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Socioeconomic status amplifies the achievement gap throughout compulsory education independent of intelligence

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ABSTRACT

Children from lower socioeconomic status (SES) families tend to perform worse in school than children from more privileged backgrounds. However, it is unclear to what extent differences in intelligence account for the academic achievement gap between high and low SES children. A large, UK representative sample of 5804 children was assessed on intelligence and academic performance at the ages 7, 9, 10, 12, 14 and 16 years. Latent growth curve analysis showed that SES was positively associated with academic performance at age 7 (i.e. intercept; Est = 0.07; CI 95% 0.06 to 0.07; $\beta = 0.32$) and gains in academic performance or growth from age 7 to 16 (i.e. slope; Est = 0.02; CI 95% 0.01 to 0.02; $\beta = 0.44$). The associations were substantially attenuated but remained significant after adding IQ (intercept: Est = 0.03; CI 95% 0.04 to 0.07; $\beta = 0.14$; slope: Est = 0.01; CI 95% 0.01 to 0.01; $\beta = 0.28$), which accounted for 40% of the variance in academic performance and growth, respectively. Although IQ was the strongest predictor of academic performance from age 7 through 16, SES was associated with an independent benefit of half a grade level on average by the end of compulsory education.

Educational attainment affects a wide range of important life outcomes, including socioeconomic status, health, and quality of life (e.g. von Stumm, Deary, & Hagger-Johnson, 2013). The type and level of educational qualifications that people complete vary as a function of academic achievement: Children who perform badly in school obtain overall fewer educational qualifications than those who do well (Schoon, Jones, Cheng, & Maughan, 2012). Children's differences in academic achievement are associated with their cognitive ability, which are both related to their family's socioeconomic status (SES), with children from less privileged families struggling more on average to achieve good grades and perform well in cognitive tests than children of higher SES (Bradley & Corwyn, 2002; Hart & Risley, 1995; Heckman, 2006).

A recent analysis of a subsample from the Twins Early Development Study (TEDS) tested the relationship between family SES and children's intelligence at age 2, as well as with their IQ gains or cognitive growth from age 2 to 16 years (von Stumm & Plomin, 2015a). At the age of 2 years, children from the highest and lowest SES backgrounds were on average separated by 6 IQ points; by age 16, the IQ gap had almost tripled, exceeding one standard deviation in IQ (i.e. 15 points; von Stumm & Plomin, 2015a). The authors concluded that SES has a profound, lasting and increasing impact on cognitive development. Because intelligence and academic achievement are highly correlated (Deary, Strand, Smith, & Fernandes, 2007; Frey & Detterman, 2004), we predicted that the same pattern of association holds true when SES is related to academic performance. In particular, we explored for the first time the association between SES and academic performance in the early years of school (i.e. at age 7) and with change in academic performance over the course of compulsory schooling (i.e. from age 7 to 16 years). We hypothesized that SES will be positively associated with academic performance at age 7 years, and with gains in academic performance over time from age 7 to 16 years, akin to its link with cognitive growth. In other words, we expected that the advantage of children from higher SES backgrounds in school performance is evident early on and magnifies over time. Even more importantly, we then tested to what extent the positive association between SES with academic achievement could be explained by children's differences in contemporaneous intelligence. A substantial attenuation of the SES link with academic achievement will imply that SES-related differences in academic performance simply mirror children's SES-related differences in intelligence (cf. von Stumm & Plomin, 2015a). In this case, we might conclude that SES is associated with better academic outcomes purely because of its relationship with intelligence. By contrast, a strong association between SES and academic performance independent of intelligence will suggest that SES-related benefits for school grades operate through pathways other than advantages in cognitive ability.

In addition, we sought to extend the previous literature by testing for the first time if SES moderated the relationship between IQ and academic growth across the course of compulsory schooling. It has been argued that intelligence accelerates school performance in children from privileged family backgrounds, where their learning needs are often adequately addressed, compared to those from low SES homes, where

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study support is typically scarce (Schoon et al., 2012). That is, children from high SES families may do better in school, even when they have lower intelligence, because they receive the help that they need to do well. By comparison, children from low SES homes, who experience less academic support, are likely to perform worse than high SES children across levels of intelligence (Bradley & Corwyn, 2002).

1. Methods

1.1. Sample

The Twins Early Development Study (TEDS) recruited initially over 15,000 families of twins born in England and Wales between 1994 and 1996. Although TEDS has seen substantial attrition over the years, the sample has remained representative of the U.K. population (Kovas, Haworth, Dale, & Plomin, 2007). For the current study, we excluded all twins from the analysis who suffered from severe medical problems during pregnancy, currently or at birth (e.g. postnatal surgery; N = 1672); whose first language was not English (N = 520); and who had been assessed on academic achievement fewer than two times between the ages of 7 and 16 years (N = 14006). For the final analysis sample, we randomly selected one twin from each pair (N = 5804 with 3075 girls and 2729 boys). All analyses were replicated in the other twins (N = 5778 with 3057 girls and 2721 boys). Because estimates were almost identical across both samples, in line with previous analyses of TEDS (von Stumm & Plomin, 2015a, 2015b), the results from the other twins' sample are reported in the supplementary materials.

2. Measures

2.1. School achievement

At the twins' ages 7 through 14, teachers rated their achievement in English, including the categories 'speaking', 'reading', and 'writing', and Maths, including 'use & applying', 'numbers', and 'shapes, spaces and measures', relative to 'the national expected standard' of children of the same age on a 5-point scale that ranged from 0 = 'working to towards level 1' and 1 = 'level 1', indicating achievement below the national expected standard, to 2 = 'level 2' that represented achievement at the expected standard, to 3 = 'level 3' and 4 = 'level 4+' that marked achievement above the national expected standard. From the twins' age of 9 years onward, teachers also rated their achievement in Science, including the categories 'scientific enquiry', 'life processes', and 'physical processes', using the same 5-point scale. At the twins' age of 12, teachers rated their achievement in the same subjects as described above on a 9-point rating scale that corresponds corresponding to National Curriculum Levels (https://www.gov.uk/national-curriculum/overview). For one subcategory of English, 50% of the sample had missing data; this category was therefore excluded from the analyses. Maths and Science each included additional categories of 'handling data' and 'science materials', respectively, resulting in overall 10 sub-categories with teacher ratings for academic achievement at age 12. At the twins' age of 14, teachers rated their 'overall achievement' in English, Maths and Science on the same 9-point scale used at age 12. At the twins' age of 16, their GCSE grades, which are based on national school examinations, were extracted from official records for English, including 'language' and 'literature', Maths, and Science that ranged from the top A* (i.e. "A-star") to A, B, C, D, E, F and G.

2.2. Socioeconomic status (SES)

Parental education and occupation (mother's and father's highest educational qualification and job status) were recorded at the first contact with the families, when twins were 2 years old, and again when they were 7 years old. Family income was assessed when the twins were 9 years old. A composite of parental education and occupation at twins' age of 2 years correlated at 0.77 with a composite of parental education and occupation at twins' age 7, which in turn correlated at 0.57 with family income at twins' age 9, suggesting that SES was stable over time in TEDS (Hanscombe et al., 2012).

2.3. Intelligence (IQ)

The twins' IQ assessments at 7, 9, 10, 12, and 14 used parent-administered and web- and phone-based tests, which have been described in detail elsewhere (Hanscombe et al., 2012) and are only briefly reviewed here. *Measures at age 7*: Children were tested on verbal and nonverbal abilities by telephone (Petrill, Rempell, Oliver, & Plomin, 2002). Prior to the telephone call, parents were sent a booklet of test items along with testing instructions for two verbal tests (Similarities subtest and Vocabulary subtest from the Wechsler Intelligence Scale for Children (WISC-III-UK; Wechsler, 1992), and two nonverbal tests (Picture Completion subtest from the WISC-III-UK and Conceptual Grouping from the McCarthy Scales of Children's Abilities; McCarthy, 1972). *Measures at age 9*: Participants were mailed a test booklet with two verbal and two nonverbal tests to be administered under the supervision of the parent, who had received a corresponding instruction booklet. The verbal tests comprised vocabulary and general knowledge tests adapted from the multiple-choice version of the WISC-III-UK (Wechsler, 1992). The nonverbal tests included a Puzzle test adapted from the Figure Classification subtest of the Cognitive Abilities Test 3 (CAT3; Smith, Fernandes, & Strand, 2001) and a Shapes test also adapted from the CAT3 Figure Analogies subtest (Davis, Arden, & Plomin, 2008). *Measures at age 10*: Testing was web-based, and children completed two verbal and two non-verbal tests using their home computers. Tests were drawn from the WISC-III-PI, including Multiple Choice Information (General Knowledge), Vocabulary Multiple Choice, and Picture Completion (Wechsler, 1992), and from Raven's Standard Progressive Matrices (Raven, Court, & Raven, 1996). *Measures at age 12*: Testing was web-based and conducted using home computers with age-matched versions of the two verbal and two non-verbal tests previously used at age 10. *Measures at age 14*: Twins completed two web-based tests at their home computers: WISC-III-PI Vocabulary Multiple Choice for 14-year olds (Wechsler, 1992) and Raven's Progressive Matrices (Raven et al., 1996). *Measures at age 16*: Twins completed web-based adaptations of Raven's Standard and Advanced Progressive and the Mill-Hill Vocabulary Scale using their home computers (Raven, Court, & Raven, 1998; Raven et al., 1996).

3. Statistical analysis

Teacher ratings of academic performance at the ages 7, 9, and 10 were recorded on a scale from 0 to 4. To enable comparing academic achievement across time, ratings and grades at ages 12, 14 and 16 were rescaled to also range from 0 to 4. Recoded and original scores correlated above 0.98 in all cases. Unit-weighted composite scores adjusted for the number of subject categories were computed for each age (i.e. 7 through 16 years).

At each assessment age (i.e. 7, 9, 10, 12, 14 and 16 years), the first principal component was extracted from the intelligence tests that were administered at the time. Regression factor scores were retained (mean = 0, SD = 1), representing age-matched *g*-scores herein referred to as IQ, and specified as reflective indicators of a latent IQ factor from age 7 through 16. Rather than modeling the IQ scores as time-variant covariates in the latent growth factor models (details below), modeling a latent IQ factor is more appropriate, because IQ scores are causally related over time.[1]

For an SES index, standardized composites of parental education and occupation at the ages 2 and 7 years were summed together with the

[1] I thank an anonymous reviewer for this modeling suggestion.

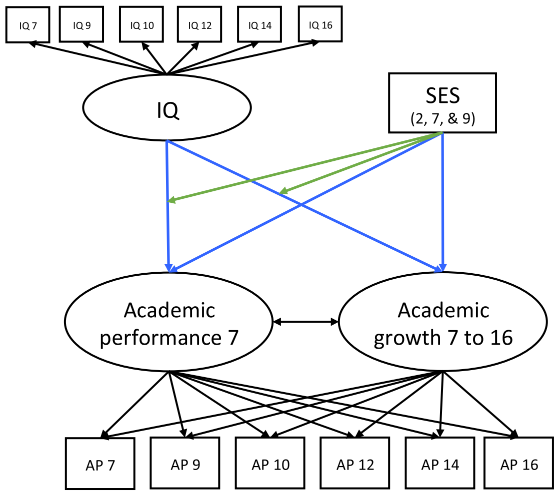

Fig. 1. Latent growth curve model of academic performance with latent IQ factor from 7 through and SES index as (interacting) predictors. Note. AP stands for academic performance. Intercept and slope were extracted as latent growth factors from academic performance at each assessment age from 7 through 16. Factor loadings for the intercept were 1, and 0, 2, 3, 5, 7 and 9 for the slope. Regression paths that test associations between academic growth factors with SES and IQ are shown in blue. The interaction paths, which test if SES moderates the association between IQ and academic performance factors, are in green.

standardized variable of income at age 9. In families where data was missing on one or more SES makers (i.e. age 2, 7, or 9), the available data were used to compute SES. Because SES markers were highly inter-correlated across time, summarizing them into one time-invariant SES index was appropriate.

Latent growth curve (LGC) models were fitted with the R-package lavaan (Rosseel, 2012) and used full information maximum likelihood estimation (FIML), assuming data to be missing at random. LGC models separated variance in academic performance that occurred early (i.e. at age 7) from variance that involved change in academic achievement over time. To determine the correct number of LGC factors, the fit (i.e. χ^2 (df)) of LGC models with one (intercept), two (slope) and three (quadratic term) growth factors were compared (i.e. χ^2 difference). The intercept represented the mean level of the academic performance at the first assessment (i.e., at age 7 years); the slope referred to the average rate of linear change in in academic achievement over time; and the quadratic term captured the non-linear acceleration or deceleration of the growth trend (i.e. systematic curvilinear change not accounted for by the slope). At each age, the intercept loadings were fixed to 1, while the slope loadings were defined as 0, 2, 3, 5, 7, and 9, representing *time periods* in years between each assessment point, ranging in *real time* from 7 to 16 years. With that, the intercept was defined where the slope had a zero loading (i.e. at age 7). Loadings on the quadratic term were the square of the slope loadings.

Gender differences in academic growth were examined by comparing the fit of an 'unrestricted' model to the fit of 'restricted' models that held intercepts, means and residuals, respectively, equal across groups (i.e. multi-group LGC). A significant difference between the 'unrestricted' and the 'restricted' model fits indicates that boys and girls differ systematically in their LGC factors.

Next, the SES index was specified as time-invariant direct predictor of the growth factors for academic performance. Associated parameter estimates are equivalent to regression weights. Subsequently, the models were extended to include the latent IQ factor from age 7 through 16 to test the extent to which IQ attenuated the association between SES and academic growth factors (Fig. 1). Finally, models were extended once more to test for the interaction between SES and IQ in the prediction of academic growth factors (Fig. 1). The R package lavaan does not support modeling interactions with latent variables (i.e. IQ factor) and thus, building an interaction term based on directly observed data was necessary. Because estimating factor regression scores requires complete data, a 'longitudinal' IQ composite was built by adding each participant's *g*-scores from age 7 through 16 and adjusting for the number of observations (i.e. number of completed cognitive ability assessments). This composite score correlated 0.99 with the factor regression scores obtained from the latent IQ factor (N = 629 participants with g-scores at all 6 assessment occasions). The interaction term was the product of the SES index and the IQ composite, which was included as predictor of the academic performance growth factors in addition to SES and the latent IQ factor.

4. Results

4.1. Descriptive statistics

Table 1 summarizes the descriptive statistics for the academic performance variables, which were all normally distributed and showed good internal consistency (i.e. Cronbach's α).

Table 2 shows the correlations between all variables, which were substantial and positive. SES correlated on average 0.30 with academic performance and IQ across assessment ages ranging from 0.24 to 0.39. Academic achievement scores were positively inter-correlated (>0.50) over time. Likewise, IQ scores were positively inter-correlated (>0.39), albeit to a lesser extent, possibly because they reflect changes in the IQ assessment methods (i.e. parent- versus phone- and web-administered; von Stumm & Plomin, 2015a, 2015b), as well as actual changes in intelligence over time.

5. Latent growth curve models

A one-factor growth model fitted significantly worse (χ^2 (19) = 2801.65) than a two-factor solution (χ^2 (16) = 2032.42), which fitted significantly worse than a three-factor growth model (χ^2 (12) = 1271.35). However, the third growth factor – the quadratic term – had zero variance and its associated parameters were non-significant. We therefore retained the two-factor solution that decomposed the variance in academic performance into intercept (i.e. starting point; Est = 2.156; S.E. = 0.007) and slope (i.e. change over time; Est = −0.006, S.E. = 0.002), which correlated at r = 0.20. The model's CFI was 0.708 and its RMSEA was 0.147 (CI 90% from 0.142 to 0.153),

Table 1
Descriptive statistics for academic performance from age 7 through 16 in TEDS.

	N	n	Mean	SD	Min	Max	Skew	Kurt	α
AP 7	4695	6	2.15	0.51	0	3.67	−0.55	1.45	0.93
AP 9	2456	9	2.01	0.58	0	4.00	−0.34	0.67	0.95
AP 10	2549	9	2.38	0.64	0	4.00	−0.28	0.22	0.96
AP 12	3169	10	2.40	0.80	0	4.00	−0.26	−0.05	0.98
AP 14	2496	3	2.20	0.87	0	4.00	−0.45	−0.29	0.85
AP 16	2370	4	1.82	0.93	0	4.00	0.20	−0.52	0.87

Note. n refers to the number of subject categories summed up for each age's academic achievement score. α is Cronbach's alpha. AP refers to academic performance.

Table 2
Correlations between all study variables.

		1	2	3	4	5	6	7	8	9	10	11	12
1	AP 7	–											
2	AP 9	0.68	–										
3	AP 10	0.66	0.70	–									
4	AP 12	0.51	0.63	0.64	–								
5	AP 14	0.56	0.63	0.65	0.53	–							
6	AP 16	0.50	0.55	0.56	0.51	0.75	–						
7	IQ 7	0.42	0.44	0.43	0.43	0.45	0.36	–					
8	IQ 9	0.44	0.46	0.45	0.46	0.52	0.40	0.40	–				
9	IQ 10	0.40	0.41	0.43	0.41	0.49	0.37	0.41	0.56	–			
10	IQ 12	0.40	0.50	0.48	0.53	0.50	0.44	0.45	0.57	0.62	–		
11	IQ 14	0.44	0.45	0.49	0.51	0.57	0.51	0.39	0.46	0.49	0.63	–	
12	IQ 16	0.40	0.43	0.44	0.46	0.57	0.48	0.42	0.46	0.51	0.59	0.63	–
13	SES	0.29	0.32	0.33	0.31	0.39	0.38	0.29	0.28	0.24	0.31	0.33	0.34

Note. AP refers to academic performance. Correlations are computed after pairwise omission.

suggesting a comparatively poor fit of the model to the data. However, LGC models are notoriously poor fitting, because they are more constrained than other structural equation models, which have relatively many free parameters, resulting in an unrealistically good fit (Preacher, 2010).

The multi-group LGC model showed no meaningful model differences across boys and girls (restricted residuals: $\chi^2_{\text{diff}}\,(6) = 5.55$, $p = 0.48$; restricted intercepts: $\chi^2_{\text{diff}}\,(4) = 3.11$, $p = 0.54$; restricted means: $\chi^2_{\text{diff}}\,(2) = 0.42$, $p = 0.81$); their data are therefore analyzed together.

The SES index was positively associated with academic performance intercept factor (unstandardized estimate = 0.07; CI 95% from 0.06 to 0.07) with a standardized β value of 0.32, accounting for 10% of the variance. SES was also positively associated with the slope (unstandardized estimate = 0.02; CI 95% from 0.01 to 0.02), with a standardized β value of 0.44, accounting for 19% of the variance. After including the latent IQ factor in the model, the association between SES and the growth factors reduced, for the intercept to 0.14 (unstandardized estimate = 0.03; CI 95% from 0.02 to 0.03) and for the slope to 0.28 (unstandardized estimate = 0.01, CI 95% from 0.01 to 0.01), accounting for 2% and 8% of the variance, respectively. Furthermore, IQ was also positively associated with the latent growth factors for academic performance, at 0.63 for both intercept (unstandardized estimate = 0.45; CI 95% from 0.41 to 0.48) and slope (unstandardized estimate = 0.07; CI 95% from 0.06 to 0.08), accounting for 40% of their variance, respectively. Thus, IQ explained the greatest amount of variance in academic performance factors and accounted for some, but not all of the association between academic performance and SES.

Fig. 2 shows these results graphically by trisecting the sample into low, medium and high SES families. At age 7, low and high SES children differed in average by 0.43, which corresponds to less than half a grade level. By the age of 16, the gap had substantially increased to 1.25, more than entire grade. After adjusting for IQ, SES-related differences in academic performance at age 7 were on average 0.15, equivalent to seventh part of a grade level. By the age of 16 years when students completed compulsory education, they had accumulated to 0.50, which is equivalent to half a grade.

The interaction term between SES and IQ was negatively associated with the intercept factor of academic performance (standardized estimate = −0.04; unstandardized estimate = −0.003; CI 95% from −0.006 to −0.001), suggesting that children from more privileged families performed better at school than those from low SES homes, even when they had lower levels of IQ. The same interaction term was positively associated with the slope factor (standardized estimate = 0.04; unstandardized estimate = 0.001; CI 95% 0.000 to 0.001), suggesting that children from more advantaged homes with higher intelligence show exponential performance gains in school over time. However, the interaction effects were overall small and their corresponding confidence intervals were close to 0.

6. Discussion

Confirming our hypotheses and the previous literature (e.g. Bradley & Corwyn, 2002; Heckman, 2006; Schoon et al., 2012), children from less privileged families performed worse in school than children from high socioeconomic status (SES) homes. This disadvantage was evident in the early stages of schooling at children's age 7, when our sample was in primary school and assessed for the first time on academic performance. The discrepancy between high and low SES children in academic performance widened further until the sample's age of 16 years, mirroring the results reported previously about the relationship between SES and intelligence from age 2 to 16 years, also in a subsample

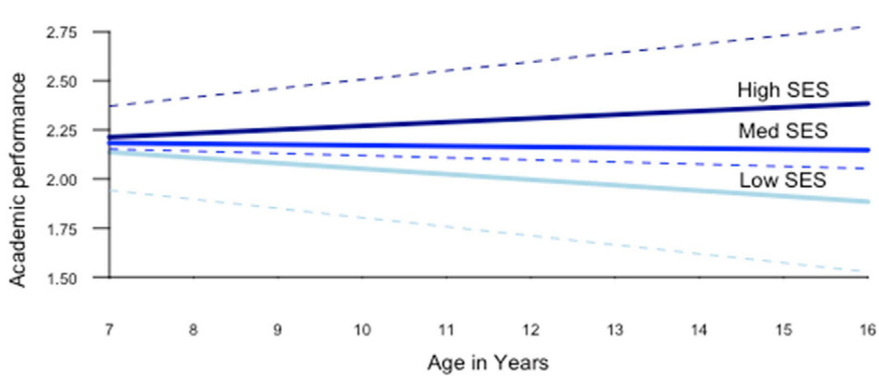

Fig. 2. Academic performance trajectories from age 7 to 16 in children from low, medium and high SES families. Note. The trajectories are based on subsample of children with complete SES information (N = 5707). Low SES refers to one SD below the mean in SES (N = 928); medium SES refers to children's families within one SD above and one below the mean (N = 3744); and high SES refers to those one SD and more above the mean in SES (N = 1035). Dashed lines show trajectories unadjusted for contemporaneous IQ.

from TEDS (von Stumm & Plomin, 2015a). Although SES-related benefits were substantial for academic performance before and after including children's differences in intelligence in our models, intelligence substantially attenuated the association between SES and academic performance. In fact, IQ accounted for the greatest amount of variance in academic performance at age 7 and in academic growth from age 7 through 16, approximating 40% for both outcomes. By comparison, SES accounted only for 2% and 8%, respectively, of the variance in academic performance and growth. However even after adjusting for intelligence, children from low SES backgrounds scored on average half a grade level below high SES children at age 16, which corresponds to the end of compulsory education in Britain. It follows that the positive association between SES and school performance is not fully accounted for by individual differences in cognitive ability. This finding is important, because it elucidates the lasting influence that socioeconomic family background variables have on life course development. In particular, British students' long-term educational choices depend heavily on their school performance at age 16, because the latter is a key admission criterion for subsequent secondary and tertiary education in the UK. It therefore is reasonable to suspect that the SES-related disadvantages in academic performance will affect individuals' education paths beyond school, as well as all other life outcomes that are associated with education (Bradley & Corwyn, 2002; Heckman, 2006). Future research will have to investigate the pathways through which SES exerts an effect on academic achievement, which the current study only allows speculating about, for example through the learning support and encouragement that children receive (e.g. extra tutoring), as well as their parents' attitudes towards education (e.g. Tucker-Drob, 2013). It is important to emphasize here, too, that these SES influences comprise not only environmental variance but their association with children's development is partially mediated by genetic factors (Krapohl & Plomin, 2015).

The current study also tested if SES moderated the association between IQ and academic performance. Indeed, the results suggested that children from more privileged family backgrounds performed at age 7 better in school, even if their intelligence was low, compared to children from lower SES families. Thus, high SES may act as a buffer that balances out the effects of children's lower intelligence on academic performance at the beginning of their school career. Conversely, children from low SES backgrounds, who lack this protective mechanism, will perform more poorly in the early school years than high SES children at the same intelligence levels. Regarding academic growth from age 7 through 16, the benefits of intelligence for gains in academic performance increased at higher levels of SES. In other words, the combined influence of high SES and high IQ for academic performance was greater than the sum of their effects, suggesting that children from high SES homes with high intelligence show exponential academic growth. Summing up the interaction results, it appears that children from lower SES homes are particularly disadvantaged with regards to school performance: In the early school years, low SES children perform academically worse than high SES children at the same intelligence levels, and in later school years they experience significantly less academic growth or gains in performance (cf. Fig. 2).

7. Strengths and limitations

This study has notable strengths, including a large sample representative of the UK population (Kovas et al., 2007) that was assessed on academic performance and intelligence 6 times between the ages of 7 and 16 years. One weakness of this research is that children's grades came from different sources (i.e. teacher ratings versus official records) and were recorded with different scales at different ages. However, the internal consistencies and correlations across assessment ages were high for academic achievement, suggesting that residual confounding due to measurement inconsistencies is unlikely. A second limitation is that family SES was treated as a time-invariant covariate in the analyses, although it varies somewhat over time in TEDS (Hanscombe et al., 2012). However, SES markers were assessed only twice within the currently analyzed study period (i.e. at age 7 and 9), and once earlier (i.e. at age 2), which made modeling SES as time-variant covariate impossible in the current analyses. Finally, genetic analyses were not conducted here, despite working with a twin sample, mainly because SES is a between-family variable, which is inapplicable for genetic analysis with the twin method.

8. Conclusion

Children from low SES families performed worse in the early years of school than children from high SES homes, and their disadvantage amplified over the course of compulsory education. After adjusting for children's differences in intelligence, the association between SES and academic performance was substantially attenuated but remained significant. Thus, children from low SES homes attained on average half a grade level less than children from higher status families at age 16 when compulsory schooling ends. To identify the pathways – other than intelligence – by which the benefits of SES for academic achievement are transmitted and to explore their underlying mechanisms at both genotypic and phenotypic levels is a pivotal challenge for future research.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.intell.2016.11.006.

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