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Review

The intergenerational transmission of early educational advantages: New results based on an adoption design☆

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ABSTRACT

Sociological research has traditionally emphasized the importance of post-birth factors (i.e., social, economic, and cultural capital) in the intergenerational transmission of educational advantages, to the neglect of potentially consequential pre-birth endowments (e.g., heritable traits) that are passed from parent to child. In this study, we leverage an experiment of *nurture*—children who were adopted at birth into nonrelative families—in an effort to simultaneously model the effects associated with both pathways. To do so, we fit a series of simple linear regression models that relate the academic achievement of adopted children to the educational attainments of their adoptive and biological parents, using U.S. data from a recent nationwide sample of birth and adoptive families (the Early Growth and Development Study). Because our dataset includes both "genetic" and "environmental" relatives, but not "genetic-*and*-environmental" relatives, the separate contributions of each pathway can be identified, as well as possible interactions between the two. Our results show that children's early achievements are influenced not only by the attainments of their adoptive parents, but also the attainments of their *birth* parents—suggesting the presence of environmental *and* genetically mediated effects. Supplementary analyses provide little evidence of effect moderation, using both distal and proximate measures of the childhood environment to model gene-by-environment interactions. These findings are robust to a variety of parameterizations, withstand a series of auxiliary checks, and remain intact even after controlling for intrauterine exposures and other measurable variables that could compromise our design. The implications of our results for theory and research in the stratification literature, and for those interested in educational mobility, are discussed.

1. Introduction

The strong association between parental education and children's educational outcomes is well documented in the social sciences (see e.g., Blau & Duncan, 1967; Coleman et al., 1966; Haveman & Wolfe, 1995; Mare, 1981; McLoyd, 1998; Sewell & Shah, 1968; Shavit & Blossfeld, 1993). Children with more highly educated parents tend to achieve more highly themselves and obtain superior credentials than their counterparts from less advantaged (and less well-educated) families. The intervening mechanisms that give rise to these relationships have received intense scrutiny from social scientists, spawning large literatures on the beneficial aspects of social capital (Coleman, 1988), the value of cultural assets (Bourdieu & Passeron, 1990; DiMaggio, 1982), and the importance of financial resources (Blau, 1999; Boudon, 1974), to name just a few. Although diverse in terms of theoretical orientation and methodological approach, these studies all share a common focus on the importance of environmental factors in the production of academic achievement and educational outcomes more generally.

Work in behavioral genetics and elsewhere suggests that this focus may produce an incomplete picture of the intergenerational transmission process (Bartels, Rietveld, Van Baal, & Boomsma, 2002; Freese & Jao, 2015; Heath et al., 1985; Kovas et al., 2013; Neiss & Rowe, 2000; Nielsen & Roos, 2015; Okbay et al., 2016; Plomin, DeFries, Knopik, & Neiderhiser, 2016; Plomin, Fulker, Corley, & DeFries, 1997; Plomin, Owen, & McGuffin, 1994; Scarr & Weinberg, 1977). Parents not only

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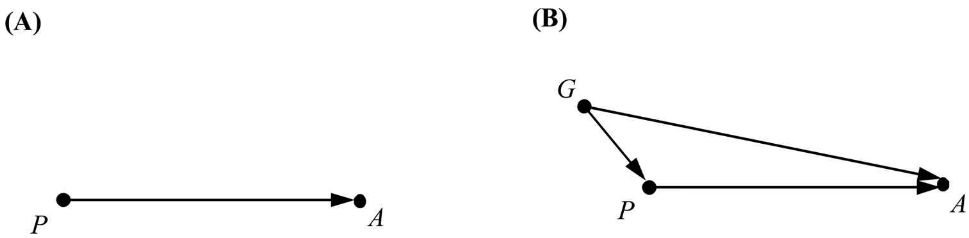

Fig. 1. Reduced-form causal diagrams showing the relationship between parental education (P), shared genetic endowments (G), and children's early achievement (A). The graph on the right allows for genetic confounding (due to the presence of common hereditary traits within biologically related parent-child pairs), whereas the graph on the left does not.

transfer educational advantages to their offspring through available social, financial, and cultural channels, they also pass on a wide array of biologically heritable traits before the child is born. If these traits influence the educational achievements of both parents and children (Thompson, Detterman, & Plomin, 1991), they could, in the extreme, induce an association across generations that would exist even in the absence of meaningful environmental effects (Eckland, 1967; Scarr & Weinberg, 1978). In recent years, this recognition has sparked renewed calls from sociologists and others to integrate genetically-informed research designs into analyses of stratification processes (Adkins & Guo, 2008; Freese, 2008; Freese & Jao, 2015; Nielsen, 2006; Udry, 1995).

In this study, we seek to model the influences of social and heritable factors on children's early academic success using an adoption-at-birth design (Haugaard & Hazan, 2003; Leve et al., 2019; Plomin, DeFries, Knopik, & Neiderheiser, 2013; Scarr & Weinberg, 1983). Under this approach, adopted children's educational outcomes are expressed as a function of birth parents' characteristics (e.g., highest level of schooling completed), parallel characteristics for their genetically unrelated adoptive parents, and possible interactions between the two. Because adopted children share environments with their adoptive parents (but not pre-birth genetic endowments) and 50% of their genes with each biological parent (but not post-birth environments), the separate contributions of each can be identified along with potential moderating effects. Key identifying assumptions regarding the sorting of children into adoptive families and the post-natal exposure of children to their birth parents must be justified (Leve et al., 2013), but these assumptions can be assessed given appropriate data.

We divide the remainder of the paper into four main sections. In the section that follows, we provide a broad overview of the literature on intergenerational education effects, concentrating in particular on contributions made within sociology and the field of behavioral genetics. As a part of this discussion, we summarize past attempts to estimate the importance of environmental and genetic pathways in the intergenerational transmission process. Next, we introduce the data (from the U.S.-based Early Growth and Development Study) and methods we use to partition parental contributions to children's academic achievement into social and hereditary components, and explain the identifying assumptions that underlie the use of our modeling approach. We then present the "topline" results from our analyses, and results from a series of sensitivity checks designed to evaluate the validity of our modeling assumptions. Finally, we conclude by recapitulating our main findings and suggesting avenues of future research for scholars who are interested in studying the intergenerational transmission of educational advantages using genetically-sensitive designs.

2. Literature review

Enumerating the multiple ways that parents transmit educational advantages to their offspring represents a major project in the sociology of education, and in the stratification literature more broadly (Blau & Duncan, 1967; Jencks, 1972). The findings coming out of this literature should be familiar to most stratification researchers. The amount of family resources devoted to children (Richard & Jonsson, 2005), the nature of these resources (Blau, 1999; Coleman, 1988; DiMaggio & Mohr, 1985; Teachman, 1987), the timing of their allocation (Guo, 1998), and the choices parents make with respect to family size (Blake, 1989; Downey, 1995), family structure (Biblarz & Raftery, 1999), neighborhood of residence (Wodtke, Harding, & Elwert, 2011), and the schools their children attend (Jennings, Deming, Jencks, Lopuch, & Schueler, 2015), have all been shown to be important predictors of the next generation's educational success. These findings have been replicated across time periods, sub-populations, and data sets, and have proven robust to differences in operationalization, measurement, and the estimation strategy used.

The amount of education obtained by the parental generation is generally thought to be a key driver of many of these processes (as indicated by the causal arrow connecting parental education, P, and children's academic achievement, A, in Fig. 1). Parents with more education typically have more human, material, and network-based resources at their disposal, which they can deploy to their child's advantage in various ways (Duncan, Yeung, Brooks-Gunn, & Smith, 1998; Haveman & Wolfe, 1995; Kalmijn, 1994; Nan, 1999). The educational climate in families where the parents achieved highly themselves may further encourage positive orientations to school among children, again leading to higher levels of educational success (Bozick, Alexander, Entwisle, Dauber, & Kerr, 2010; Morgan, 2005). Even the practices that more highly educated parents adopt when interacting with teachers and school administrators—and when advising their children on how to approach and manage such interactions on their own—have been shown to be beneficial with respect to key achievement-related outcomes (Calarco, 2014).

The implicit assumption in this research is that the presence of parental resources—secured by parents through education and then transferred on to their children—is what gives rise to the reproduction of educational advantages from one generation to the next. This is, at its core, a causal argument. An alternative view, albeit not entirely incompatible, emerges from work in behavioral genetics and social science genomics (see, e.g., Adkins & Stephen, 2009; Conley & Fletcher, 2017). There, researchers emphasize the importance of both environmental and hereditary factors, producing a more complicated causal diagram that includes multiple pathways linking parents and children (as shown in Fig. 1b). Under this framework, shared genes (G) act as a confounding variable, affecting the attainments of parents ($G \rightarrow P$) while also shaping the outcomes of their biologically-related offspring $G \rightarrow A$).[1] Although not shown in the diagram, the mechanisms connecting G and A are usually assumed to include both direct and indirect components, with the latter set of effects arising as children's genetic propensities influence their environmental exposures and, in turn, achievement (Plomin, DeFries, & Loehlin, 1977).

Estimating the effect associated with parental education under these conditions requires a strong research design. One approach is to identify situations where the pathway connecting shared G to A is broken,

[1] Note that the model depicted in Fig. 1b also includes an indirect path from $G \rightarrow P \rightarrow A$. The existence of this path implies that genetic effects can be transmitted through social and/or environmental channels, or what behavioral geneticists refer to as passive gene-environment correlations. Our research design, as we explain below, eliminates this path by manipulating the genetic and environmental relationship between parents and children. The upshot is that we are left with defensible estimates of the direct effect of G.

deactivating the suspected confound, and, in the process, allowing for cleaner estimates of $P \rightarrow A$. Parents of a non-relative adopted child, when the adoption occurs shortly after birth, fit this description: they provide post-birth resources, as described above, but are biologically unrelated to the adoptee and thus do not directly pass genetic information on to their child. This allows for identification of educational effects that have been purged of hereditary influence due to sharing of genes. If information on the adopted child's biological parents is also available, the opposite comparison can be made (i.e., a measure of the child's achievement can be regressed onto the education of their birth parents, with whom they share no post-birth exposures but do share genes), yielding estimates of genetic effects ($G \rightarrow A$) that are unconfounded by environmental factors. Behavioral geneticists refer to this setup as a "full" parent-offspring adoption design.

Analyses of adopted children and their parents are not without precedent in the social sciences. In a provocative article published in the *American Sociological Review* more than forty years ago, Scarr and Weinberg (1978) found that variation in intellectual performance (IQ) among adopted children was primarily driven by variation in their biological parents' socioeconomic characteristics (i.e., educational and occupational attainment, as well as family income) and not the measured background characteristics or intelligence of their adoptive mothers and fathers (see also Scarr & Weinberg, 1977, 1983). The same was not true among a subsample of children reared in their biological families: for these individuals the inclusion of parental characteristics markedly improved the amount of variance explained. Scarr and Weinberg (1978) took these results as evidence of "genetic bias" in studies that ignore (or are otherwise unable to account for) the confounding effects of shared genes. This interpretation is fully consistent with the causal diagram presented in Fig. 1b.[2]

Since the publication of Scarr and Weinberg's (1978) piece, researchers have sought to clarify the role that genes and environments play in influencing educational outcomes, often using a twin design that partitions variance into genetic, shared environmental (common to both twins), and unshared environmental (unique to each twin) components (Bartels et al., 2002; Behrman & Rosenzweig, 2002; Branigan, McCallum, & Freese, 2013; Heath et al., 1985; Kovas et al., 2013; Krapohl et al., 2014; Nielsen, 2006). Results from these studies suggest three main conclusions: (1) there is a substantial genetic component underlying the transmission of educational attainment and IQ from one generation to the next; (2) shared environmental effects on these outcomes exist but are generally thought to be smaller in magnitude and (in the case of IQ) to decrease with age; and (3) there may be important feedback mechanisms through which broader social environments influence the expression of genes and genes influence selection into environments, setting up a complex and potentially dynamic interplay between heritable and environmental factors.

Over the past few years, studies using molecular genomic data have further refined our understanding of genetic influences on education and cognition (Conley, 2016; Diewald, 2016). Researchers have now identified a subset of genetic variants that, in the aggregate, explain roughly 12% of the variation in years of schooling and 9% of the variation in cognitive ability among individuals with European ancestry (Lee et al., 2018).[3] Many of the genes implicated in this work have been tied to important brain-related functions, including memory formation, perception, language, and thought. Importantly, the variants identified in this work have also been implicated in models of status attainment. In a pair of recent studies, researchers showed that controlling for their combined effects—through the use of polygenic scores—reduces the association between parents' education and children's education by 16–20% (Conley et al., 2015; Liu, 2018). This implies a possible path from G to P and G to A, as in Fig. 1b.

In the present study, we seek to add to this literature in multiple ways. Most of the research described above has used measures of IQ (ascertained in late adolescence or early adulthood) and/or years of schooling completed (ascertained as an adult) as focal outcomes.[4] Substantially fewer studies have examined the etiology of *early* school achievement using a design that allows for credible estimates of environmental influences *net of genes* (but see Kovas et al., 2013; Walker, Petrill, Spinath, & Plomin, 2004). We see this as an important omission. There is now considerable evidence to suggest that early success at school is pivotal for many children, laying the foundation for their cognitive and social development, and setting the stage for improved attainments at older ages (Alexander, Entwisle, & Horsey, 1997; Andrew, 2014; Claessens, Duncan, & Engel, 2009; Cunha, Heckman, Lochner, & Masterov, 2006; Heckman, Pinto, & Savelyev, 2013). How parents contribute to these *early* successes—and whether their contributions are transmitted via social or biological channels (or some complex function thereof)—are logical next questions.

Specific consideration of early school outcomes (as opposed to attainments measured in late adolescence or adulthood) is also important given evidence that heritabilities can vary across the life course. A large and robust body of work in behavioral genetics—drawing on a wide assortment of data resources and modeling strategies—has shown that the heritability of intelligence grows linearly with age (Davis, Haworth, & Plomin, 2009; Fulker, DeFries, & Plomin, 1988; Haworth et al., 2010; Trzaskowski, Yang, Visscher, & Plomin, 2014), rising from approximately 20% in infancy to as much as 80% in later adulthood (Plomin & Deary, 2015).[5] During the first years of school, heritability estimates typically reside around the middle of this range, with genetic influences accounting for 50–60% of the variation in children's cognitive ability and post-birth (shared and non-shared) environmental exposures accounting for the rest (Fulker et al., 1988). Although research on school performance (and early school performance in particular) is more limited, it is possible that cognitively loaded measures of achievement behave in a similar way (Kovas et al., 2013; Krapohl et al., 2014;

[2] In a related study, Sacerdote (2007) found that Korean-born children adopted into American families during the 1960s–1980s tended to fare better with respect to education if they were adopted into more highly-educated households with fewer children (comparable effects were not observed for adult outcomes such as drinking and the selectivity of college attended, nor were effects observed for characteristics like family income and neighborhood quality). He interpreted this as evidence of a positive, but somewhat circumscribed, environmental effect on education, at least within the period in question. For similar results from the same historical era, but using domestic adoptions, see Plug (2004) and Erik and Vijverberg (2003). For more recent studies using data from Europe, see Björklund, Lindahl, and Plug (2006), Kendler, Turkheimer, Ohlsson, Sundquist, and Sundquist (2015), and Scheeren, Das, and Liefbroer (2017).

[3] It is likely that some of this association is environmentally mediated. As we noted earlier, if parents create environments that are consistent with their own genotypes, and if these environments contribute to their children's educational success, then (a portion of) the genetic effects would be indirect, operating through environmental variables (Selzam et al., 2019). This complicates the causal model considerably.

[4] Nielsen (2006) represents an exception. In addition to modeling students' verbal IQ, he also considered their grade point average in high school and their college-going plans. His results—which mirror related estimates obtained in other national contexts (Krapohl & Plomin, 2016)—showed substantial heritabilities for all three outcomes.

[5] Research in behavioral genetics suggests that this pattern derives from two sets of processes, termed "innovation" and "amplification" (Plomin & Deary, 2015). Under the former, biological changes associated with maturation activate new or previously latent genetic influences, leading to increased heritability (and reduced environmentality) as individuals age. Under the latter, small genetic differences between individuals become magnified over time as people select, or are selected into, environments that are correlated with their genetic propensities. Meta-analyses suggest that these processes may be time ordered, with innovation dominating the early childhood period and amplification taking over during middle childhood and beyond (Briley & Tucker-Drob, 2013).

Walker et al., 2004).

In the sections that follow, we use a full parent-offspring adoption design to shed light on these questions (DeFries & Plomin, 1978). Our data include detailed information on adoptees' academic performance, observed shortly after they entered the school system (i.e., in the first grade), as well as measures of their adoptive and biological parents' educational attainments, demographic characteristics, health behaviors (including those that occurred during the birth mother's pregnancy), parenting practices, and post-adoption interactions with the birth parents. Together, these features allow us to (1) specify and test a model of early academic achievement that allows for separate heritable and environmental components; and (2) consider possible interactions between these separate components. In the next section of the paper, we describe our data in more detail and provide further information about the modeling strategy we use to identify the role that genetic and environmental factors play in the transmission of early educational advantages.

3. Data

Data for our analyses come from the Early Growth and Development Study (EGDS), a multi-site prospective longitudinal study conducted in the U.S. that collected information on triads of adoptive parents, birth parents, and adopted children (Leve et al., 2013).[6] Recruitment efforts took place between 2003 and 2010 and began with the selection of adoption agencies (n = 45) located in 15 states in the Mid-Atlantic, West/Southwest, Midwest, and Pacific Northwest regions.[7] Agencies included private, religious, and secular organizations. Liaisons within each organization identified participants who completed an adoption plan through their agency and met the following criteria: (1) the adoption placement was domestic; (2) the baby was placed within three months postpartum; (3) the baby was placed with a nonrelative adoptive family; (4) the baby had no known major medical conditions (e.g., extreme prematurity); and (5) the birth and adoptive parents were able to read or understand English at an eighth-grade level or better. A total of 3293 triads satisfied these requirements.

Each eligible adoptive family was contacted via mail approximately two to four weeks post-placement. Adoptive families received a letter on agency letterhead describing the study, a study brochure, and a postcard to return if they did not wish to be contacted again. Two weeks later, agency liaisons called birth mothers who were linked to adoptive families that did not return a postcard (n = 2635); 47% of birth mothers could be located using agency records (n = 1237). During the recruitment phone call, the liaison described the EGDS and asked for the birth mother's permission to have project staff contact her directly. 89% of birth mothers gave their consent, and 79% of these mothers agreed to participate in the study when contacted by the EGDS (210 birth fathers were also enrolled). Once a birth mother was active in the study, staff members proceeded to recruit adoptive parents from the same triad. 65% of adoptive parents were successfully enrolled, resulting in a final sample size of 561 triads (see Appendix A for a flow chart depicting the steps involved in sample selection). The mean age of placement among children in these triads was 6.2 days (SD = 12.5 days).

To consider the possible implications of non-participation for our analyses, we compared EGDS participants and eligible non-participants with respect to education, income, and age using information provided by adoption agencies about eligible non-participants (see Appendix table B1). Six of the eleven comparisons we made produced statistically significant differences ($p < 0.05$), but the differences were trivial from a substantive standpoint (e.g., participating birth mothers, birth fathers, and adoptive parents were all slightly younger than eligible non-participants, on average, and participating adoptive parents completed around 0.25 more years of schooling than non-participants). Importantly, there were no significant differences with respect to birth mother's education or income, birth father's education or income, or adoptive parents' incomes. Although these findings do not *guarantee* that non-participation is “ignorable” from a statistical standpoint, they do offer at least some reassurance against the threat of selective non-response.

Our final analytic sample includes those triads in which the focal child was selected to take achievement tests in the first grade (n = 340).[8] Supplementary analyses suggest that attrition after enrollment (i.e., those who provided data in the base year) was unrelated to our key independent variables (i.e., the educational attainments of the birth and adoptive parents) and was orthogonal to other measurable background characteristics (i.e., the race/ethnicity of the adoptive parents, their family income, the number of children they had, their marital status, their ages, and the birth weight of the adopted child), as ascertained at baseline. The specific measures of achievement that we use were derived from three Woodcock Johnson Tests of Achievement III (WJIII-ACH) subtests: letter-word identification, word attack, and math fluency. These subtests are designed to measure test-takers' reading skills, auditory processing skills, and numerical facility, respectively, and have good psychometric properties. A variety of metrics can be used to characterize children's performance on each subtest; we use standard scores because they adjust for slight differences in ages between test takers.

To measure the educational attainments of the parents within each triad, we created two identically coded variables (one for the birth family and one for the adoptive family). At baseline, parents were asked to report the highest level of education they had completed (answer categories included less than high school, GED, regular high school degree, some college, bachelors' degree, and advanced degree). Responses were then updated in later waves if the respondent obtained additional schooling. To simplify our analyses, we constructed a continuously coded version of this item (where less than high school = 10, GED = 11, regular high school degree = 12, some college = 14, bachelors' degree = 16, and advanced degree = 18) and then took the maximum value in families where information was available for more than one parent (see Table 1 for descriptive statistics).[9] To confirm that

[6] The EGDS includes data on two cohorts of children and families; data collection procedures were broadly similar for both groups, but not all members of the second cohort were asked to take achievement tests due to budget constraints. This means that some of the missingness in the data is by design. In our analyses, we pool the two cohorts to maximize power, and include a control for cohort membership in all models to account for any extraneous differences that might exist between the two.

[7] The EGDS recruitment procedures were designed to accomplish five objectives: (1) reduce the likelihood of recruiting only one member of the adoption triad (child, adoptive parents, and birth parents); (2) minimize potential ethical concerns by not initiating contact until after the period of revocation; (3) minimize the probability that participation in the study would cause information to be transferred across participants, including adoption agencies; (4) recruit a sample that would contain ethnic diversity and varying levels of adoption openness (contact and knowledge between birth and adoptive families); and (5) recruit a large sub-sample of birth fathers. All adoption agencies in each region were contacted, and if they placed at least 5–10 infant domestic adoptions per year, they were invited to participate. Although the eventual “sample” of agencies came from only 15 states, the data are not limited to families living in those states. Adoption agencies often work across state lines, and some participants have moved residence since the time of the adoption placement. As of now, EGDS participants reside in 46 states and the District of Columbia.

[8] As noted earlier, not all members of the second EGDS cohort were asked to take the achievement tests, due to budget constraints.

[9] Although the EGDS features an unusually large sample of birth fathers for an adoption study, the level of participation from this group was still lower than birth mothers and adoptive parents (valid information on educational attainment was obtained from 199 birth fathers in total, or just over one-third of the sample). This “missing heritability” could attenuate our estimates for birth

Table 1
Descriptive statistics for key measures and controls.

	Descriptive statistics				
	Mean/%	(Std. Dev)	Min	Max	% Missing
Achievement					
Letter-word identification	109.65	(13.91)	63.00	169.00	39.4
Word attack	107.92	(11.25)	58.00	140.00	39.8
Math fluency	99.44	(15.18)	66.00	147.00	39.8
Parental education (years)					
Biological parents	12.64	(1.84)	10.00	18.00	1.1
Adoptive parents	16.75	(1.64)	12.00	18.00	1.8
Mean age					
Biological parents	24.79	(6.32)	13.71	58.91	0.0
Adoptive parents	37.90	(5.35)	24.06	54.05	0.2
Sex of child					
Female	43.00				0.0
Male	57.00				0.0
Race/ethnicity of the child					
White	55.62				0.0
Black	13.01				0.0
Hispanic	10.87				0.0
Other	20.50				0.0
Race of adoptive parents					
White	84.85				0.0
White and non-white	11.05				0.0
Non-white	4.10				0.0
Scales measuring perinatal risk					
Labor/delievery complications	6.55	(4.96)	0.00	24.00	30.7
Exposure to toxins	1.04	(1.56)	0.00	6.00	0.0
Drug and alcohol use	2.41	(3.96)	0.00	25.00	0.0
Neonatal complications	6.37	(3.74)	0.00	34.00	30.7
Pregnancy complications	4.57	(4.30)	0.00	24.00	0.0
Previous pregnancy issues	1.02	(1.69)	0.00	6.00	30.7
Internalizing symptoms	1.64	(2.70)	0.00	8.00	0.0
Openness of adoption scale	0.04	(0.93)	−2.23	1.86	0.5
Type of adoption agency					
Religious	32.46				31.9
Secular	67.02				31.9
Other	0.52				31.9

Note: Parental education is expressed in terms of years of schooling. The maximum of parental education was taken when information on both parents is available; otherwise information on the sole parent was used. Missingness on the achievement variables was partly by design-not all children were given the WJIII achievement test. See text for more details.

our results are robust to alternative parameterizations, we also experimented with discrete measures of education and versions that only used the birth mother and adoptive mother's information; the findings were unchanged (see Appendix Tables B2 and B3).

3.1. Covariates

Our primary goal in this project is to assess the importance of different intergenerational pathways in the production of early educational advantages. To do so, we must first cleave parental contributions to children's academic achievements into distinct genetic and environmental components, allowing for separate assessments of each as well as their interaction. Threats to identification would arise if the post-birth "firewall" between birth parents and adopted children is somehow breached, opening up additional (non-genetic) pathways for intergenerational educational effects (Björklund et al., 2006; Leve et al., 2019; Plomin et al., 2013). This could occur in at least one of three ways: (1) birth parents maintain ties or have some level of contact with their adopted-away children after placement; (2) intrauterine exposures and/or complications during labor and delivery have a lasting effect on the child (see e.g., Torche, 2011); and/or (3) agencies selectively place children into adoptive families such that the characteristics of the adoptive parents resemble those of the birth parents (Plomin et al., 1997).

(footnote continued)
parents, but not adoptive parents, if birth mothers' educational attainments are poor proxies for the unavailable birth father data.

Table 2
Pairwise correlations between adoptees' birth and adoptive parents.

Birth parents	Adoptive parents				
	[1]	[2]	[3]	[4]	[5]
[1] Years of schooling	−0.03				
[2] Average age		0.01			
[3] Household income			0.04		
[4] Mother's anxiety				0.05	
[5] Mother's depression					−0.05

Note: The maximum of years of schooling is taken when information on both parents is available; otherwise information on the sole parent is used. Anxiety and depression were measured using the Beck Anxiety and Depression Inventories (Beck & Steer, 1993). None of the correlation coefficients are significant by conventional standards. See text for further details.

Results from prior research—which we replicate in Table 2 using a subset of variables, and in Appendix C using a broader assortment of measures—suggest that threat (3) is of little concern in the EGDS (Leve et al., 2019). Correlations between birth and adoptive parents' characteristics are generally weak, producing fewer significant associations than one would expect to observe by chance. We believe this gives us a defensible claim to quasi-random assignment. To address the remaining concerns, we constructed two sets of control variables. The first includes a composite measure of openness during and after the adoption process. In the EGDS, birth parents and adoptive parents were asked to describe the level of contact they had with each other (ranging from 1 = never to 5 = daily), the extent of knowledge they had about each other (ranging from 1 = a lot to 4 = nothing), and their perceptions regarding the openness of the adoption (ranging from 1 = very closed to 7 = very open).[10] To arrive at a single construct, we standardized each item, averaged within subscales, and then summed the results. Previous studies using EGDS data have used the same measure (Ge et al., 2008).

Our second set of controls provides an index of perinatal risk. In the first wave of the survey, a trained interviewer gave each birth mother a life history calendar and a detailed pregnancy screener. The goal was to obtain information about various medical aspects of their pregnancy (Marceau et al., 2016). Topics covered included pregnancy complications (e.g., maternal age-related risk, weight loss, pre-eclampsia symptoms, upper respiratory infections, and rubella); neonatal complications (e.g., low birth weight and prematurity); substance use (e.g., cigarettes, secondhand smoke, alcohol use, sedatives, illicit substances, and prescription painkillers); exposure to toxins (e.g., radiation, X-rays, lead, and other chemicals); and perinatal internalizing (e.g., maternal anxiety or depressive symptoms). We used this information—in combination with data obtained from birth mothers' medical records—to construct several scales measuring different classes of pregnancy risk (scales were calculated by summing instances of risks within classes).[11]

[10] Reports provided by the birth and adoptive parents were generally highly correlated, suggesting good inter-rater reliability.

[11] Women's medical records contained some of the same information referenced above, plus additional details on labor and delivery (labor length, abnormal presentation, cephalopelvic disproportion, intrapartum fetal heart rate tracing abnormalities, meconium stained amniotic fluid, and use of analgesics/anesthetics), complications during pregnancy (fetal arrhythmia, placental abnormalities, and vaginal bleeding), and other neonatal issues (spina bifida, genital tract malformation, fetal alcohol syndrome, and congenital infections). A set of rules was developed to handle instances where self-reported data and medical records provided overlapping information on the same pregnancy risk factor. See Marceau et al. (2016) and Neiderhiser et al. (2016) for details.

Further details on these scales can be found in Appendix D.

In addition to the covariates described above, we also constructed a measure of the child's race/ethnicity (1 = white, 2 = black, 3 = Hispanic, 4 = other/multiple), sex, and variables indicating the age and race/ethnicity of their adoptive parents (age was set to the mean at adoption within parents in two parent families), and the type of agency that handled the adoption. Prior studies have shown that these variables can impact estimates of genetic and environmental influences, as well as their relative importance, when modeling results using an adoption design (Ge et al., 1996). To handle missing data on these and other measures, we fit all of our models using full information maximum likelihood (ML). ML—which integrates missing values out of the likelihood function, as opposed to imputing them via a model-based approach—has been shown to outperform alternative missing data strategies (with respect to efficiency and unbiasedness) in both large- and small-*N* settings (von Hippel, 2016; Wang & Robins, 1998). In our analytic sample, 29% of cases were missing data on one righthand-side variable, and 1% were missing data on two or more.

3.2. Modeling strategy

Conventional analyses of intergenerational educational effects usually proceed by fitting a reduced-form model that relates some measure of parents' educational attainment, S, to the achievement of their offspring, Y:

$$Y_j^{bc} = \beta_0 + \beta_1 S_j^{bp} + \mathbf{Z}\beta + \varepsilon_j, \quad (1)$$

where superscripts *bc* and *bp* denote the biological child and parent, respectively; subscript j denotes the family in which the child was born and raised (for $j = 1, \ldots, N$); $\mathbf{Z}$ is a vector of controls that does *not* include pre-birth resources (heritable traits) or perinatal exposures that could affect the unborn child in important ways; and ε_j is a child-specific error term that is assumed to be uncorrelated with S_j^{bp}. Estimates of β_1 will provide an unbiased assessment of the total effect associated with parental education if there is no unobserved (genetic, biological, or environmental) confounding, i.e., $\mathrm{Cov}(S_j^{bp}, \varepsilon_j | \mathbf{Z}) = 0$, and if other usual assumptions for an estimator of this sort are met.

Our analyses begin with a somewhat different model:

$$Y_j^{ac} = \alpha_0 + \alpha_1 S_k^{bp} + \alpha_2 S_k^{ap} + \mathbf{W}\alpha + \varepsilon_k, \quad (2)$$

where the superscripts *ac* and *ap* denote adopted children and adoptive parents; k denotes triads of children, adoptive parents, and birth parents (for $k = 1, \ldots, N$) for which we have data; and $\mathbf{W}$ represents a set of background characteristics (age of adoptive parents and race). In the first part of our analysis, we use this equation to estimate the relative contributions of pre-birth (heritable and biological) and post-birth (environmental and social) factors to children's early academic achievement, with S^{bp} indexing the former and S^{ap} indexing the latter.[12] We then supplement our baseline specification with controls for openness/post-adoption contact with the birth parents and perinatal risk factors, as defined earlier, in order to refine our assessment of pre-birth characteristics. Finally, we fit revised versions of Eq. (2) that allow for interactions between S^{bp} and S^{ap}, as well as other theoretically relevant environmental characteristics.

3.3. Results

In Table 3, we report baseline estimates from a series of unweighted ordinary least squares (OLS) regression models of the form written in Eq. (2). Coefficients for parental education are arranged into three columns and two rows, with columns corresponding to different measures of academic achievement (i.e., children's scaled scores on the letter-word identification, word attack, and math fluency WJIII-ACH subtests), and rows corresponding to different types of parents (i.e., adoptive versus birth). All models include controls for the age of the adoptive parents at the time of the adoption, their race/ethnicity, and the gender and race/ethnicity of the adoptee, but no controls are entered for intrauterine exposures, complications during labor or delivery, or post-adoption contact between the focal child and their birth parents. This means that the estimates for birth parents' educational outcomes could be picking up on genetically-based effects ($G \rightarrow A$) *and/or* effects that operate via the prenatal/behavioral pathways outlined above.

Table 3
OLS regression of achivement onto parental education.

	Woodcock–Johnson sub-tests		
	Letter-word identification	Word attack	Math fluency
Adoptive parents' education	0.60	0.69*	0.63
	(0.45)	(0.36)	(0.50)
Biological parents' education	1.22***	0.97***	1.17**
	(0.41)	(0.33)	(0.45)

Note: Point estimates are provided in rows, with standard errors (in parentheses) beneath them. Parents' education is expressed in terms of years of schooling completed. The maximum of parental education is taken when information on both parents is available; otherwise information on the only available parent is used. All models also include controls for the adopted child's race and gender, the age and race/ethnicity of the adoptive parents, the type of agency that handled the adoption, and the survey cohort. Reading from left to right, the sample sizes are 340, 338, and 338, respectively. See text for more details.

* $p < 0.10$.
** $p < 0.05$
*** $p < 0.01$

The key results are easy to summarize due to their consistency: there is a positive and statistically significant relationship between adoptees' achievements in the first grade and the educational attainments of their *birth* parents ($p < 0.01$ for two out of the three outcomes), but smaller and less precisely estimated effects for adoptive parents (all three education coefficients are attenuated, albeit still not centered over zero, with one reaching significance at conventional levels). The effect sizes here are modest but by no means trivial. A one-standard deviation increase in the maximum number of years of schooling completed among birth parents ($\sigma_S^{bp} = 1.84$) corresponds to approximately 16% of a standard deviation increase in a child's letter-word identification score and word attack score, and 14% of standard deviation increase in their math fluency score. If one takes the point estimates at face value, the analogous effect sizes for adoptive parents' educational attainments ($\sigma_S^{ap} = 1.64$) are 7%, 10%, and 7% of a standard deviation, respectively.[13]

These findings suggest that the educational attainments of adoptive parents are predictive of (at least some) child achievement outcomes, but that birth parents' education also plays a role—as anticipated by the causal diagram presented in Fig. 1b. To further isolate the processes that drive the latter set of effects, we next fit an expanded model that included controls for perinatal risk and post-adoption contact/openness of the adoption process. Results are provided in Tables 4 and Table 5. Overall, we see a very similar pattern across specifications: the educational attainment of adoptees' birth parents remains a significant

[12] Under this formulation, $\hat{\alpha}_2$ provides an estimate of the total effect of educational attainment among adoptive parents. This includes direct effects and indirect effects that operate through downstream variables (e.g., family income).

[13] In auxiliary analyses, we replaced parental education with measures of family income. The general picture that emerged was similar to the story for education.

Table 4
OLS models with controls for perinatal risk.

	Woodcock–Johnson sub-tests		
	Letter-word identification	Word attack	Math fluency
Adoptive parents' education	0.54	0.68*	0.64
	(0.46)	(0.37)	(0.50)
Biological parents' education	1.16***	0.94***	1.02**
	(0.42)	(0.34)	(0.47)
Labor/delievery complications	0.08	0.19	0.53**
	(0.20)	(0.17)	(0.21)
Exposure to toxins	−0.18	−0.26	0.13
	(0.49)	(0.40)	(0.53)
Drug and alcohol use	−0.06	−0.10	0.03
	(0.22)	(0.18)	(0.24)
Neonatal complications	−0.15	0.02	−0.37
	(0.24)	(0.20)	(0.25)
Pregnancy complications	−0.19	0.02	−0.60***
	(0.18)	(0.14)	(0.19)
Previous pregnancy issues	0.33	0.17	−0.18
	(0.60)	(0.50)	(0.63)
Internalizing symptoms	0.40	−0.01	0.04
	(0.30)	(0.24)	(0.33)

Note: Point estimates are provided in rows, with standard errors (in parentheses) beneath them. Parents' education is expressed in terms of years of schooling. The maximum of parental education is taken when information on both parents is available; otherwise information on the only available parent is used. All models also include the original set of controls. Reading from left to right, the sample sizes are 340, 338, and 338, respectively. See Appendix D for more details.

* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

Table 5
OLS models with controls for post-natal contact with birth parents.

	Woodcock–Johnson sub-tests		
	Letter-word identification	Word attack	Math fluency
Adoptive parents' education	0.60	0.71*	0.63
	(0.45)	(0.36)	(0.50)
Biological parents' education	1.22***	1.00***	1.17**
	(0.42)	(0.33)	(0.46)
Openness of adoption	0.00	−0.31	0.07
	(0.87)	(0.70)	(0.96)

Note: Point estimates are provided in rows, with standard errors (in parentheses) beneath them. The openness scale was constructed from a series of questions that asked birth and adoptive parents to describe the level of contact they have with each other, how much they know about one another, and their perceptions regarding the openness of the adoption. All models include the original set of controls. See text for more details.

* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

predictor of children's first-grade reading and math achievements, even net of the additional controls, while the attainments of their adoptive parents show significant effects but only for one of the three outcomes (word attack). That the estimates for birth parents are virtually unchanged relative to those presented earlier suggests that hereditary traits, and not other (non-genetic) pathways, are the most likely drivers of the observed relationship between birth parents' attainments and the achievements of their offspring.[14]

3.4. Testing for $G \times E$ interactions

The estimates reported above underscore the importance of genetic factors in the transmission of educational advantages; these can be thought of as *main* effects. Although we have not yet shown whether genetic pathways are themselves environmentally sensitive, there are at least some reason to expect *moderated* effects as well (Capron & Duyme, 1991; Grant et al., 2010; Guo & Stearns, 2002; Turkheimer, Haley, Waldron, DöOnofrio, & Gottesman, 2003). If it is the case that exposure to favorable post-birth environments helps children to more fully realize their genetic potential by providing additional opportunities for learning and growth, then we should observe a positive gene-environment ($G \times E$) interaction (i.e., larger birth parent effects among those children who were placed in more highly advantaged adoptive families).[15] Prior theoretical work—-which has thus far received only mixed empirical support (Bates, Hansell, Martin, & Wright, 2016; Hanscombe et al., 2012; Paige, Turkheimer, & Loehlin, 2007; Tucker-Drob & Bates, 2016; Van Den Oord & Rowe, 1997)—sometimes refers to this proposition as the bioecological hypothesis (Bronfenbrenner & Ceci, 1994).

Testing for interactions within the context of an adoption design is straightforward, practically speaking. Regression models can be fit that allow for main effects of genetic propensities and environmental factors, as before, plus an additional cross-product term capturing the interaction between the two. In our analyses, we considered two such interactions: one between S^{bp} and S^{ap}, and another between S^{bp} and a variable measuring the child's home literacy environment. The latter variable was derived from a question that asked adoptive parents how many days per week they typically read to the focal child (we summed responses across parents in order to get a total count).[16] We include this measure in our models to allow for the possibility of effect moderation at a more proximate level, involving genetic propensities and aspects of the childhood environment that may not be captured by a distal measure of parental education. Power analyses, based on a series of simulations, suggest that we are sufficiently powered to identify modest to large interaction effects.

Estimates obtained from models with $G \times E$ interactions are presented in Table 6, with separate columns for each outcome and separate panels for each type of interaction we fit. The results provide few signs of environmental contingencies: none of the estimated coefficients for the cross-product terms are significant by conventional standards ($p > 0.10$ for all interactions), nor are the point estimates especially large from a substantive standpoint. This is true for all three measures of early academic achievement, and holds for interactions that involve distal and proximate measures of advantage in children's adoptive families. We see two possible explanations for these results: $G \times E$ interactions are either (1) too small for us to detect in the available sample; or (2) driven by characteristics of

[14] We use the "most likely" qualifier because we cannot completely rule out the possibility of unobserved non-genetic pathways that connect birth parents and children. What we can say is that for such pathways to matter, they would have to be more important than, and empirically distinct from, the set of behavioral and biological controls that we entered into our expanded model.

[15] Other, more complicated contingencies (e.g., enhanced sensitivity to both favorable *and* unfavorable environments among certain subsets of children or goodness-of-fit type scenarios where the quality of the match between the child and their environment determines the direction and magnitude of the interaction) are also possible (Belsky & Pluess, 2009), but have received less attention in the literature on the heritability of achievement-related outcomes. See Boardman, Daw, and Freese (2013), Reiss, Leve, and Neiderhiser (2013), and Shanahan and Hofer (2005) for more details.

[16] We also examined measures of how frequently the adoptive parents read to themselves, how many books they have in the home, how many newspaper and magazine subscriptions they have, and whether or not they have a library card. Models that included interactions with these items produced similar results.

Table 6
OLS models with main effects and distal and proximate interactions.

	Woodcock–Johnson sub-tests		
	Letter-word identification	Word attack	Math Fluency
A. Distal model			
[1] Adoptive parents' education	1.61	2.45	5.18
	(2.85)	(2.29)	(3.15)
[2] Biological parents' education	2.50	3.20	6.93*
	(3.59)	(2.88)	(3.97)
[1] × [2]	−0.08	−0.14	−0.35
	(0.22)	(0.17)	(0.24)
B. Proximate model			
[1] Home literacy environment	0.49	0.83	0.89
	(1.43)	(1.15)	(1.59)
[2] Biological parents' education	1.24	1.36	1.58
	(1.17)	(0.95)	(1.31)
[1] × [2]	−0.01	−0.05	−0.05
	(0.11)	(0.09)	(0.12)

Note: Point estimates are provided in rows, with standard errors (in parentheses) beneath them. Home literacy environment captures the frequency with which children are read to by their parents in an average week. The maximum value equals 14, which corresponds to a situation in which both adoptive parents read to their child every day. All models also include the original set of controls. Reading from left to right, the sample sizes are 340, 338, and 338, respectively. See text for more details.
*p < 0.10.
**p < 0.05.
***p < 0.01.

the early-life environment that are not well-proxied by the post-birth measures (educational attainment and the child's home literacy environment) included in our models. We will return to both of these possibilities in the discussion section.

4. Robustness checks

Adoption designs have unique strengths with respect to inference, but they also come with notable limitations. One of the primary concerns that has been raised in response to prior adoption studies has to do with external validity (see, e.g., Taylor, 1980). In this section, we consider this issue in more detail and, to the extent that we are able, evaluate its implications for our findings.

4.1. Can the experiences of adopted children be generalized?

Adoption, by definition, entails a break from one parental unit and the formation of attachment relationships with another. There is at least some reason to think that this process—and the myriad challenges it presents—could alter the strength of the intergenerational association between the achievements of adopted children and the attainments of their adoptive parents.[17] Although we do not have the means to test this possibility directly, we can examine it *indirectly* by comparing our results to estimates obtained from a comparable, but nationally representative, sample of own-birth children raised by their biological parents. The latter set of estimates—which can be thought of as $\hat{\beta}_1$ from Eq. (1)—capture the combined effects of biological and social influences, and, as a result, should approximate the sum of $\hat{\alpha}_1$ (S^{bp}) and $\hat{\alpha}_2$ (S^{ap}) from Eq. (2), provided there are no contaminating effects of adoption *per se* (see e.g., Lindahl, Lundberg, Palme, & Simeonova, 2016).

We use data from the WJIII norming sample for the purposes of these analyses (McGrew & Woodcock, 2001).[18] The norming sample was constructed using a three-stage stratified sampling strategy that was designed to yield representative data for the U.S. population, ages 2–90, as of the year 2000. Members of the sample (n = 8818) were given selected WJIII-ACH subtests and were also asked to provide information about their sociodemographic characteristics (e.g., age, gender, and race/ethnicity) and social background (e.g., the educational attainments of their mother and father). We used these items to create parallel measures of parental education and academic achievement (letter-word identification, word-attack, and math fluency), and then fit Eq. (1) using the subsample of respondents who were age appropriate at the time of assessment (n = 849). Missing data on the key right-hand side variable was handled using procedures identical to those outlined above.

Results are provided in Table 7. The first two rows of the table contain the same baseline estimates for adoptive and birth parents' education that we presented earlier; the third row provides the sum of these estimates and the corresponding standard errors; and the fourth row gives estimates and standard errors for the WJIII norming sample, as defined above. Comparisons of the results provided in the last two rows reveal few, if any, differences: point estimates for the combined effect of adoptive and birth parents in the EGDS-based analyses approximate the estimates we recovered using our parallel sample of own-birth children, with confidence intervals overlapping in every instance (cross-sample tests for differences in the relevant estimates were all non-significant). The fact that this occurs despite large differences in sampling methods and target populations should help to ease concerns about the unique experiences of adopted children.

4.2. Constrained variance?

Data from the norming sample can also be used to examine the effects of so-called "range restrictions" in the distribution of educational outcomes among adoptive parents (Stoolmiller, 1999). Because the educational distribution is truncated—there are no adoptive families in our sample with less than a high school degree—our estimates of the effects associated with S^{ap} could be biased (and the bias could run in either direction).[19] To carry out a crude check, we imposed the same range restriction on the norming sample (i.e., children whose parents completed less than 12 years of schooling were dropped) and then refit those models using an identical specification. Imposing this restriction eliminated 9% of cases. Point estimates, which we present in Fig. 2 alongside the original unrestricted estimates, were slightly attenuated in one instance and slightly larger in the other two, but none of the differences were statistically significant or especially meaningful.[20]

[17] Support for this line of reasoning is, at best, mixed. Some studies suggest that adoptive parents face unique obstacles that, together, limit the amount and quality of resources they can devote to their children (see e.g., Bartholet, 1993), whereas other studies show the opposite (see e.g., Hamilton, Cheng, & Powell, 2007). We tend to find the latter argument more convincing, especially in cases like ours where placement occurred more-or-less at birth and where attachment relationships between the adoptive parents and child are firmly established.

[18] Although some members of the norming sample were probably themselves adopted, current rates of adoption in the U.S. imply that this group is likely to be few in number.

[19] If the relationship between parental education and achievement is linear, range restrictions should have minimal effect. The formula for the slope coefficient from a regression of y on x is simply $\mathrm{Cov}(x, y)/\mathrm{Var}(x)$. When we impose a restriction on the variance of x, the covariance between x and y should diminish proportionately, leading to an equivalent result. The same would not be true, however, if the relationship between parental education and achievement has nonlinearities.

[20] This pattern is largely consistent with prior research, which finds measurable but still fairly modest amounts of bias in adoption studies where the environmental variance is artificially constrained (McGue et al., 2007).

Table 7
Comparison estimates using a representative sample of own-birth children.

	Woodcock–Johnson sub-tests		
	Letter-word identification	Word attack	Math fluency
[1] Adoptive parents' education	0.60	0.69*	0.63
	(0.45)	(0.36)	(0.50)
[2] Biological parents' education	1.22***	0.97***	1.17**
	(0.41)	(0.33)	(0.45)
[3] Sum of [1] and [2]	1.82***	1.66***	1.80***
	(0.62)	(0.50)	(0.69)
[4] Estimates from norming sample	1.74***	1.53***	1.68***
	(0.24)	(0.25)	(0.36)

Note: Estimates of parental educational effects in the nationally representative WJIII norming sample were obtained using identical procedures and age appropriate respondents ($n = 849$). Point estimates are provided in rows, with standard errors (in parentheses) beneath them. See text for more details.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

shared genetic endowments (or heritable traits) within biologically related parent–child pairs. Although this latter perspective may be less frequently articulated in the social sciences (but see Nielsen & Roos, 2015), its theoretical basis is no less compelling. If children inherit success-related traits from their biological parents, as large literatures in behavioral genetics suggest (see, e.g., Rietveld et al., 2013), then expanding the set of pathways to include these genetic factors, *in addition to environmental factors*, would seem like a reasonable choice.

To offer a test of the aforementioned models we drew on data from an ongoing study of adopted-at-birth children and their biological and adoptive parents. By virtue of the study design, we were able to decompose the intergenerational effects of parental education into genetic and environmental components and, within a simple regression framework, examine possible dependencies between the two.[22] Results from these analyses produced plausible evidence of genetic effects on children's early academic achievements, while also showing signs of environmental effects on at least some educational outcomes (i.e., children's word attack scores). These findings held across several measures of early academic achievement (including measures of both reading and math skills), were robust to multiple model parameterizations, and withstood a pair of auxiliary checks specifically designed to evaluate issues related to external validity. Together, these

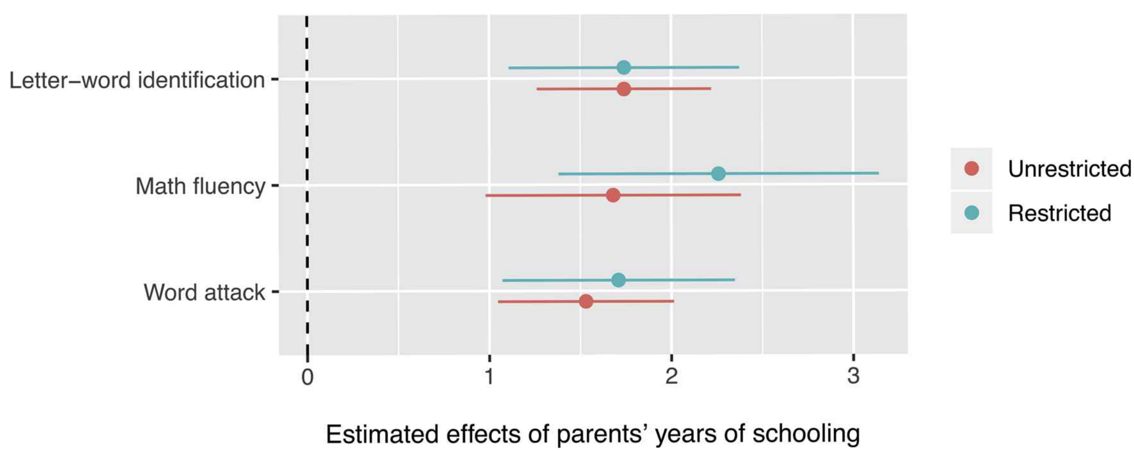

Fig. 2. Estimated effect of parents' years of schooling, with and without range restrictions. The unrestricted estimates, shown in red, use the full range of educational attainments observed in the WJIII norming sample. The restricted estimates, shown in blue, were obtained from models that excluded children whose parents completed less than 12 years of schooling. The latter scenario more closely approximates the distribution we observe in the EGDS data for adoptive parents. See text for further details. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Although we think some degree of skepticism over the generalizability of our results remains warranted, we find these estimates encouraging.[21]

5. Discussion

We began this article by specifying two possible models of the link between parental advantages and the early educational achievements of children. The first model highlighted the importance of parental resources, which include social, cultural, and economic assets passed from one generation to the next. This model should be familiar to most sociologists as it dominates our theoretical and empirical research. The second model we presented incorporated an additional set of pathways to accommodate the presence (and potentially confounding effects) of

results provide support for a more expansive view of the intergenerational transmission process (i.e., Fig. 1b).[23]

We believe this interpretation has important practical implications. If one is willing to accept the existence of pathways that lead from $G \rightarrow A$ and $G \rightarrow P$, as stipulated by the model in Fig. 1b, then one must also be willing to accept that the intergenerational effects of $P \rightarrow A$ will

[21] Range restrictions could also have implications for our analyses of gene-by-environment interactions. Although the interactions we report are all non-significant, it is possible our findings would look different if we were able to compare genetic effects across the full range of environments—instead of a truncated region of the adoptive parent educational distribution.

[22] We selected parental education for our analysis because it allows for like-to-like comparisons, and because it occupies a central place in sociological theories of status attainment and intergenerational mobility. That does not mean we think education is the only, or even primary, way that parents secure, consolidate, and transmit advantages to their children; other aspects of the family environment, uncorrelated with or weakly related to parental education, may also shape children's early educational outcomes. This remains the case regardless of whether or not genetic pathways are operative.

[23] A word of caution here is in order. Just because our preferred model of *individual* differences in achievement allows for genetic influences (in addition to environmental influences), that does not mean genetic effects must also give rise to differences that exist *between groups*. One does not follow from the other, as scholars have repeatedly pointed out in the literature on intelligence (see e.g., Fischer, Jankowski, Lucas, Swidler, & Voss, 1996; Plomin et al., 2013).

be confounded in the absence of controls for shared genetic endowments (G).[24] Others have referred to this proposition as "the possibility of pervasive unobserved heterogeneity" (Freese, 2008). One potential consequence of this scenario—as we saw in our comparison sample of own-birth children and as others have observed when modeling outcomes like cognitive ability and educational attainment (Conley et al., 2015)—is that a portion of the variance in A (achievement) will be incorrectly attributed to differences in P (parental education) in instances where adjustments for genetic influences cannot be made. In our case, this led to upwardly biased estimates of parental education effects when we collapsed genetic and environmental pathways into a single coefficient.

What does this mean for sociologists and others who study the intergenerational transmission of educational advantages? The most immediate practical takeaway is straightforward: researchers ought to seek out and implement techniques that allow for at least moderate amounts of genetic inheritance when modeling achievement-related outcomes. Adoption designs like ours represent one useful avenue for doing so (especially if the interest is in estimating environmental effects that are unconfounded by genes), but the choice set is by no means limited (Liu & Guo, 2016). Opportunities to incorporate genetic data into social science research now include a wide array of kinship-based approaches (e.g., twin studies and population-based sibling studies) and genome-wide methods (e.g., polygenic risk score analysis).[25] Harnessing the unique strengths of these different approaches, in combination with one another and the approach used here, should produce a more robust and sophisticated assessment of intergenerational educational effects than has previously been possible.

Our results also have implications for how researchers think about the relationship between genetic and environmental resources in the production of early educational advantages. Although some studies have pointed to the possibility of meaningful $G \times E$ interactions (Turkheimer et al., 2003), the results from our analyses, though only suggestive due to sample size constraints, were somewhat less optimistic. Adoptees who were placed in educationally advantaged homes were no more or less likely to realize their genetic potential than those who were not, and the effects of advantaged environments were uniform across levels of genetic potential. Conceptually, this suggests that genetic and environmental pathways *could* operate like "separate systems of ascription" (Conley et al., 2015), independently influencing children's early achievements in a way that is neither conditionally dependent nor synergistic in nature. We say "could" because we consider this issue still very much open. Whether our findings holds in larger, more representative, and more highly powered samples—and whether $G \times E$ interactions exist with distal or proximate aspects of the childhood environment not considered in our analyses—remains to be seen.

In addition to these questions, future researchers would also do well to consider the importance of genetic and environmental pathways using alternative measures of academic achievement and outcomes observed at multiple stages in the educational career. Our analyses focused on children's early reading and math scores because achievement in these areas has been shown to be an important precursor to subsequent attainments (Alexander et al., 1997; Bodovski & Farkas, 2007), but that does not mean our inferences map perfectly onto students at older ages and/or different markers of educational success (e.g., academic achievement in middle school, college completion, or performance in STEM fields). A more refined approach would adopt a longitudinal framework that allows for age-to-age changes in the contributions of heritable and environmental resources, dynamic interactions between them, and real differences across outcomes. In time, we believe that such analyses will help shed new light on the interplay between genetic and environmental components, the emergence of genotype-environment correlations, and the potentially domain-specific ways in which these processes operate.

Although we think these opportunities represent exciting new directions for social scientists, we also recognize the need for circumspection. The literature on genetics and achievement has an unfortunate history of inflammatory rhetoric about the "primacy" of inborn qualities, passed from one generation to the next in a way that is impervious to environmental intervention (Herrnstein & Murray, 1996). Not only do we consider these claims to be damaging and distasteful, we also view them as out of step with established scientific consensus (see, e.g, Conley & Domingue, 2016; Fischer et al., 1996; Kendler et al., 2015; Nisbett et al., 2012). In our work, we have sought to avoid these problems by placing genes and the environment alongside one another in a unified conceptual model. Under this framework, each factor is allowed to contribute to children's early educational achievements (through complex pathways and to possibly varying degrees), but the more important point is that the two factors exist in tandem. Neither one operates alone and neither one fully explains the persistent intergenerational effects of education.

Who achieves highly in the first years of school and how achievement varies by social background characteristics (like parental education) are critically important questions. If we are serious about answering these questions—and if we wish to do so in a comprehensive and empirically defensible way—we must first clarify the mechanisms that give rise to early academic success. None of the findings we presented in this article imply that genes are deterministic or that children are somehow "hard-wired" at birth to achieve at a certain level (Asbury & Plomin, 2014), but they do paint a more detailed picture of the underlying causal configuration and the multiple social and biological pathways involved. We are hopeful that this information will be of use to researchers as they continue to probe the etiology of early academic achievement, and the unique role that genetic and family endowments play in the transmission of intergenerational effects.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.rssm.2020.100486.

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[24] Entering controls for all of the mediating variables, observed or otherwise, that lie on the paths from $G \rightarrow A$ and $G \rightarrow P$ would also eliminate the possibility of confounding, assuming these variables are measured without error.

[25] We do not mean to suggest that genetically-informed approaches are the only way to address unobserved heterogeneity due to unmeasured genetic influences. Within-person designs and instrumental variable estimators can also prove useful in this regard.

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