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The Role of Childhood Executive Function in Explaining Income Disparities in Long-Term Academic Achievement

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This study utilized data from the Avon Longitudinal Study of Parents and Children (N = 14,860) to examine whether early-life family income (age 0–5) predicted long-term academic achievement (age 16–18) and to investigate the role of executive function (EF) assessed multiple times across age 7–11 in explaining this association. Task-based EF was a significant mediator between early-life family income and later academic achievement in every model. This mediating pathway persisted when adjusting for a comprehensive panel of covariates including verbal IQ, sex, family income at ages 8 and 18, and early-life temperament. Additionally, teacher-rated and parent-rated EF mediated in some models. Overall, these findings suggest that childhood EF may play an important role in perpetuating income-based educational disparities.

Children growing up in economically disadvantaged contexts are at risk of underperforming academically, as shown by decades of evidence in developmental psychology, sociology, education, and economics (Blair & Raver, 2015; Duncan & Murnane, 2011; Noble & Farah, 2013; Reardon, 2011). Research examining the developmental pathways through which family economic circumstances affect children's academic outcomes is important for informing targeted efforts to promote academic success in students from economically disadvantaged households. Many relevant pathways have been examined, including studies on the mediating role of family characteristics (Aikens & Barbarin, 2008; Yeung, Linver, & Brooks-Gunn, 2002) or the school environment (McLoyd, 1998; Sirin, 2005). There are likely to be multiple mechanisms and processes linking economic hardship with academic outcomes, some of which may be more amenable to intervention than others. This study was conducted to evaluate a critical factor within the child, EF, which is both important for academic achievement (Blair & Raver, 2015; Raver, 2012) and is malleable through certain interventions (Blair & Raver, 2014; Diamond & Lee, 2011). Specifically, this study capitalized on the unique and comprehensive data from the Avon Longitudinal Study of Parents and Children (ALSPAC, also known as "Children of the 90s"; Boyd et al., 2013; Fraser et al., 2013) to test the role of children's EF in explaining the association between family income in the first years of life and high school academic achievement.

Income-Based Disparities in Academic Achievement

Income-based disparities in academic achievement emerge early in life and have been noted across the globe (Duncan, Magnuson, & Votruba-Drzal, 2017; Sirin, 2005). For instance, children from low-income families already show deficits in a number of academic proficiencies by kindergarten (Duncan et al., 2017). This pattern persists into later childhood and adolescence (Duncan et al., 2017). By adulthood, those from low-income backgrounds complete less schooling overall (Duncan, Yeung,

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Brooks-Gunn, & Smith, 1998; Duncan, Ziol-Guest, & Kalil, 2010). Additionally, children from low-income communities are less likely to participate in extracurricular activities (Fredricks & Simpkins, 2012), which have been shown to improve academic achievement in low-income populations (Morris, 2015). Overall, income-based disparities in academic achievement are concerning, because education provides one of the most important mechanisms for improving one's socioeconomic conditions, especially in today's global economy (Autor, 2014). Because the academic achievement gap between low-income youth and their financially better-off peers often translates into a gap in adult earnings and overall socioeconomic status, limited education contributes to the transmission of socioeconomic disadvantage to the next generation (Duncan et al., 1998, 2010). To break this vicious cycle, we need more research that can clarify the pathways between early-life family income and young adult academic achievement in order to suggest possible targets for intervention.

The Role of EF in Academic Achievement

Executive function is an umbrella term for a collection of "attention-regulation skills that make it possible to sustain attention, keep goals and information in mind, refrain from responding immediately, resist distraction, tolerate frustration, consider the consequences of different behaviors, reflect on past experiences, and plan for the future" (Zelazo, Blair, & Willoughby, 2016, p. 1). Executive function reflects activity in prefrontal neural systems that allow children to exercise increasing levels of cognitive control over their responses to environmental stimuli across development (Munakata, Snyder, & Chatham, 2012). In adults, EF has been modeled as three separable but correlated factors reflecting inhibition, working memory and updating, and mental set shifting (Miyake et al., 2000). There is less consensus on the latent structure of EF in middle-to-late childhood. Some researchers have found that a single EF factor fit their data best (e.g., Brydges, Reid, Fox, & Anderson, 2012), others have identified two or three factors resembling those identified in adults by Miyake et al. (e.g., Demetriou & Spanoudis, 2015; Lehto, Juujärvi, Kooistra, & Pulkkinen, 2003). In addition, some studies have suggested qualitative differentiations of EF by age (e.g., 8 years old vs. 10 years old, Brydges, Fox, Reid, & Anderson, 2014), whereas others have shown differentiation by measurement strategy, with objective cognitive tasks capturing unique variance and predicting academic achievement more strongly compared to EF ratings by teachers and parents (Dekker, Ziermans, Spruijt, & Swaab, 2017). Given these mixed findings and the assessment of multiple facets of EF at different ages by different informants in this study, we used exploratory factor analysis to select the best measurement model in a data-driven way.

It is important to focus on EF during this developmental period because previous research has indicated that EF skills are malleable in childhood. A number of interventions have been effective in improving EF abilities across early and middle childhood (reviewed in Diamond & Lee, 2011). This may be especially true for children who have experienced poverty, as one study found that intervening to improve EF during kindergarten was particularly beneficial for children in schools with high rates of poverty (Blair & Raver, 2014).

Accumulating evidence suggests that children need more than just content knowledge to perform well in school, and that EF skills are also essential for succeeding in an academic environment (Blair & Raver, 2015; Diamond, 2010). Importantly, these skills are associated with successful academic outcomes independently of general cognitive ability as indexed by IQ (Blair & Razza, 2007; Bull & Lee, 2014; Checa & Rueda, 2011).

When examining which cognitive skills best explain and predict economic disparities in academic achievement, some studies have suggested that EF plays a prominent role (Hackman & Farah, 2009; Noble, Norman, & Farah, 2005). Prevailing theory suggests that chronic exposure to poverty-related stressors (e.g., neighborhood violence, family chaos, racial discrimination, noise, and pollution) leads to alterations in the neurobiological systems that support EF, shifting children from a more "reflective" to a more "reactive" pattern of responding that is adaptive in their environment (Blair, 2010; Blair & Raver, 2016; Hackman & Farah, 2009; Ursache & Noble, 2016). This behavioral pattern leads children from homes with low financial resources to be seen by their parents or teachers as less competent in various aspects of self-regulation (Brody, Flor, & Gibson, 1999; Evans, Gonnella, Marcynyszyn, Gentile, & Salpekar, 2005), and to exhibit poorer performance on task-based measures of inhibitory control, working memory, and attention shifting (Blair et al., 2011; Evans & English, 2002; Farah et al., 2006; Noble, McCandliss, & Farah, 2007; Raver, Blair, & Willoughby, 2013; Sarsour et al., 2011). These effects appear to be enduring, as shown in a longitudinal study that linked childhood poverty exposure to impairments in young adult working memory (Evans & Schamberg, 2009). Importantly, there is encouraging evidence that intervening to improve EF skills can improve academic achievement for children from high-poverty schools and thereby reduce the achievement gap (Blair & Raver, 2014). Such studies point to the importance of EF in the relation between early-life economic conditions and later academic achievement. However, few studies have examined the long-term associations of low family income and low childhood EF with academic achievement in late adolescence. This study aims to address this gap.

This study focused on EF during middle childhood because these skills become consolidated during middle childhood and adolescence (reviewed in Anderson, 2002). Prior research has devoted much less attention to EF in middle childhood relative to early childhood and adolescence, despite the likely importance of EF during middle childhood for school performance. Additionally, this is an important developmental period when children begin to learn to manage their own behavior with less supervision from adults, suggesting that individual differences in EF measured at this stage may be meaningful in predicting long-term outcomes.

The Role of Early-Life Conditions

There is evidence that chronic exposure to poverty is more detrimental to children's cognitive and social development than transitory exposure (NICHD Early Child Care Research Network, 2005). In addition, some have argued that even when exposure is transitory, certain developmental periods are more vulnerable to the negative effects of low income with respect to specific outcomes. For instance, there is some evidence from the United States that low family income from birth to age five is a stronger predictor of low academic achievement compared to low family income during later developmental stages (Duncan et al., 1998; Johnson & Schoeni, 2011). The first few years of life might be a period of vulnerability to stress exposure because neural regions important for inhibiting the stress response (e.g., the hippocampus) develop during this period (Lupien, McEwen, Gunnar, & Heim, 2009). For these reasons, we hypothesized that early-life family income would show associations with long-term academic achievement, even when adjusting for later family income.

Hypotheses

The present project aimed to examine the association between early-life family income (birth to age 5) and late-adolescence academic achievement (16–18 years), as well as to test the mediating role of EF in middle-to-late childhood (7–11 years). These ages were chosen based on prior literature suggesting that birth to age five may be a period of sensitivity to economic hardship, that academic achievement around the end of high school is critical in determining one's future socioeconomic standing, and that middle childhood is an important period of consolidation for EF abilities. Specifically, we aimed to examine the following three hypotheses: (1) lower early-life family income would be associated with lower levels of academic achievement in late adolescence; (2) EF skills would act as statistical mediators of the association between early-life family income and academic achievement in late adolescence; and (3) this mediation effect would remain significant even after adjusting for a comprehensive panel of covariates including verbal IQ, sex, family income at later time points (ages 8 and 18), two EF-like measures from toddlerhood, parental education, and extracurricular activities in late childhood (age 11). These covariates were selected because they account for the temporal ordering of exposure to low income (income at ages 8 and 18), prior EF development (toddlerhood measures), and a number of other factors that might influence the predicted associations (verbal IQ, sex, parental education, and extracurricular activities).

Method

Sample

The sample in this study consists of participants from the ALSPAC who had data available on any of our measures of interest. ALSPAC is an ongoing birth cohort study that aims to follow more than 14,000 participants from birth into adulthood to understand the role of environmental and genetic factors in shaping a wide range of developmental and health outcomes. Mothers were recruited if they had an expected delivery date between April 1, 1991 and December 31, 1992 and lived in the former county of Avon in the United Kingdom. Their recruitment resulted in an initial sample of 14,541 pregnant mothers, resulting in 14,676 fetuses, 14,062 of whom were alive at birth and 13,988 children who were alive at 1 year of age. When the oldest children were approximately 7 years of age, an attempt was

Table 1
Sample Characteristics

	N	Minimum	Maximum	*M*	*SD*
Family income—Age 0–5	9,999	1.00	5.00	3.37	1.22
Teacher—Age 8 attention	6,339	0.00	20.00	15.18	5.46
Teacher—Age 8 activity	6,335	0.00	18.00	16.07	3.73
Teacher—Age 11 attention	7,573	0.00	20.00	16.02	5.08
Teacher—Age 11 activity	7,563	0.00	18.00	16.11	3.72
Parent—Age 8 attention	8,132	0.00	18.00	15.50	3.72
Parent—Age 8 activity	8,142	0.00	18.00	15.53	3.65
Sky Search—Age 8	7,299	1.00	19.00	8.71	2.39
Dual Attention—Age 8	7,050	1.00	19.00	7.57	3.78
Opposite Worlds—Age 8	7,201	1.00	19.00	18.24	1.70
Counting Span—Age 10	7,006	0.00	5.00	3.42	0.85
Sky Search—Age 11	7,118	1.00	17.00	9.12	2.43
Dual Attention—Age 11	6,987	1.00	19.00	7.76	2.33
Opposite Worlds—Age 11	6,796	1.00	19.00	18.44	1.36
Academic achievement	3,215	0.00	4.00	2.57	1.55
Persistence score	10,306	0.00	35.00	18.73	4.89
Distractibility score	10,313	0.00	40.00	24.54	4.68
Family income—Age 8	7,107	1.00	5.00	4.09	1.11
Family income—Age 18	3,490	1.00	10.00	6.72	2.77
Parental education—Age 8	7,195	1.00	13.00	8.11	4.08
Verbal IQ	7,378	46.00	155.00	106.96	16.80
Extracurricular activities	6,359	0.00	7.00	3.07	1.29
Sex (% female)	14,854			46.7	
Ethnicity (% White)	14,854			96.1	
Academic achievement	Level 0	Level 1	Level 2	Level 3	Level 4
% of sample in each category	16.9	13.1	10.4	14.9	44.7

Note. Family income at ages 0–5 and age 8 were ordinal variables ranging from 1 to 5 and representing weekly income in pounds: 1 = < 100; 2 = 100–199; 3 = 200–299; 4 = 300–399; 5 = > 400. Family income at age 18 was an ordinal variable ranging from 1 to 10 representing monthly income in pounds, which was rescaled to the same 1–5 range representing weekly income as the family income variables for ages 0–5 and 8. Parental education was an ordinal variable ranging from 1 to 13 with the following levels: 1 = no educational qualifications, 2 = has CSE/GCSE (D, E, F, G); 3 = has O-level/GCSE (A, B, C); 4 = has A-levels; 5 = has vocational qualification; 6 = has done apprenticeship; 7 = is a state enrolled nurse; 8 = is a state registered nurse; 9 = has city and guilds intermediate technical qualification; 10 = has city and guilds final technical qualification; 11 = has city and guilds full technical qualification; 12 = has a teaching qualification; and 13 = has a university degree. Academic achievement was an ordinal variable ranging from 0 to 4 with the following levels: 0 = did not complete any academic milestones; 1 = only completed the AS exams; 2 = completed both AS and A2 exams, and did not apply to university; 3 = completed the exams and applied to university, but was not admitted, 4 = completed the exams, applied for and gained university admission. See Method section for additional details on how we computed and scaled each variable.

made to bolster the initial sample with eligible cases who had failed to join the study originally, resulting in a total sample size of 15,454. Of this sample, 14,901 were alive at age one. This rich data set includes many waves of data collection, including questionnaires completed by children, parents, and teachers; administrative records; observational data; clinical assessments; and biological samples. Please note that the study website contains details of all the data that are available through a fully searchable data dictionary and variable search tool: http://www.bristol.ac.uk/alspac/researchers/our-data/. For further information regarding sample enrollment, participant characteristics, and general study methodology, we refer the reader to publications from the ALSPAC team that have profiled this cohort (Boyd et al., 2013; Fraser et al., 2013; Golding, Pembrey, Jones, & Team, 2001). Ethical approval for the study was obtained from the ALSPAC Ethics and Law Committee and the Local Research Ethics Committees. Informed consent for the use of the data collected via questionnaires and clinics was obtained from participants following the recommendations of the ALSPAC Ethics and Law Committee at the time.

Our most inclusive structural equation model used data from N = 14,860, which was the total number of participants that contributed data to at least one of our measures of interest (see Table 1 for descriptive statistics on this sample and Figure 1 for a flowchart of participation numbers).

Please note that the sample was 96.1% White and there were no significant associations with ethnicity in these analyses or changes in our results when this variable was included, thus we report the more parsimonious models that do not include this variable.

Measures

Early-Life Family Income

Total family weekly income was assessed through maternal self-report at two time points before the child turned 5 years old: when the child was 33 and 47 months of age (r = .80). These were averaged to yield one value due to our interest in estimating children's aggregate exposure to low income.

Academic Achievement

Four measures were available and used to exemplify offspring's academic achievement when they were 16–18 years old: (a) completion of AS qualification exams, (b) completion of A2 level qualification exams, (c) whether they applied to university, and (d) whether they were accepted into university. These measures were assessed through self-report by the study participants when they were 18 years old. The AS and A2 are both exams taken at the end of secondary education in the United Kingdom. These measures build on each other, as follows: one has to have taken the AS level exams in order to take A2 level exams, and one has to have taken these examinations before they can apply and be accepted into university. Given the interdependence (and multicollinearity) between these variables (mean r = .51), we constructed one continuous hierarchical index of academic achievement that had five levels: 0, for those who did not complete any of these academic milestones; 1 for those who only completed their AS exams; 2 for those who completed both AS and A2 exams, but did not apply to university; 3 for those who completed their AS and A2 levels and applied to university, but did not gain admission; and 4 if they passed their AS and A2 levels, applied for and gained university admission.

Executive Function

Executive function was assessed at multiple time points and through multiple informants between ages 7 and 11. Thirteen measures of EF from three

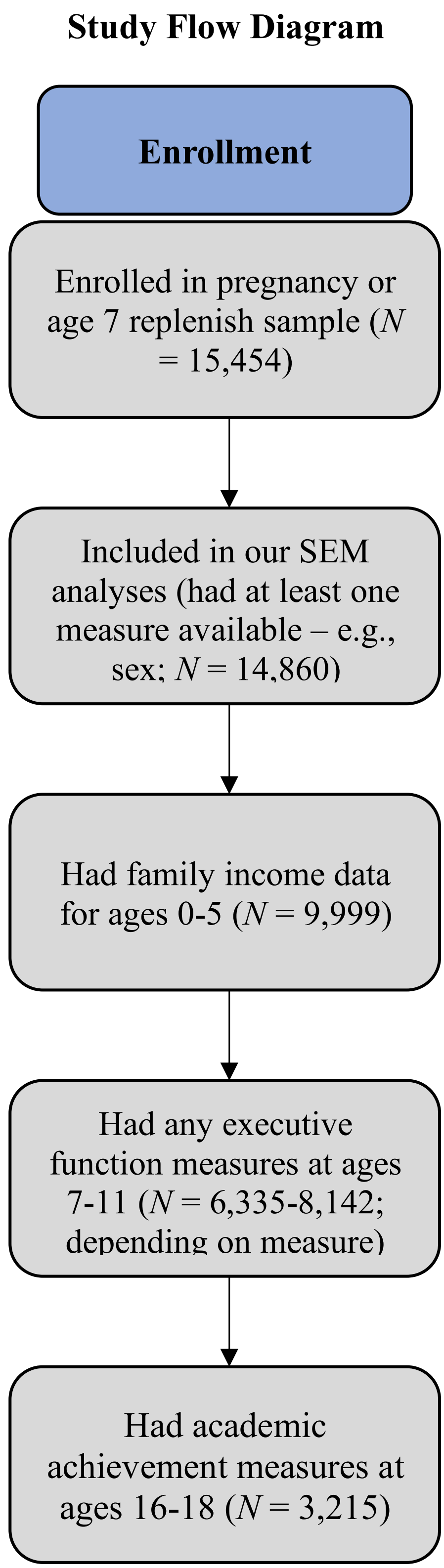

Figure 1. Flow chart with participant numbers for the main variables of interest.

different informants served as indicators for the latent variables. EF was assessed in the clinic using three subtests of the Test of Everyday Attention for Children (TEACh; Manly, Robertson, Anderson, & Nimmo-Smith, 1998) when the study children were 8 and 11 years old and by the Counting Span Task (Case, Kurland, & Goldberg, 1982) when the study children were 10 years old, by parent report when the children were 8 years old, and by teacher report during school years when the children were 7 or 8 years old, and when they were 10 or 11 years old. The three subtests of the TEACh used in these analyses were the Opposite Worlds, Sky Search, and Dual Attention tasks. The Opposite Worlds task is similar to the Stroop task and was used to measure cognitive inhibition (age 8: $M = 18.24$, $SD = 1.70$; age 11: $M = 18.44$, $SD = 1.36$). The Sky Search task assesses a child's ability to focus on relevant stimuli and measures selective attention (age 8: $M = 8.71$, $SD = 2.39$; age 11: $M = 9.11$, $SD = 2.43$). The Dual Attention task builds on the Sky Search task and measures the ability to divide attention, as it requires children to multitask (age 8: $M = 7.57$, $SD = 3.78$; age 11: $M = 7.75$, $SD = 2.33$). These measures all have good test–retest reliability (Sky Search $r = .90$, Dual attention $r = .81$, Opposite Worlds $r = .92$; Manly et al., 2001). The Counting Span Task (Case et al., 1982) measures children's working memory abilities. Children can earn a score up to 5 based on the number of sets they can correctly recall. Each child's teacher and parent reported the child's activity and attention abilities using the Attention and Activity subscales of the Development and Well-Being (DAWBA; Goodman, Ford, Richards, Gatward, & Meltzer, 2000) assessment. These scales were included in order to capture behavioral aspects of inhibitory control. For example, teachers assessed students on statements like "Finds it hard to wait his/her turn," and parents rated their children with questions like "Does she often blurt out an answer before he/she has heard the question properly?" The Attention scale was a weighted composite of ten items and the Activity score was a weighted composite of nine items (all Cronbach's $\alpha > .91$).

Covariates

Our most complex model included a comprehensive panel of potentially confounding covariates. Temperament in toddlerhood, family income when the study child was 8 and 18 years old, parental education when the study child was 8 years old, sex, verbal IQ, and extracurricular activities in middle-to-late childhood were used as covariates in this final model. The ALSPAC data set does not have information regarding early EF skills (ages 0–5), but we included two indices of children's persistence and distractibility as measured by the Carey Infant Temperament Scale (Carey & DeVitt, 1978) as the closest EF-like measures available. These scales were assessed via parent report when the study children were 24 months of age (both $\alpha = .71$). High values on the distractibility measure indicate that the children were rated by their parents as more distractible and high values on the persistence measure indicate that children were rated by their parents as having high levels of persistence (note: we reverse-coded the persistence variable from the ALSPAC data set, which originally indicated lower persistence for higher values). Family income at ages 8 and 18 was indexed through parental report of weekly and monthly income, respectively. Parental education level at age 8 was assessed through maternal report. The highest level achieved by the mother or the father was used. Sex recorded on the child's birth certificate was used as the sex variable in the present analyses. Verbal IQ was estimated using the most widely used cognitive ability test for children worldwide, the Wechsler Intelligence Scale for Children (WISC-III^{UK}; Wechsler, Golombok, & Rust, 1992) and was measured when the study child was 8 years old. There were five verbal IQ subtests: information, similarities, arithmetic, vocabulary, and comprehension. Lastly, extracurricular activities were assessed through parent-report when the child was 11 years of age. Parents were asked whether their child participated in seven activities including: sports, swimming, languages, music, singing, religion, and other groups like Scouts. The number of activities that the child participated in was used to create a measure of extracurricular involvement.

Data Analysis Plan

Structural equation models were used to allow the inclusion of both latent and observed variables. Analyses were conducted using the *R* statistical programming language, version 3.4.0 (R Core Team, 2017) and SPSS Version 25. The exploratory factor analysis and missing data imputation were conducted using SPSS. Structural equation models were estimated using the lavaan package in *R*, version 0.6-1 (Rosseel, 2012). To account for the missing data in the sample, we used full-information maximum likelihood (FIML) estimation, which introduces the least amount of bias compared to listwise deletion of participants with missing data and other available methodologies of correcting for missing data (Enders & Bandalos, 2001). To best model non-normal data, we used maximum likelihood with robust corrections using the MLR estimator (Yuan & Bentler, 2000). Figures and text both report the standardized paths from these models.

We aimed to examine two models that tested the mediating role of childhood EF for the link between early-life family income and late adolescent academic achievement under increasingly complex assumptions. Given the lack of consensus regarding the structure of EFs in childhood, we first conducted an exploratory factor analysis with the 13 indicators of EF abilities measured between the ages of 8 and 11. These analyses indicated four factors, corresponding to a teacher ratings factor, a parent ratings factor, a task-based factor tapping primarily into Lower-Order EF skills (e.g., selective attention, inhibitory control), and a task-based factor that captured multiple facets of higher order EF skills (e.g., divided attention, working memory). We defined each factor based on the common practice of allocating the measures loading 0.30 or higher on that factor in the exploratory factor analysis (Osborne, Costello, & Kellow, 2008; see highlighted cells in Table 3 for loadings). We then conducted a confirmatory factor analysis (Model 1, Figure 2) that assessed the fit of a four-factor model suggested by the exploratory factor analysis, such that measures were set to load on a factor if they had a loading of 0.30 or higher on that same factor in the exploratory factor analysis. Next, we tested two structural models to evaluate our main hypotheses. We started with the most basic model that tested the mediating role of EF in the relation between early-life family income and later academic achievement, without the inclusion of any covariates (Model 2, Figure 3). Our second model added the two temperament variables, family income at age 8 and 18, parental education at age 8, sex, verbal IQ, and extracurricular activities at age 11 as covariates in order to account for other potential influences on EF and academic achievement (Model 3, Figure 4). We chose these covariates a priori based on previous literature linking them to EF or academic achievement. The mediating effect of task-based EF was significant irrespective of whether these covariates were entered one at a time or simultaneously as a block. The addition of covariates was implemented by adding paths from each of these covariates to the EF latent factor and the academic achievement measure. The paths from the covariates to the main variables of interest are not shown in the figures due to space constraints, but are discussed in the main text. The first two hypotheses are tested in Model 2 and the third hypothesis is tested in Model 3.

In all of the above models, several indices of model fit were considered jointly to assess the models based on current recommendations for best practice. The chi-square test of model fit is often significant in large samples such as this one, so we relied more heavily on the following indicators of good fit: a root mean square error of approximation (RMSEA) below .05 for good fit and below .08 for acceptable fit; the comparative fit index (CFI) and Tucker–Lewis index (TLI) being at least .90 for acceptable fit and at least .95 for good fit, and the standardized root-mean-square residual (SRMR) being below .05 for good fit and below .08 for acceptable fit (Hu & Bentler, 1999).

Missing Data

To test whether data were missing completely at random, we conducted Little's MCAR (Missing Completely at Random) test. The test was significant ($p < .001$), indicating that the data were not missing completely at random. A previous paper from ALSPAC reported that attrition over time was dependent on several variables in the data set such that participants who remained in the study were more likely to be female, have higher educational attainment, and were less likely to be eligible for free school meals (Boyd et al., 2013). Missing pattern analyses with the sample from the current analyses confirmed these results. For instance, academic achievement data were more likely to be available at age 16–18 if participants were female, had higher family income at age 0-5, and higher levels of parental education. In the current analyses, we used FIML to account for missing data in SEM, as this allows all participants to provide information from some variables even if they have missing data on other variables. Additionally, we re-tested our models with five complete data sets generated via multiple imputation (Fully Conditional Specification method), as can be seen in Supporting Information. Results were identical or stronger with the imputed data (see Figures S1–S3).

Results

Table 1 displays sample characteristics. Table 2 displays bivariate correlations among the major variables.

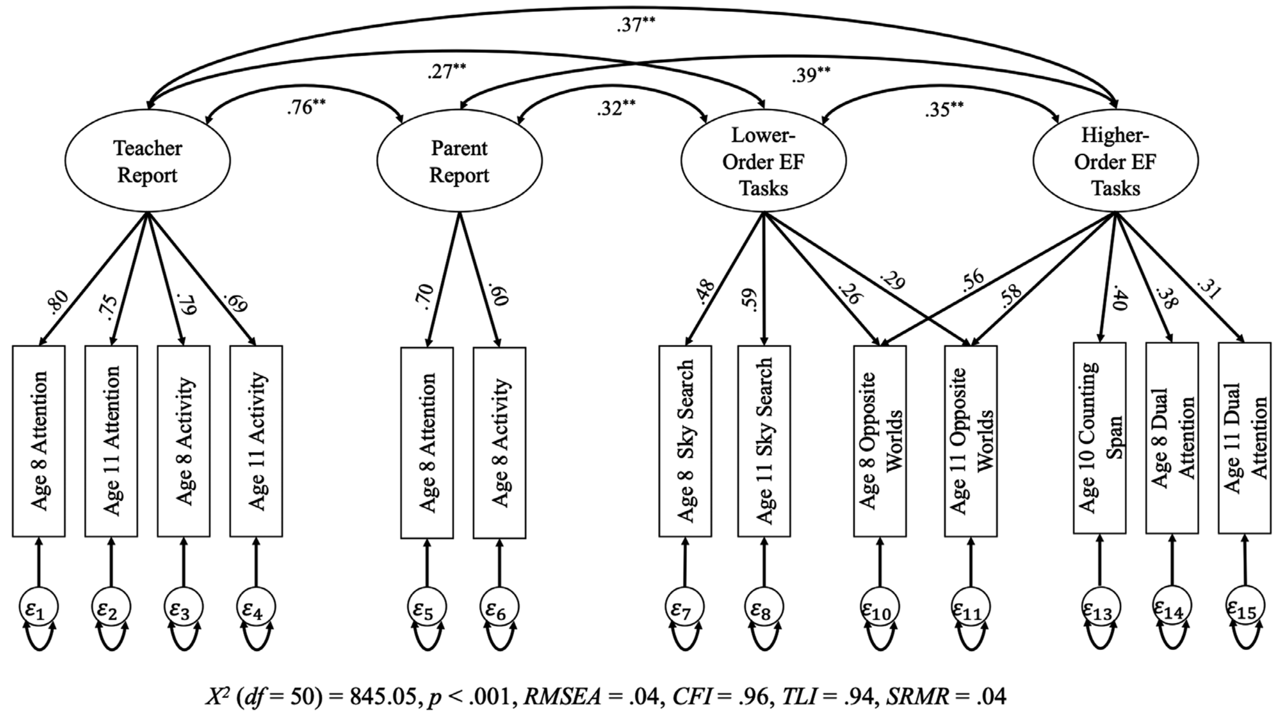

Figure 2. Model 1 was a confirmatory factor analysis for the executive function latent factors. $^{**}p < .01$ (2-tailed). Standardized coefficients are shown on each path in this model and all subsequent models.

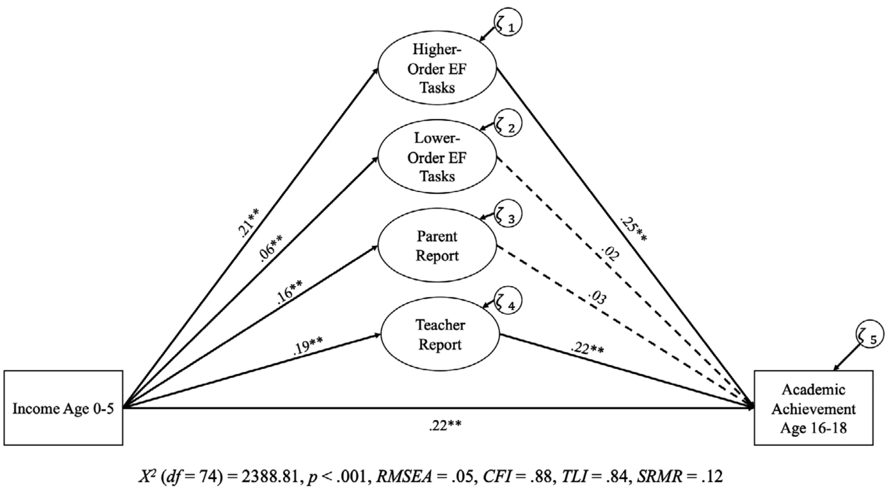

Figure 3. Model 2 tested the structural model including mediation by the four executive function factors, without covariates. $^{**}p < .01$ (2-tailed).

As expected, there were significant associations among all our measures of EF. The academic achievement index was significantly and positively associated with the measure of early-life family income. In bivariate correlations (see Table 2), this academic index exhibited associations of comparable size with family income at ages 0–5, age 8, and 18. When examining the associations among EF measures and early-life income, the Opposite Worlds task (a measure of cognitive inhibition), Counting Span (a measure of working memory), and the teacher-reported measure of behavioral inhibition showed the strongest associations with indices of early-life income.

Exploratory Factor Analysis

The exploratory factor analysis for the EF measures identified four distinct factors with eigenvalues

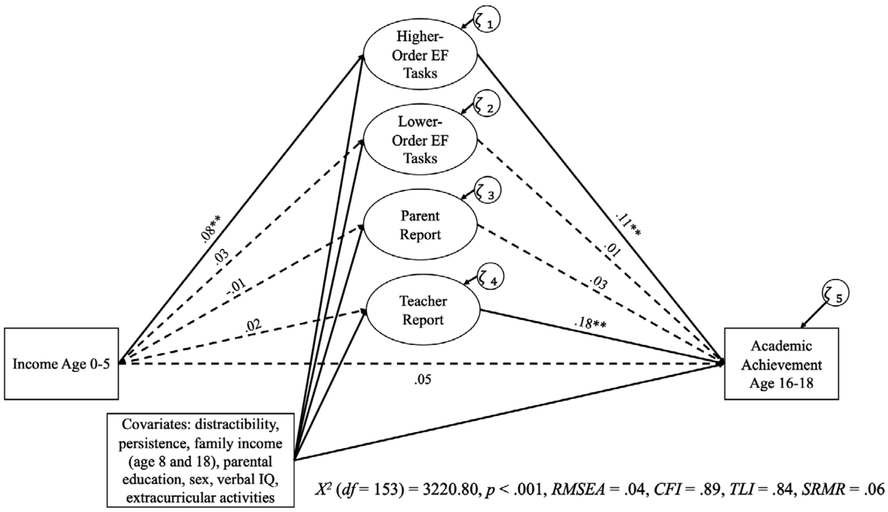

Figure 4. Model 3 revealed that the mediation pathway from age 0-5 income to academic achievement via the Higher-Order EF Tasks factor retained explanatory power after accounting for our panel of covariates (paths involving covariates not shown to improve readability but path statistics are included in text). ECAs = extracurricular activities. $^{**}p < .01$.

> 1. The minimum criteria used for deciding whether an individual measure loaded on a factor was that it had a primary factor loading of at least 0.3 (Osborne et al., 2008; Table 3).

This analysis indicated a separation of the measures by informant and facet of EF, but not age of measurement. The eigenvalues indicated that there was one factor defined most strongly by the teacher ratings, a second defined by the parent ratings, a third factor defined most strongly by the Sky Search tasks at both time points and the Opposite Worlds task at both time points (for ease of discussion we are labeling this factor the Lower-Order EF tasks factor given that these tasks index lower order EF tasks like selective attention and inhibitory control, while also recognizing that this may recruit other facets of EF), and a final factor consisting of the Dual Attention task at both time points (measures of set shifting), the Opposite Worlds task at both time points (measures of inhibition), and the Counting Span task at age 10 (a measure of working memory). We refer to these factors from here on respectively as: Teacher Report factor, Parent Report factor, Lower-Order EF tasks factor, and Higher-Order EF tasks factor.

Confirmatory Factor Analysis

Model 1

The CFA for the measurement model of EF indicated excellent model fit (see Figure 2): $\chi^2(50) = 845.05$, $p < .001$, RMSEA = .04, CFI = .96, TLI = .94, SRMR = .04.

The Teacher Report factor was well defined by the teachers' report of the child's attention abilities at age 8 and age 11 and of the child's activity levels at age 8 and 11 (the standardized loadings were all significant at $p < .001$: .80, .75, .79, and .69, respectively). The two parent reported measures loaded strongly on the Parent Report factor (the standardized paths were both significant at $p < .001$: .70, and .60, respectively). As suggested by the high modification indices for the first model we tested, we allowed the teacher reported measures to co-vary with each other, the parent report measures to co-vary with each other, and the teacher and parent measures at age 8 to co-vary. Four measures loaded on the Lower-Order EF tasks factor: the Sky Search and Opposite Worlds subtests of the TEACh at both age 8 and 11 (the standardized paths were all significant at $p < .001$: .48, .60, .26, and .29, respectively). Lastly, five measures loaded on the Higher-Order EF tasks factor: the Dual Attention and Opposite Worlds subtests of the TEACh at age 8 and age 11, and the Counting Span task measured at age 10 (the standardized paths were all significant at $p < .001$: .38, .31, .56, .58, and .40, respectively).

Structural Model Testing

Model 2

We began by testing the mediating pathways from early-life income to later academic achievement via the four EF factors. This was a basic

Table 2
Correlations among the Major Variables

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.	18.	19.	20.	21.	22.	23.
1.	—																						
2.	.15**	—																					
3.	.09**	.65**	—																				
4.	.14**	.57**	.47**	—																			
5.	.10**	.42**	.56**	.69**	—																		
6.	.06**	.46**	.35**	.38**	.28**	—																	
7.	.10**	.36**	.42**	.32**	.33**	.72**	—																
8.	.03**	.12**	.04*	.09**	.01	.09**	.04**	—															
9.	.09**	.11**	.04*	.10**	.01	.10**	.07**	.04**	—														
10.	.11**	.21**	.11**	.21**	.08**	.18**	.10**	.24**	.21**	—													
11.	.15**	.21**	.09**	.19**	.07**	.13**	.07**	.11**	.17**	.21**	—												
12.	.06**	.20**	.11**	.17**	.08**	.18**	.09**	.28**	.10**	.22**	.12**	—											
13.	.06**	.17**	.11**	.18**	.13**	.13**	.10**	.06**	.17**	.13**	.13**	−.03*	—										
14.	.09**	.26**	.14**	.21**	.10**	.18**	.10**	.18**	.17**	.48**	.22**	.27**	.16**	—									
15.	.27**	.25**	.16**	.20**	.11**	.13**	.10**	.03	.09**	.14**	.16**	.03	.08**	.11**	—								
16.	.001	.05**	.05**	.10**	.06**	.16**	.16**	.04**	.05**	.02	.03*	.05**	.03**	.02	.01	—							
17.	.04**	.01	.001	.03*	.04**	.01	.01	−.03*	−.02	−.02	−.001	−.02	−.02	.01	.03	−.15**	—						
18.	.66**	.11**	.07**	.09**	.08**	.07**	.12**	.02	.09**	.08**	.13**	.03*	.05**	.06**	.26**	−.01	.05**	—					
19.	.51**	.13**	.06*	.08**	.05*	.07**	.11**	−.01	.07**	.08**	.14**	.03	.06**	.09**	.26**	.03	.02	.53**	—				
20.	.37**	.06**	.04*	.09**	.06**	.04**	.07**	.04**	.08**	.05**	.11**	.01	.03*	.06**	.24**	.02	.01	.33**	.30**	—			
21.	.27**	.33**	.17**	.30**	.12**	.20**	.14**	.14**	.23**	.26**	.32**	.13**	.13**	.21**	.37**	.08**	−.02	.22**	.21**	.26**	—		
22.	.17**	.06**	.06**	.08**	.04*	.06**	.07**	.04**	.05**	.08**	.12**	.04**	.07**	.10**	.17**	.04**	.02	.16**	.14**	.20**	.16**	—	
23.	.01	.26**	.27**	.30**	.28**	.16**	.14**	−.03**	−.12**	−.02	.03*	.20**	.17**	.10**	.01	.06**	.02*	−.01	.01	.01	−.04*	.12**	—

Note. 1 = family income age 0–5, 2 = teacher report of age 8 attention, 3 = teacher report of age 8 activity, 4 = teacher report of age 11 attention, 5 = teacher report of age 11 activity, 6 = parent report of age 8 attention, 7 = parent report of age 8 activity, 8 = Sky Search task age 8, 9 = Dual Attention task age 8, 10 = Opposite Worlds age 8, 11 = Counting Span age 10, 12 = Sky Search age 11, 13 = Dual Attention age 11, 14 = Opposite Worlds age 11, 15 = academic achievement, 16 = persistence score, 17 = distractibility score, 18 = family income age 8, 19 = family income age 18, 20 = parental education age 8, 21 = verbal IQ, 22 = extracurricular activities, 23 = sex.
*Correlation is significant at the .05 level (two-tailed). **Correlation is significant at the .01 level (two-tailed).

Table 3
Factor Loadings for the Four EF Latent Factors

	Teacher Report factor (Eigenvalue 3.56)	Lower-Order EF tasks (Eigenvalue 1.71)	Parent Report factor (Eigenvalue 1.20)	Higher-Order EF tasks (Eigenvalue 1.13)
Teacher—Age 8 attention	**0.68**	0.11	0.13	0.07
Teacher—Age 11 attention	**0.84**	0.03	−0.01	0.02
Teacher—Age 8 activity	**0.81**	−0.04	0.06	−0.05
Teacher—Age 11 activity	**0.90**	−0.09	−0.09	−0.09
Parent—Age 8 attention	0.00	0.06	**0.90**	0.04
Parent—Age 8 activity	0.04	−0.04	**0.90**	0.01
Sky Search—Age 8	−0.08	**0.71**	0.03	−0.04
Sky Search—Age 11	−0.02	**0.80**	0.08	−0.22
Dual Attention—Age 8	−0.22	−0.07	0.10	**0.73**
Dual Attention—Age 11	0.13	−0.25	0.02	**0.64**
Opposite Worlds—Age 8	0.03	**0.36**	−0.05	**0.40**
Opposite Worlds—Age 11	0.10	**0.55**	−0.11	**0.26**
Counting Span—Age 10	0.04	0.20	−0.06	**0.51**

Note. We conducted an exploratory factor analysis to reduce the 13 observed executive function (EF) measures using Principal Components Analysis with a Promax rotation (note that the same pattern of results was obtained with a Varimax rotation). We retained all factors having eigenvalues > 1. Factor loadings are shown for each measure and the four factors. We defined each factor based on the common practice of allocating measures loading at 0.30 or higher (see highlighted cells; Osborne et al., 2008). Because the tasks loaded on two separate factors, we labeled one as "Lower-Order EF Tasks" for easier differentiation in text because the Sky Search tasks loaded strongly and almost exclusively on this factor and it is primarily an attention task.

model, without additional covariates (see Figure 3 for complete details).

Consistent with our first hypothesis, higher early-life income predicted better academic achievement in late adolescence (β = .22, *SE* = .07, p < .001). There was a significant positive direct path from early-life income to the Higher-Order EF tasks factor (β = .21, *SE* = .03, p < .001), the Lower-Order EF tasks factor (β = .06, *SE* = .02, p = .004), the Parent Report factor (β = .16, *SE* = .04, p < .001), and the Teacher Report factor (β = .19, *SE* = .02, p < .001). There were also significant positive paths from the Higher-Order EF tasks factor to academic achievement (β = .25, *SE* = .04, p < .001) and from the Teacher Report factor to academic achievement (β = .22, *SE* = .02, p < .001), with paths from the Lower-Order EF tasks factor and Parent Report to academic achievement not significant (p's > .05). There were significant mediating pathways through both the Higher-Order EF tasks (indirect effect: β = .05, *SE* = .01, p < .001) and the Teacher Report factors (indirect effect: β = .04, *SE* = .01, p < .001).

Model 3

The final model included all of the covariates (the two temperament variables, family income at age 8 and 18, parental education at age 8, sex, verbal IQ, and extracurricular activities at age 11, see Figure 4 for details).

We explored this model as a robustness check to test whether our central mediation model retained explanatory power after accounting for a number of potentially confounding variables. In this model, there was only a significant positive direct path from early-life income to the Higher-Order EF tasks factor (β = .08, *SE* = .04, p = .001), with the paths from early-life income to the other three EF factors being nonsignificant (p > .05). As in the previous model, there was a significant positive direct path from the Higher-Order EF tasks factor to academic achievement (β = .11, *SE* = .04, p = .005) and from the Teacher Report to academic achievement (β = .18, *SE* = .02, p < .001), but not from the other two factors to academic achievement (p's > .05). Overall, there was only one significant mediating pathway through the Higher-Order EF tasks factor (β = .01, *SE* = .01, p = .03), but not any of the others (p's > .05).

There were a number of significant paths involving the covariates, as follows. Persistence and distractibility in toddlerhood were related to both Teacher Report (β = .06, *SE* = .01, p < .001, and β = .03, *SE* = .01, p = .02, respectively) and Parent Report (β = .16, *SE* = .01, p < .001, and β = .03, *SE* = .01, p = .02, respectively), such that children who had high levels of persistence and distractibility were rated as having better EF abilities later on. Higher family income at age 8 was a significant predictor of higher EF abilities as reported by teachers ($\beta = .08$, $SE = .06$, $p = .002$) and parents ($\beta = .08$, $SE = .06$, $p < .001$), as well as higher academic achievement in late adolescence ($\beta = .06$, $SE = .04$, $p = .04$). Higher family income at age 18 was also significantly related to higher academic achievement ($\beta = .10$, $SE = .02$, $p = .001$). Higher parental education measured in middle childhood was linked to higher academic achievement ($\beta = .08$, $SE = .01$, $p < .001$). Higher verbal IQ ability predicted higher teacher ratings ($\beta = .37$, $SE = .003$, $p < .001$) and parent ratings ($\beta = .23$, $SE = .003$, $p < .001$) of EF, stronger performance on the Lower-Order EF tasks ($\beta = .19$, $SE = .002$, $p < .001$) and Higher-Order EF tasks ($\beta = .46$, $SE = .003$, $p < .001$), as well as higher academic achievement ($\beta = .20$, $SE = .002$, $p < .001$). Female participants were rated as having higher EF abilities by their teachers ($\beta = .38$, $SE = .08$, $p < .001$) and parents ($\beta = .18$, $SE = .07$, $p < .001$), and performed better on the Lower-Order EF tasks ($\beta = .16$, $SE = .08$, $p < .001$). There were no significant effects of sex on the Higher-Order EF tasks factor ($\beta = -.03$, $SE = .07$, $p = .18$) or academic achievement ($\beta = -.02$, $SE = .07$, $p = .42$). Lastly, participating in more extracurricular activities was associated with better performance on the Higher-Order EF tasks ($\beta = .10$, $SE = .03$, $p < .001$) and higher academic achievement ($\beta = .06$, $SE = .02$, $p = .001$), but was not associated with any of the other EF factors (p's $> .28$).

Discussion

Economic disparities in academic achievement exist worldwide and perpetuate inequality from one generation to the next (Duncan et al., 2017; Sirin, 2005). Much of the existing research on pathways from low family income to low academic achievement has focused on the role of family, school, or neighborhood characteristics. This study aimed to add to this important literature by focusing on a pathway involving EF, a within-child process that is sensitive to disruption under economic hardship (Blair & Raver, 2015; Raver, 2012), but which is also amenable to interventions (Blair & Raver, 2014; Diamond & Lee, 2011).

As hypothesized, lower early-life family income predicted lower academic achievement in adolescence. This observation is consistent with prior literature on the achievement gap between low-income children and their better-off counterparts (Duncan et al., 2017; Sirin, 2005). Although some studies have shown concurrent associations between socioeconomic status and university admission outcomes (Sackett et al., 2012), this study adds novel evidence by showing that family income many years prior is associated with long-term academic achievement around the time of university admission. The large sample size in this study afforded us the unique opportunity to test whether early-life family income continued to predict academic outcomes via EF when we statistically adjusted for family income at ages 8 and 18, and it did. This finding suggests a potentially important and independent role of early experience in setting up the foundation for later academic achievement.

We also found support for our second and third hypotheses. Namely, the link between early-life income and academic achievement was significantly mediated through the Higher-Order EF tasks factor in all model specifications (with and without covariates, with covariates entered as a block or one at a time, and with mediation models conducted with FIML or with imputed data). In addition, the Teacher Report of EF factor mediated in models without covariates and in the imputed data sets (see Supporting Information). The Parent Report and Lower-Order EF tasks only mediated in the imputed data sets without covariates (Figure S2). Overall, these results are consistent with prior findings that cognitive testing and teacher report, but not parent report, were predictive of academic success in 6- to 8-year-old children (Dekker et al., 2017), and that cognitive tests were stronger predictors than teacher report (Dekker et al., 2017). Cognitive tests may have more predictive power due to their objective nature, whereas teacher report may be stronger than parent report in predicting academic achievement because it reflects skills evidenced within the academic context. Parents' ratings may be anchored more closely to family dynamics and involve comparison of the child's behavior to that of other family members, which may be less informative of the child's potential for future academic achievement than teacher perceptions.

Overall, the mediating role of task-based EF is consistent with previous studies, which found a similar mediating path through EF over the preschool years (Fitzpatrick, McKinnon, Blair, & Willoughby, 2014) and over short time periods during childhood (Lawson & Farah, 2017). This study extends these findings to a much longer time span from early childhood to middle-to-late childhood and late adolescence. This report did not examine potential mediators between early-life family income and EF, but prevailing theory suggests important roles for stress neurobiology and the quality of parent–child interactions (Blair, 2010; Blair & Raver, 2016; Hackman & Farah, 2009; Ursache & Noble, 2016).

Furthermore, this study added evidence that EF skills are important predictors of academic success. To provide just a few examples that might explain these associations, EF allows children to shift and maintain attention as needed during a lesson, remember classroom rules, inhibit inappropriate impulses, hold and manipulate items in working memory to aid reasoning, and use planning to solve problems effectively. It is increasingly recognized that these behaviors and abilities are equally important in education as content knowledge, if not more important (Blair & Raver, 2015). Nevertheless, it must be noted that our analyses suggested partial, not full mediation of lower early-life income predicting academic achievement in late adolescence via EF, as a direct path between low early-life family income and academic achievement persisted after accounting for the role of EF in our basic model without covariates. It should not be surprising that full mediation was not observed; there are likely to be multiple mediating mechanisms in addition to EF by which family income influences academic achievement. Previous studies have highlighted the mediating role of family, school, and neighborhood processes (Aikens & Barbarin, 2008; McLoyd, 1998; Sirin, 2005; Yeung et al., 2002), and more research is necessary to elucidate these pathways and their relative importance.

Accounting for Covariates

The large sample size in the ALSPAC Study allowed us the unique opportunity to statistically adjust for a number of variables that might confound the associations of interest: early-life distractibility and persistence, family income at ages 8 and 18 years, parental education at age 8, sex, verbal IQ, and extracurricular activities in middle-to-late childhood. We discuss findings related to each covariate in turn.

In order to infer that early-life family income contributes to the development of EF in middle-to-late childhood, it would be important to statistically adjust for EF in early childhood. Toward this goal, our models regressed EF in middle-to-late childhood on two proxy measures of early-life EF skills assessed at age two, the Distractibility and Persistence scales from the Carey Infant Temperament Questionnaire (Carey & DeVitt, 1978). Both the Distractibility and Persistence scales were significant predictors of later EF as reported by the teacher and parent, and early-life income continued to predict EF as reported by the teacher and captured by the EF tasks after partialing out the effect of these two variables. This analysis provides some hints about the potential contribution of low family income to the development of EF, but this finding should be interpreted with caution given the correlational study design and the limitation that this early measure was a weaker assessment of EF than the age 7-11 measures.

Higher family income measured when the child was 8 years old and 18 years old was also related to higher academic achievement. This is not surprising, given that financial circumstances in late childhood and adolescence may constrain youth's decision to continue schooling and orient them toward seeking employment rather than pursuing a university education if they come from families who are struggling financially. Once these two covariates were added into the model, the role of early-life income was weakened because both of these variables were strongly correlated with the early-life income measure. Nevertheless, the indirect path from early-life income to academic achievement via EF tasks remained significant, suggesting a foundational role for early-life income in predicting later academic achievement. This finding is consistent with some prior evidence from national data sets in the United States highlighting the role of early-life income above the role of subsequent family income (Duncan et al., 1998; Johnson & Schoeni, 2011).

As expected, parental education at age 8 was positively related to later academic achievement. The logic behind the inclusion of this covariate was two-fold. First, we wanted to examine whether family income would retain its predictive power after we account for this other important facet of socioeconomic status. This is useful to examine in order to inform future interventions, which may focus on improving family finances, parental education, or both. Secondly, parents' educational attainment shapes offspring academic aspirations through pathways such as parental beliefs, expectations, and modeling of desirable goals (Davis-Kean, 2005; Eccles, 2005), which would be different pathways to explaining our outcomes than our hypothesis that EF is directly involved in and a facilitator of academic performance. Analyses indicated that, even after accounting for parental education, income continued to predict academic achievement and EF remained a predictor of academic achievement.

Interestingly, sex was related to three aspects of EF but not academic achievement. In this study, female participants demonstrated better EF abilities as reported by their parents and teachers and performed better on the Lower-Order EF tasks relative to male participants. This is consistent with previous research, which has indicated a sex effect favoring females in EF, particularly in studies of young children (reviewed in Zelazo, Carlson, & Kesek, 2008). However, females did not differ from males on our academic achievement composite, which included performance on end-of-high school qualification exams and university application or admission outcomes. The fact that the female advantage in aspects of EF did not translate into higher academic achievement is intriguing. This result may dovetail with meta-analytic evidence suggesting that females receive higher school marks than males on almost any subject, but this advantage disappears when examining national achievement tests (Voyer & Voyer, 2014). Perhaps females' higher EF skills in the classroom allow them to perform better in daily school contexts and when being evaluated by their teachers who observe other aspects of competence, such as behavioral self-regulation. However, this advantage may diminish in the context of standardized national exams, which are often one-time tests that both males and females try to prepare well for. The fact that the female advantage not only disappears but is reversed in some standardized achievement tests such as mathematics tests (Voyer & Voyer, 2014) also suggests that female performance might suffer in these circumstances due to stereotype threat, which is perhaps reducing the scholastic advantage they otherwise exhibit when school marks are considered.

As expected, verbal IQ at age 8 was related to all four EF factors and later academic achievement, such that participants who had higher verbal IQ exhibited better EF and better later academic achievement. This is in line with an extensive body of prior research (e.g., Arffa, 2007; Roth et al., 2015). Verbal IQ was also significantly associated with early-life family income (see Table 2), such that participants with higher family income scored higher on this test. This finding is consistent with prior longitudinal research in the United Kingdom indicating that children of lower socioeconomic status already exhibit lower IQ compared to high-socioeconomic status children by the time they are 2 years old, and these differences widen over time (von Stumm & Plomin, 2015). Nevertheless, EF explained variability in academic achievement even after accounting for the association of verbal IQ with both EF and academic achievement.

Participation in extracurricular activities (sports, swimming, languages, music, singing, religion, and other groups like Scouts) exhibited positive associations with both of the task-based Higher- and Lower-Order EF factors as well as later academic achievement, consistent with prior research on the positive developmental outcomes associated with participating in such activities (Farb & Matjasko, 2012). We included this covariate to reflect the potential influence of the broader social context that school-aged children encounter and because extracurricular activities are associated with both income and academic achievement (Morris, 2015). We found that early family income retained significant associations with task-based EF and academic achievement even after accounting for the role of these enriching social activities.

Limitations, Strengths, and Conclusions

This study was not without limitations. First, although the long-term prospective longitudinal design was a major strength because it allowed us to link early-life experiences to long-term outcomes, it also resulted in significant attrition in our outcome measure (only 3,215 participants, representing 21% of the original sample, completed the academic assessment at age 16–18). This is a significant limitation of this study. Although not uncommon among studies that span such long time periods, this high attrition rate left the sample less representative and of higher socioeconomic status than the initial sample (Boyd et al., 2012), limiting generalizability. Furthermore, we believe that this likely resulted in an underestimation of the true magnitude of the effects, since many of the low-income participants from the initial sample were lost to follow-up and this restricted the range of income observed in the final sample. This interpretation is supported by results from the imputed data, which were stronger and showed mediation by all four EF factors with complete, imputed data sets (see Figure S2). Thus, our analyses should be interpreted as evidence that the pathways we tested matter for the target outcomes and as potential hints about the lower bound of the possible effect sizes, rather than as exact point estimates for the true effects in the population.

A second limitation is that the self-report nature of the academic achievement data may introduce some bias. We believe that memory biases are mitigated by the fact that these data were collected very close in time to the relevant qualification exams and university application deadlines. Furthermore, subjectivity biases were mitigated by the concrete and unambiguous nature of the questions (whether they passed certain qualification exams or not, applied for university admission or not, and gained university admission or not).

Finally, another limitation is that this study is correlational, thus we cannot definitively ascertain causality. We statistically controlled for early-life distractibility and persistence at age 2 as proxy measures of early EF, thus revealing that early-life family income continued to predict EF in middle-to-late childhood, consistent with our hypothesis about a potential contribution of early family income to the development of EF from age 2 to ages 7–11. A measure of academic achievement at ages 7–11 was not available to conduct similar adjustment for prior levels of academic achievement. Ultimately, the correlational design in this study precludes stronger causal inferences about the role of family income in shaping child EF given that we cannot rule out alternative explanations (e.g., the contribution of genetics to both parent and child EF, which could impact parental earnings and contribute to the association we observed). Other studies with experimental and quasi-experimental designs (e.g., cash transfer programs, laboratory experiments that induce resource scarcity mindsets) suggest that a causal effect is theoretically plausible, as these studies demonstrate that resource scarcity leads to a pattern of decision-making that favors smaller short-term gains over greater long-term benefits (Haushofer & Fehr, 2014), which would be reflected in low EF skills as assessed with various tasks.

Despite these limitations, this study also had a number of methodological strengths. The long developmental time span covered and large sample size were unique assets of this study that allowed us an expanded window for observing associations with early-life family income independently of later income. Furthermore, the thorough assessment of EF through multiple indices and across multiple waves of data collection strengthens confidence in our findings. The availability of both task-based measures of EF as well as parent and teacher reports limited the contribution of reporting biases by allowing us to parse measurement variance out through latent factor modeling.

In conclusion, this study supports the role of EF in middle-to-late childhood as a foundation for long-term academic success, and as a mediator between early-life family income and academic achievement. These findings support the value of intervention programs that aim to improve EF to reduce income-based disparities in academic achievement. Indeed, evidence exists that boosting EF in the preschool years may help close the achievement gap between poor children and their better-off peers (Blair & Raver, 2014). Our study also highlights EF between the ages of 7 and 11 as another possible target, with potentially far-reaching benefits for academic achievement.

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Supporting Information

Additional supporting information may be found in the online version of this article at the publisher's website:

Figure S1. Confirmatory Factor Analysis With Imputed Data

Figure S2. Mediation Model Without Covariates (Imputed Data)

Figure S3. Mediation Model With Covariates (Imputed Data)

Table S1. Exploratory Factor Analysis With 13 Observed Executive Function Measures and All Missing Data Imputed Returned the Same Results as Our Primary Analyses: Four Factors With Eigenvalues > 1