best in samples with similar ancestries as the GWAS discovery sample. While GWAS on other ancestries than European are getting increasingly well-powered, to date there is no well-powered GWAS on educational attainment in other ancestries than European. In addition, ALSPAC only provides genetic information children with European ancestries. Hopefully, the increasing ancestral inequality in sociogenetic research will be address by future data collections among diverse populations.

With these limitations in mind, our study offers some interesting theoretical implications. While we know that educational attainment has a genetic component (Branigan et al. 2013; Conley et al. 2015), the mechanisms are unclear. Within sociology, it is a long held idea that genotype elicits certain responses from the social environment such as parents and that these social responses create the outcome (Jencks 1972, 1980). Up until recently, this hypothesis was untestable. Our study provides the first evidence, that children's genetic propensity towards educational success affects the amount of cognitive stimulation they receive in early childhood. Moreover, this evocative genotype-environment correlation itself is likely dependent on the social environment. This finding highlights the complex interplay between social and genetic factors in creating the outcomes we observe. In the decades to come, where genotyping will become cheaper, and potentially an everyday tool, it is important to keep in mind that genetic effects are contingent on social factors and cannot be seen in isolation from the social environment.

Ethical approval and informed consent: Ethical approval for the study was obtained from the ALSPAC Ethics and Law Committee and the Local Research Ethics Committees. Informed consent for the use of data collected via questionnaires and clinics was obtained from participants following the recommendations of the ALSPAC Ethics and Law Committee at the time. Consent for biological samples has been collected in accordance with the Human Tissue Act (2004).

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Appendix A: Full Regression Tables and Supplementary Analyses

Table A1 Means and Standard Deviations of Variables Specific to the Appendix A

	Full sample		Subsample	
	Mean	Standard dev.	Mean	Standard dev.
Mother's edu. att.[a]	3.16	1.24		
Education PGS[b]				
Child			6.56E-05	3.90E-06
Mother			6.55E-05	3.90E-06
Father			6.56E-05	3.59E-06
Height PGS[b]				
Child	4.11E-05	9.91E-06		
Mother[c]	4.14E-05	9.80E-06		
Father[d]	4.16E-05	9.53E-06		
BMI PGS[b]				
Child	-1.7E-05	7.94E-06		
Mother[c]	-1.7E-05	7.93E-06		
Father[d]	-1.8E-05	7.69E-06		
Parenting age 6 mth[e]	-1.4E-08	1	0.09	0.94
Professional occ.	0.11	0.31	0.17	0.38
Income > 400 UKP	0.28	0.45	0.40	0.49
	7,738		1,426	

Note: [a]Mothers’ educational attainment is measured as an ordinal variable with 5 values: (1) CES, (2) vocational education, (3) O level, (4) A level, and (5) college degree. [b]Polygenic scores are not standardized in this table. When used in analyses, the PGSes are standardized to mean zero and standard deviation. [c]N=6,008. [d]N=1,641. [e]Parenting at age 6 months is standardized within the full sample to have mean zero and standard deviation 1 (N=7,291). For analyses on the subsample, parenting at age six months is standardized within the subsample (N=1,404).

Table A2 Mothers' Educational Attainment Regressed on Mothers' Education Polygenic Score

	coef.	s.e.
Mother's Education PGS	0.473***	(0.013)
Constant	3.084***	(0.013)
N	8,053	
R^2	0.146	

Note: Cluster robust standard errors. *** p<0.001; ** p<0.01; * p<0.05; (two-tailed tests). The model includes the first eight PCs. Mothers' educational attainment is measured as an ordinal variable with 5 values: (1) CES, (2) vocational education, (3) O level, (4) A level, and (5) college degree.

Table A3 Post-Hoc Power Calculation for Children's Education PGS

Model	R^2 without PGS	R^2 with PGS	Incremental R^2	Power
Model 1, N=7,738	0.04644	0.04736	0.00092	0.76
Model 2, N=7,738	0.03343	0.03462	0.00119	0.86
Model 3, N=7,738	0.04662	0.04769	0.00107	0.82
Subsample, N=1,426	0.00510	0.00603	0.00093	0.21

Table A4 Parenting during Early Childhood Regressed on Child's Education Polygenic Score

	Model 1		Model 2		Model 3		Model 4	
	coef.	s.e.	coef.	s.e.	coef.	s.e.	coef.	s.e.
Child's PGS	0.033**	(0.012)	0.042**	(0.014)	0.046**	(0.014)	0.048	(0.041)
Female child	0.135***	(0.022)	0.137***	(0.022)	0.137***	(0.023)		
Mother's educational attainment (ref.=CSE or vocational)								
O Level	0.130***	(0.035)						
A Level	0.236***	(0.038)						
Degree	0.129**	(0.046)						
Missing	0.286*	(0.120)						
Father's educational attainment (ref.=CSE or vocational)								
O Level	0.098**	(0.035)	0.148***	(0.035)	0.151***	(0.035)		
A Level	0.114**	(0.036)	0.185***	(0.034)	0.188***	(0.034)		
Degree	0.177***	(0.043)	0.258***	(0.038)	0.265***	(0.038)		
Missing	-0.100	(0.087)	-0.001	(0.067)	0.001	(0.066)		
Mother's occupational class (ref.=II – Man. or tech.)								
V – Unskilled	-0.403***	(0.083)						
IV – Semi-skill.	-0.120**	(0.040)						
III – Manual	-0.162**	(0.059)						
III – Non-man.	-0.124***	(0.029)						
I – Professional	-0.251***	(0.055)						
Missing	-0.159	(0.101)						
Father's occupational class (ref.=II – Man. or tech.)								
V – Unskilled	-0.281***	(0.082)	-0.341***	(0.082)	-0.342***	(0.082)		
IV – Semi-skill.	-0.037	(0.054)	-0.090	(0.054)	-0.088	(0.054)		
III – Manual	-0.012	(0.031)	-0.049	(0.030)	-0.049	(0.030)		
III – Non-man.	0.001	(0.036)	-0.005	(0.037)	-0.006	(0.037)		
I – Professional	0.083*	(0.037)	0.065	(0.037)	0.070	(0.037)		
Missing	-0.025	(0.072)	-0.050	(0.069)	-0.052	(0.069)		
Family income	-0.003	(0.015)						
Income missing	-0.009	(0.040)						
Mother's PGS			0.001	(0.015)	0.000	(0.015)	0.022	(0.033)
Father's PGS					-0.023	(0.024)	0.024	(0.034)
Mother's PGS missing			-0.101***	(0.029)	-0.121	(0.072)		
Father's PGS missing					0.023	(0.028)		
Both PGS missing					-0.071	(0.037)		
Constant	-0.163***	(0.047)	-0.139***	(0.036)	-0.165***	(0.042)	0.000	(0.027)
N	7,738		7,738		7,738		1,426	
R^2	0.047		0.035		0.032		0.006	

Note: Cluster robust standard errors. *** p<0.001; ** p<0.01; * p<0.05; (two-tailed tests). Model 1 and 2 include the first eight child PCs. Model 2 include the first eight mother PCs.

Table A5 Parenting during Early Childhood Regressed on Child's Education Polygenic Score in Subsample with Both Parents' Genotypes

	Model 1		Model 2	
	coef.	s.e.	coef.	s.e.
Child's PGS	0.048	(0.041)	0.064	(0.048)
Degree			0.161**	(0.059)
Child's PGS x degree			-0.031	(0.055)
Parental education missing			0.051	(0.291)
Child's PGS x parental education missing			0.059	(0.272)
Mother's PGS	0.022	(0.033)	-0.005	(0.035)
Father's PGS	0.024	(0.034)	0.004	(0.035)
Constant	0.000	(0.027)	-0.055	(0.037)
N	1,426		1,426	
R^2	0.006		0.011	

Note: Cluster robust standard errors. *** p<0.001; ** p<0.01; * p<0.05; (two-tailed tests).

Table A6 Parenting during Early Childhood Regressed on Child's Height PGS & BMI PGS

	Model 1		Model 2		Model 3		Model 4	
	coef.	s.e.	coef.	s.e.	coef.	s.e.	coef.	s.e.
Child's height PGS	0.006	(0.012)	-0.003	(0.013)				
Child's BMI PGS					-0.020	(0.011)	-0.008	(0.013)
Female child			0.136***	(0.023)			0.136***	(0.023)
Father's edu. att. (ref.=CSE or vocational)								
O Level			0.159***	(0.035)			0.158***	(0.035)
A Level			0.200***	(0.034)			0.200***	(0.034)
Degree			0.292***	(0.038)			0.290***	(0.038)
Missing edu.			0.003	(0.066)			0.003	(0.066)
Father's occ. class (ref.=II – Man. or tech.)								
V – Unskilled			-0.354***	(0.081)			-0.355***	(0.081)
IV – Semi-skill.			-0.102	(0.054)			-0.101	(0.054)
III – Manual			-0.058	(0.030)			-0.058	(0.030)
III – Non-man.			-0.007	(0.037)			-0.007	(0.037)
I – Professional			0.075*	(0.037)			0.075*	(0.037)
Missing occ.			-0.065	(0.069)			-0.065	(0.069)
Mother's PGS			0.000	(0.014)			0.002	(0.014)
Father's PGS			0.021	(0.022)			-0.018	(0.025)
Mother's PGS missing			0.016	(0.028)			0.017	(0.028)
Father's PGS missing			-0.127	(0.073)			-0.124	(0.072)
Both PGS missing			-0.079*	(0.037)			-0.078*	(0.037)
Constant	-0.000	(0.012)	-0.164***	(0.042)	-0.000	(0.012)	-0.164***	(0.042)
N	7,738		7,738		7,738		7,738	
R^2	0.000		0.031		0.000		0.031	

Note: Cluster robust standard errors. *** p<0.001; ** p<0.01; * p<0.05; (two-tailed tests).

Table A7 Parenting at Age 6 Months Regressed on Child's Education PGS

	Model 1		Model 2		Model 3		Model 4	
	coef.	s.e.	coef.	s.e.	coef.	s.e.	coef.	s.e.
Child's PGS	-0.008	(0.012)	0.001	(0.014)	0.005	(0.014)	0.011	(0.039)
Female child	0.008	(0.023)	0.009	(0.023)	0.010	(0.023)		
Mother's edu. att. (ref.=CSE or voc.)								
O Level	0.130***	(0.035)						
A Level	0.229***	(0.040)						
Degree	0.159**	(0.051)						
Missing	0.201	(0.112)						
Father's edu. att. (ref.=CSE or voc.)								
O Level	0.029	(0.037)	0.080*	(0.036)	0.077*	(0.036)		
A Level	0.091*	(0.036)	0.167***	(0.034)	0.163***	(0.034)		
Degree	0.142**	(0.045)	0.252***	(0.041)	0.250***	(0.041)		
Missing	-0.054	(0.081)	-0.014	(0.065)	-0.006	(0.064)		
Mother's occ. class (ref.=II – Man. or tech.)								
V – Unskilled	-0.447***	(0.083)						
IV – Semi-skill.	-0.169***	(0.041)						
III – Manual	-0.134*	(0.061)						
III – Non-man.	-0.152***	(0.031)						
I – Professional	-0.156*	(0.065)						
Missing	-0.335**	(0.109)						
Father's occ. class (ref.=II – Man. or tech.)								
V – Unskilled	0.072	(0.079)	0.000	(0.078)	-0.001	(0.078)		
IV – Semi-skill.	0.019	(0.055)	-0.036	(0.055)	-0.035	(0.055)		
III – Manual	0.024	(0.032)	-0.017	(0.031)	-0.017	(0.031)		
III – Non-man.	0.037	(0.040)	0.032	(0.040)	0.027	(0.040)		
I – Professional	0.003	(0.045)	-0.000	(0.044)	-0.000	(0.044)		
Missing	-0.023	(0.078)	-0.100	(0.073)	-0.095	(0.073)		
Family income	0.000	(0.015)						
Income missing	-0.026	(0.041)						
Mother's PGS			0.010	(0.016)	0.010	(0.016)	-0.004	(0.033)
Father's PGS					-0.029	(0.025)	0.002	(0.033)
Mother's PGS missing			-0.094**	(0.030)	-0.063	(0.086)		
Father's PGS missing					-0.039	(0.030)		
Both PGS missing					-0.129***	(0.038)		
Constant	-0.084	(0.047)	-0.084*	(0.037)	-0.057	(0.043)	0.000	(0.027)
N	7,291		7,291		7,291		1,404	
R^2	0.030		0.016		0.015		0.000	

Note: Cluster robust standard errors. *** p<0.001; ** p<0.01; * p<0.05; (two-tailed tests). Model 1 and 2 include the child's first eight PCs. Model 2 include the mother's first eight PCs.

Table A8 Singing, Reading, Toy Play, Cuddling, Physical Play, and Walks Regressed on Child's Education Polygenic Score

	Singing		Reading		Toy play		Cuddling		Physical Play		Walks	
	coef.	s.e.	coef.	s.e.	coef.	s.e.	coef.	s.e.	coef.	s.e.	coef.	s.e.
Child's PGS	0.039**	(0.014)	0.051***	(0.014)	0.039**	(0.015)	0.011	(0.013)	0.008	(0.015)	0.004	(0.014)
Female child	0.156***	(0.023)	0.134***	(0.022)	0.015	(0.023)	0.043	(0.023)	0.101***	(0.023)	0.040	(0.023)
Father's edu. att. (ref.=CSE or voc.)												
O Level	0.096**	(0.035)	0.208***	(0.035)	0.097**	(0.036)	0.020	(0.038)	0.035	(0.035)	0.026	(0.035)
A Level	0.124***	(0.034)	0.252***	(0.034)	0.112**	(0.035)	0.043	(0.033)	0.077*	(0.034)	0.003	(0.035)
Degree	0.156***	(0.039)	0.406***	(0.038)	0.098*	(0.041)	0.067	(0.035)	0.122**	(0.040)	-0.001	(0.042)
Missing education	-0.031	(0.066)	-0.042	(0.069)	0.046	(0.061)	-0.055	(0.096)	-0.038	(0.069)	-0.068	(0.059)
Father's occ. class (ref.=II – Man. or tech.)												
V – Unskilled	-0.343***	(0.083)	-0.268***	(0.075)	-0.092	(0.083)	-0.309*	(0.126)	-0.126	(0.082)	-0.132	(0.084)
IV – Semi-skill.	-0.087	(0.051)	-0.135*	(0.054)	0.037	(0.050)	-0.185*	(0.086)	-0.052	(0.056)	0.068	(0.052)
III – Manual	-0.107***	(0.030)	-0.091**	(0.030)	-0.022	(0.032)	-0.005	(0.027)	0.012	(0.031)	0.063*	(0.032)
III – Non-man,	-0.037	(0.037)	0.029	(0.034)	0.011	(0.037)	0.022	(0.027)	-0.015	(0.039)	0.005	(0.039)
I – Professional	-0.030	(0.041)	0.059	(0.033)	0.110**	(0.040)	0.055*	(0.024)	0.052	(0.041)	0.110*	(0.043)
Missing occ.	-0.101	(0.066)	-0.181*	(0.077)	-0.035	(0.070)	-0.056	(0.088)	0.066	(0.071)	0.212***	(0.060)
Mother's PGS	-0.003	(0.014)	0.042**	(0.015)	-0.027	(0.015)	-0.001	(0.014)	-0.009	(0.016)	-0.023	(0.015)
Father's PGS	0.016	(0.025)	-0.053*	(0.023)	-0.062*	(0.026)	-0.050**	(0.019)	-0.002	(0.026)	0.006	(0.026)
Mother's PGS missing	0.057	(0.070)	-0.117	(0.068)	-0.124	(0.076)	0.059	(0.033)	-0.039	(0.075)	-0.163*	(0.080)
Father's PGS missing	0.048	(0.029)	-0.031	(0.027)	0.007	(0.028)	-0.012	(0.023)	0.095**	(0.030)	0.022	(0.030)
Both PGS missing	-0.051	(0.038)	-0.136***	(0.036)	-0.065	(0.038)	-0.091*	(0.035)	0.037	(0.039)	-0.003	(0.038)
Constant	-0.107*	(0.042)	-0.148***	(0.042)	-0.063	(0.044)	-0.001	(0.038)	-0.166***	(0.044)	-0.072	(0.043)
N	7,737		7,738		7,679		7,738		7,583		7,584	
R^2	0.025		0.072		0.010		0.012		0.009		0.007	

Note: Cluster robust standard errors. *** p<0.001; ** p<0.01; * p<0.05; (two-tailed tests). All models include children's first eight PCs.