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REVIEW

Effects of Family Socioeconomic Status on Educational Outcomes in Primary and Secondary Education: A Systematic Review of the Causal Evidence

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Abstract
A growing body of research has examined the relationship between family socioeconomic status (SES) and educational outcomes. Meta-analyses of raw correlations generally indicate moderate associations, typically between 0.12 and 0.3 for academic achievement and around 0.18 to 0.4 for educational attainment. Causal inference studies, aimed at capturing the true effects of SES, report much weaker associations, usually around 0.1 or less. Despite the importance of these causal estimates, few studies have systematically reviewed evidence from causal research. To address this gap, we conducted a systematic review of studies on the causal effect of SES on educational achievement and attainment. A total of 24 causal inference studies published between 1990 and 2023 were reviewed. The findings contribute to the literature and theory in several ways. First, the meta-analysis revealed a small and non-significant effect of SES on academic achievement (Cohen's $d=0.03$) and a small but statistically significant effect on educational attainment ($d=0.08$). Second, moderator analyses indicated that parental education exerted a stronger influence on educational attainment than that of family income. Moreover, the absence of significant differences in SES effects between developed and developing countries, as well as across various causal inference research designs (i.e., sample size, model specification, and methodologies), calls into question the assumed context-dependent nature of SES influence. Overall, the findings challenge SES-centered theories, showing that the causal impact of family SES on educational outcomes is much smaller than generally believed, and suggest that universal mechanisms may underlie the SES-education relationship.

Keywords Family socioeconomic status · Academic achievement · Educational attainment · Causal inference

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Introduction

The impact of socioeconomic factors on educational outcomes has been a subject of extensive research. Over the last half-century, both the economics of education and education policy research have identified SES as a significant predictor of students' educational inequality. Research has documented large gaps in test scores, grades, dropout rates, high school completion, and college enrollment between students from low-SES and high-SES families (Hanushek et al., 2019, 2022; Song & Tan, 2022). In response to SES-based inequalities, policies across all levels of education have prioritized support for students from disadvantaged backgrounds. For example, in the USA, some early childhood initiatives provide academic and social support to low-SES children to foster school readiness (Gibbs et al., 2011). K–12 policies (e.g., Title I in the USA) allocate additional funding to high-poverty schools to close achievement gaps. Broad-based financial aid and affirmative action in higher education are aimed at promoting college access for low-income students (Bailey & Dynarski, 2011).

However, while SES has been recognized as a contributing factor in educational inequality, the effects of family SES on student educational outcomes (i.e., academic achievement and educational attainment) have varied over the past few decades. Meta-analyses of raw correlations generally indicate moderate associations, typically between 0.12 and 0.3 for academic achievement and around 0.18 to 0.4 for educational attainment (e.g., Kim et al., 2019; Liu et al., 2022; Sirin, 2005). Causal inference studies aimed at capturing the true effects of SES report much weaker associations, usually around 0.1 or less (e.g., Haegeland et al., 2010; Holmlund et al., 2011; Wang et al., 2020). Causal inference methods enable researchers to isolate exogenous variations in SES, thereby identifying genuine causal effects and addressing concerns about spurious relationships. For example, in order to determine the influence of parental education/schooling on children's educational attainment, children-of-twin and adoption studies are frequently employed to isolate the causal effect while accounting for potential genetic confounds (Björklund et al., 2006; Haegeland et al., 2010; Pronzato, 2012). Children-of-twin studies compare the educational outcomes of children born to identical twin mothers or fathers, examining differences between children with similar genetic backgrounds but raised in different environments (Bonjour et al., 2003). Similarly, adoption studies examine adopted children to differentiate the effects of biological and adoptive family environments on educational outcomes (Sacerdote, 2002). Moreover, techniques such as using instrumental variables (identifying a variable that predicts the exposure (e.g., SES) but only affects the outcome through SES (Klungel et al., 2015; Nguyen et al., 2016)), difference-in-differences (comparing changes over time between a treatment group exposed to the policy or intervention and a control group not exposed (Lechner, 2011)), or fixed effects (leveraging within-subject variation over time to account for all stable characteristics (Brüderl & Ludwig, 2015)) are more suitable for studying causality as they utilize exogenous income variation or changes in occupational status over time (Carneiro et al., 2013; Ruiz-Valenzuela, 2020). Furthermore, studies using causal inference methods may yield varying results due to differences in methodology and data sources. For instance, Holmlund et al. (2011) applied three different causal methods (twins, adoptees, instrumental variables) to estimate the causal effect of parental education on educational attainment in Sweden. Their study revealed that all three causal methods consistently yielded different and lower estimates compared to the corresponding OLS estimates.

Building on the foundational work of Holmlund et al. (2011), the present study acknowledges the limitations and controversies characterizing research on family SES and educational outcomes and employs a systematic review to clarify the causal relationship between these two variables. The use of a systematic review enables this study to synthesize and evaluate the existing body of literature on this topic over the past three decades from 1990 to 2023, providing clarification and a comprehensive understanding of the causal relationships between SES and educational outcomes.

This systematic review on the causal relationships between SES and educational outcomes is important for two reasons. First, while numerous studies suggest that SES significantly influences educational outcomes (Kim et al., 2019; Liu et al., 2022; Sirin, 2005), research that controls for confounding variables such as parental abilities and environmental factors has found only small to modest SES effects (Erola et al., 2022; Marks & O'Connell, 2023; O'Connell & Marks, 2022). This divergence in findings underscores a critical knowledge gap with respect to how SES truly influences educational outcomes. Furthermore, previous systematic reviews and meta-analyses, such as Sirin (2005), Kim et al. (2019), and Liu et al. (2022), have primarily focused on correlational relationships between SES and educational outcomes. However, recent methodological advances in causal inference have enabled researchers to move beyond simple associations to explore the causal mechanisms underlying the SES-education relationship. Thus, by focusing on causal relationships rather than on mere correlations, the present review provides insights into the causal pathways linking SES and educational outcomes, shedding light on the underlying mechanisms that contribute to educational outcomes.

Second, apart from theoretical importance, policymakers have a strong interest in determining whether the relationship between family SES and children's educational outcomes is causal. If a causal relationship exists, it would suggest that investing in education has positive externalities and could potentially reduce inequality. Thus, enhancing socioeconomic factors, such as educational attainment, could amplify education opportunities and improve social mobility for future generations. In contrast, if children's educational outcomes are primarily determined by inherited abilities, then inequality in educational outcomes would be largely due to genetic differences, leaving limited scope for policy interventions to make a meaningful impact (Holmlund et al., 2011; Hu et al., 2021). Therefore, clarifying the causal relationship between SES and educational outcomes can help policymakers and researchers identify effective strategies for addressing education inequalities caused by family SES.

Theoretical Framework

Family SES has long been recognized as a factor in predicting educational outcomes, including both achievement and attainment. On the one hand, studies have suggested that family SES plays a significant role in shaping educational outcomes. For example, White's (1982) seminal meta-analysis included primarily US studies between 1918 and 1975 and yielded an average correlation of 0.22 between SES and academic achievement. Sirin's (2005) updated meta-analysis focused on US studies from 1990 to 2000 and found effect sizes of 0.27 for a random effect model and 0.28 for a fixed effect model. Harwell et al. (2017) replicated White's methodology for US studies before 1980 (Pearson's $r=0.22$) and between 1980 and 2010 ($r=0.25$). Kim et al. (2019) pointed out that previous meta-analyses had excluded developing countries. They conducted a meta-analysis of studies in developing nations and found a mean correlation of 0.12 for academic achievement and 0.18 for educational attainment. Liu et al. (2020) analysis of Chinese data from 1989 to 2016 revealed a mean effect size of 0.24. More recently, Selvitopu and Kaya (2021) included both developing and developed countries, but most of the studies included in their meta-analysis were conducted in the USA, China, and Turkey. Their analysis yielded a mean effect size of 0.25 between SES and academic achievement.

On the other hand, other researchers have argued that the impact of family SES on educational outcomes has been overstated (Marks & O'Connell, 2021; O'Connell & Marks, 2022). For example, Dickson et al. (2016), exploiting the exogenous shift in parents' education levels induced by the 1972 minimum school leaving age reform in England, estimated that parental education had a significant but small causal effect on children's academic performance. A one-year increase in parental schooling resulted in a 0.1 standard deviation increase in test performance. Cui et al. (2019) leveraged China's compulsory schooling law as an instrument variable to address endogeneity in the causal relationship between maternal education and adolescents' math test performance. Each additional year of maternal schooling was associated with a 0.05 standard deviation improvement in adolescents' math performance. Rege et al. (2011), leveraging exogenous variation in paternal employment shocks, applied industry and school fixed effects to isolate the causal impact of fathers' job loss due to plant closures in Norway. Their study found that fathers' job loss in non-booming municipalities led to a reduction of approximately 0.12 standard deviation in children's GPAs during their graduation year. Michelmore (2013) adopted a difference-in-differences design with state-year fixed effects to estimate the causal effect of Earned Income Tax Credit (EITC) expansions on the educational attainment of less educated parents. She found that an increase of $1000 in tax credit benefits had led to an additional 0.11 years of schooling, 2.3% of higher high school completion, and 2.7% of higher college enrollment rates in the USA. Similarly, Marks and O'Connell (2023), controlling for parental abilities, found that family SES and home environment only accounted for a small proportion of the variance in students' academic performance. They thus indicated that the SES-achievement link may simply reflect inherited abilities.

The evidence concerning the magnitudes of SES effects, found in various studies, may be attributed to spuriousness bias, a limitation that has plagued previous research. Specifically, while prior studies have established correlations between SES and educational outcomes, these correlations could stem from confounding influences rather than from direct causal effects. Spuriousness occurs when two variables appear to have a causal relationship (e.g., SES and educational outcomes), but their correlation is actually due to a third, often unmeasured, variable (Kenny, 1975). There are two broad sources of potential spuriousness that could undermine the causal interpretation of SES effects on educational outcomes. First, omitted variable bias stems from unobserved innate abilities that likely influence both family SES and children's educational outcomes. For example, Crawford et al. (2011) noted that the correlation between parents' SES and children's academic outcomes could partly reflect high-ability parents passing on genetic endowments to high-ability children. Erola et al. (2022) suggested that the relationship between parents' SES and their children's socioeconomic outcomes may be primarily attributed to genetic factors. Furthermore, research utilizing molecular genetic approaches has established hereditary connections between educational outcomes and both cognitive skills and non-cognitive skills (Calvin et al., 2012; Lee et al., 2018; Malanchini et al., 2024). Second, in addition to parents' genes, SES may be correlated with other unobserved variables that confound causal relationships. Dahl and Lochner (2012) pointed out that the negative association between family income and children's educational outcomes in their study may have been due to the fact that parents took on additional work, thus leading to a reduction in the time they were able to spend with their children while the children were studying. Similarly, Gregg et al. (2012) found that fathers' involuntary job loss in the UK due to firm closures during the 1980s had led to a decline in their children's educational attainment. However, the authors suggested that the effects of the change in fathers' occupational status on children's educational attainment could also have been driven by unobserved differences in traits such as perseverance between displaced and non-displaced fathers. As a result, failure to control for these factors (e.g., genetic and family environment spuriousness) may have led to upward bias in estimates of the effect of SES on educational outcomes. Studies leveraging quasi-experiments and exogenous shocks help strengthen causal inferences and elucidate the degree to which family SES shapes educational outcomes. Thus, by synthesizing the literature pertaining to the causal effects of SES on educational outcomes, the present systematic review aims to identify the causal pathways and unpack the mechanisms through which SES affects educational outcomes.

Family Socioeconomic Status

Family SES is a multidimensional construct that captures the human, financial, and social capital resources available to families and their children (Rodriguez-Hernandez et al., 2020; Sirin, 2005). It is a complex concept with various definitions and operationalizations in educational and sociological research (Rodriguez-Hernandez et al., 2020). Rodriguez-Hernandez et al. (2020) categorized the measure of family SES into three levels: individual, family, and area. Individual-level indicators include education, occupation, and income; family-level indicators include household resources/possessions; while area-level indicators include neighborhood resources. Moreover, researchers also create a composite SES score or index from several SES factors to capture the multidimensionality of the construct, such as theESCS (economic, social, and cultural status) index in the Programme for International Student Assessment (PISA) assessments (OECD, 2017). Nonetheless, the question of how best to conceptualize and measure family SES remains the subject of debate (Kim et al., 2019; Marks, 2016; Rodriguez-Hernandez et al., 2020; Sirin, 2005; Zhao et al., 2012).

Furthermore, the commonly used indicators for SES, including parental education, occupational status, and family income, are employed in both correlational and causal studies. However, there is some inconsistency in the way SES is operationalized when examining correlations versus investigating causal effects on educational outcomes. Causal inference studies typically focus on manipulating single variables as the "treatment" to isolate their specific causal effect. For instance, occupational status is often assessed based on job changes, such as employment transitions or job loss, in order to identify the causal impacts of SES (Pan & Ost, 2014; Stevens & Schaller, 2011). The causal effect of family income can be examined by considering the impact of sudden increases in family income. For example, Michelmore's (2013) study used the Earned Income Tax Credit (EITC), a refundable tax credit for low- to moderate-income working individuals and couples in the USA, particularly those with children, as a potential source of exogenous variation that changed household income levels. When it comes to parental education, examining its causal impact is more complex. Some studies utilize policy changes (e.g., 9-year compulsory education policy) to observe changes in the years of parental education completed (Tsai et al., 2011), while others employ adoption or twin studies to account for genetic and environmental factors closely related to parental education that may influence children's educational outcomes (Björklund et al., 2006; Scheeren et al., 2017). Moreover, while composite SES scores in correlational studies provide a robust representation of overall SES in correlational studies, causal inference requires targeted indicators that can be directly used as intervening variables to determine causality.

Overall, many causal inference studies examining SES and educational outcomes focus on unique or extreme circumstances. This approach is often necessary in order to create a clear "treatment" effect, allowing researchers to isolate the impact of SES changes. However, while these studies provide valuable insights into causal relationships, the measurement of SES in these studies has several limitations. First, it may not fully represent the more gradual or subtle SES changes experienced by most families. Families experiencing extreme changes might have unique characteristics that influence how SES affects their children's education (Duncan et al., 2011). This limitation affects the generalizability of findings to the broader population (Murnane & Willett, 2010). Second, the influence of SES on educational outcomes may be subject to critical thresholds or tipping points. For instance, there may be an income level at which the impact of SES on educational outcomes changes dramatically. Below this threshold, educational outcomes may suffer significantly, while above it, additional income may have diminishing returns on academic performance (Dahl & Lochner, 2012; Reardon, 2013).

Limitations in SES measurement reflect the challenges faced by researchers in the field of causal inference, where these indicators are most commonly used due to their measurability and tendency to change in ways that allow for causal analysis (Morgan & Winship, 2014). In contrast, correlational studies typically measure SES under normal conditions. This difference in measurement could lead to varying results and interpretations regarding the impact of SES on educational outcomes.

Educational Outcomes

Educational outcomes refer to the desired results that students are expected to achieve at the end of a learning experience or educational program. These outcomes typically encompass various domains, including knowledge, skills, attitudes, and competencies (Bloom et al., 1956; Guskey, 2007). This study focuses on two crucial aspects of educational outcomes: achievement and attainment. Academic achievement reflects a student's mastery of the knowledge and skills imparted through the curriculum and instructional practices of the educational institution. It is typically quantified through various metrics such as grades, test scores, and the demonstration of specific skill mastery in various subjects or domains. These metrics are evaluated and assessed within the context of an educational setting, such as a school or university (Steinmayr et al., 2014). In contrast, educational attainment refers to the highest level of formal education an individual has completed or the highest academic credential they have obtained. It is a more comprehensive measure than educational achievement, encompassing the entire educational journey of a person, from primary schooling to any post-secondary or tertiary education they may have pursued (Lucas, 2001; Sullivan, 2001). An important issue highlighted in the literature is the failure to differentiate properly between academic achievement and educational attainment when examining the relationship between SES and students' educational outcomes. Many studies group these two distinct outcomes together under the umbrella of "educational outcomes" when analyzing the association with SES (Kim et al., 2019).

However, achievement and attainment are conceptually distinct (Kim et al., 2019), and research has shown they have different associations with SES. For instance, a meta-analysis by Kim et al. (2019) reported that SES had a stronger correlation with attainment compared to achievement in developing nations. Moreover, research has demonstrated that attainment outcomes, including school enrollment, graduation rates, and access to higher education institutions, are more effective in explaining the variance in students' educational outcomes in developing countries, where access to education is not uniformly available (Conn, 2017; García & Saavedra, 2017). Specifically, in developing countries, the availability of educational opportunities often varies greatly between different socioeconomic classes, and attainment outcomes provide a more accurate reflection of the specific barriers to access to education faced by students with different socioeconomic backgrounds. In contrast, achievement may be a more meaningful metric in developed contexts, where basic education is nearly universal (Betts & Tang, 2014, 2016). In these contexts, achievement gaps may shed more light on disparities in educational quality and learning experiences across socioeconomic levels than on overt barriers to access to education. In light of the distinction between achievement and attainment highlighted in the aforementioned studies, it is essential for researchers to differentiate between these two outcomes when examining the effects of SES on educational outcomes.

The Present Study

The relationship between family SES and educational outcomes has garnered significant interest in the past few decades. As highlighted in the literature review section, although many observational studies have demonstrated SES-educational outcome correlation, they cannot determine causation due to confounding factors. Studies using causal inference designs are better suited to isolating causal effects but remain rare due to data limitations and methodological complexity (Angrist & Pischke, 2010; Holmlund et al., 2011). Evaluating causal evidence meticulously yields clearer policy implications for enhancing the academic achievement and attainment of disadvantaged students. Thus, by reviewing and evaluating the findings of rigorous causal inference studies, the present study aims to advance understanding of this critical relationship between SES and educational outcomes. Specifically, this study addresses the following research questions:

RQ1: How do different causal methodological approaches address spuriousness in examining the relationship between family SES and educational outcomes in primary and secondary education?
RQ2: Does the body of causal evidence suggest a causal relationship between family SES and students' educational outcomes in primary and secondary education, and if so, what is the strength of the causal relationships between SES and educational outcomes?
RQ3: How does the relationship between family SES and educational outcomes vary across countries, different indicators of family SES and various causal inference research designs?

Method

Search Strategy

A systematic search was conducted following PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-analysis Statement) guidelines to identify relevant studies on the relationship between family SES and student educational outcomes, with a focus on establishing causality (Fig. 1 for flow diagram). Following the PRISMA guidelines helps reduce reporting biases in systematic review and ensures that key information about the systematic search, screening, eligibility criteria, and study selection process is clearly documented (Page et al., 2021).

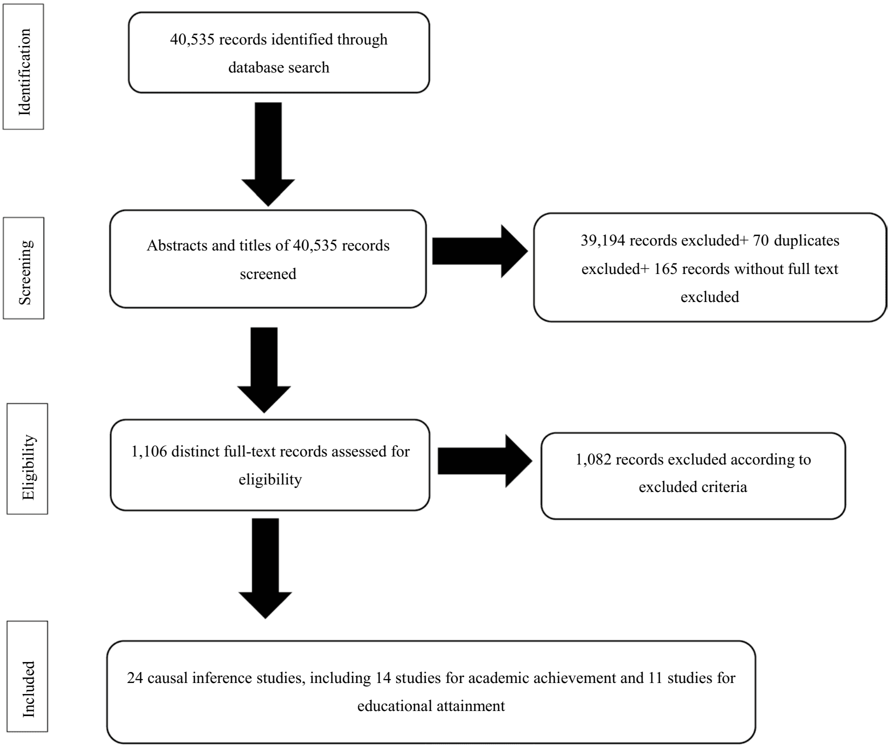

Fig. 1 PRISMA diagram. Note: One study (Cui et al. 2019) in our review reported findings for both educational attainment and academic achievement outcomes

This systematic review was conducted from December 2022 to July 2024. A combination of search strategies was employed to identify relevant scientific studies related to family SES, causal effects, and students' educational outcomes in primary and secondary education (Papaioannou et al., 2010). These included (1) database searches. Three computer databases (Taylor & Francis Online, Web of Science, and ERIC) were selected for identifying the relevant studies, and titles and abstracts of results were reviewed; (2) relevant studies for checking—references of initially selected papers were checked; (3) citation tracking studies—studies citing initially selected papers were identified and reviewed; and (4) exploring Google Scholar—Google Scholar was utilized to identify any other pertinent studies that the above steps may have missed.

The keywords for this systematic search included combinations of terms pertaining to "family SES," "parental education," "parental occupational status," "parental income," "students' educational outcomes," "students' educational attainment," and "students' academic achievement" (see details for the keywords in Table 1). The search process and literature review identified 44,879 potential studies.

Table 1 Search protocol

Database	Web of Science	ERIC	Taylor & Francis Online
Search period	December 2022 to September 2023		
Time span	1990–2023		
Language	English		
Discipline	N	N	Education, social science, economics
Search field	Full text (FT)		
Search terms	("family socioeconomic status" OR "family socio-economic status" OR "Family SES" OR "parental schooling" OR "parental education" OR "mother schooling" OR "mother education" OR "father schooling" OR "father education" OR "family income" OR "parental income" OR "family wealth" OR "parental wealth" OR "household wealth" OR "parental occupational status" OR "parental job" OR "mother occupational status" OR "mother job" OR "maternal occupational status" OR "father occupational status" OR "paternal occupational status" OR "father job" OR "maternal employment" OR "paternal employment" OR "mother job loss" OR "father job loss" OR "maternal job loss" OR "paternal job loss") AND ("educational outcomes" OR "educational attainment" OR "student schooling" OR "student educational level" OR "college enrollment" OR "education enrollment" OR "dropout" OR "academic achievement" OR "academic outcomes" OR "test scores" OR "academic performance" OR "school performance" OR "grade point average" OR "school success" OR "grade retention" OR "school completion" OR "school repetition") AND ("effect*" OR "impact*" OR "influence" OR "causal*")		
Document type	Peer-reviewed articles		
Results	40,535		
Duplicates	70		
Result and final for full-text records assessed for eligibility	1106		
Result and final included in this meta-analysis	24 causal inference records		

Eligibility Criteria

The initial 44,879 causal inference studies were then reviewed to determine whether they should be incorporated into this study. To ensure the quality and relevance of the potential articles, specific inclusion and exclusion criteria were established to guide the search and selection process. Studies were included if they (1) examined causal relationships between family SES and student educational outcomes (academic achievement and educational attainment), (2) sampled K–12 students, (3) used quantitative analytical methods, (4) were published between 1990 and 2023,[1] (5) were restricted to peer-reviewed articles, and (6) were written in English. Studies were excluded if they (1) focused on correlational relationships between SES and educational outcomes rather than on causal inference, (2) sampled preschool, higher education students pursuing a Bachelor's degree and graduate school students, (3) investigated outcomes rather than achievement and attainment, and (4) used qualitative approaches.

After 44,879 titles and abstracts had been screened for causal inference research and those without a full text and duplicate studies had been excluded, 1106 studies were found to meet the inclusion criteria. These studies were read in-depth based on their relevance to the research questions and analytical methodology. Finally, a pool of 24[2] studies from the causal inference search were included in this systematic review (see details on the search process and results in Tables 1 and 2 and Fig. 1). Furthermore, the quality of the 24 selected studies was assessed using Fernandez-Castilla et al.'s (2024) SEMI checklist, which evaluates five dimensions of primary studies in meta-analysis: title and abstract, background, methods, results, and open

[1] This study focuses on the period from 1990 to 2023 for three significant reasons, each reflecting important developments in educational research and policy. First, the 1990s marked a turning point in global education policy, with several high-profile international meetings emphasizing the importance of educational equity. For example, the UNESCO World Conference on Education for All in Jomtien, Thailand (1990) and the World Education Forum in Dakar, Senegal (2000) set the stage for a global commitment to provide quality basic education for all and reduce educational disparities (Liu et al., 2022). These initiatives sparked increased research interest in educational equity, including the role of socioeconomic status in educational outcomes. Second, the period 1990–2023 saw a substantial growth in available international datasets. Large-scale, cross-national educational data collection efforts began to proliferate (Kim et al., 2019), providing researchers with richer resources for analyzing the relationship between SES and educational outcomes across diverse contexts. This expansion of data is evident in previous meta-analyses. For example, Kim et al. (2019) included 49 empirical studies from 1990 to 2017 across 38 developing countries. Third, the period (1990–2023) saw significant advancements in research methodology, particularly in the field of causal inference. Robert LaLonde's influential paper in 1986 set the stage for a new era in causal inference research, highlighting the potential biases in observational studies. Subsequently, the 1990s and early 2000s witnessed rapid developments in causal inference techniques, including propensity score matching (PSM), IV approaches, regression discontinuity designs (RDD), and DID methods. These methodological advancements have significantly improved researchers' ability to estimate causal effects from observational data. In focusing on this timeframe, this study captures the effects of both the increased global focus on educational equity and the methodological improvements in causal inference, allowing us to analyze a body of research that is both policy-relevant and methodologically sophisticated.

[2] One study (Cui et al., 2019) in our review reported findings for both educational attainment and academic achievement outcomes.

Table 2 Overview of the studies

Study characteristics Causal inference	Description	*N*
Outcome types		
Academic achievement and educational attainment in K–12		24
Methods		
I. Children-of-twin studies		1
II. Adoption studies		2
III. IV studies		14
IV. DID		3
V. FE model		9
Indicators of family SES		
Parental education	Parental education level/schooling	14
Parental occupational status	Parental employment/job changes(loss)/parental occupation level	3
Family income/resources	Parental log earnings/family income/an increase in family income/ average parental income/income below/above a certain number	12

N represents the number of studies included in our analysis

science practices. Since all selected studies employed causal inference methods, which inherently demand rigorous methodological and data standards, they met most SEMI checklist requirements (see the complete quality assessment results in Appendix Table 2). In summary, a rigorous systematic search was undertaken to compile relevant high-quality studies investigating the causal relationship between family SES and educational outcomes.

Coding Procedure

A coding protocol was developed to systematically extract and document relevant substantive and methodological information from each study:

- Study characteristics: author(s), publication year, sample, database, country[3]
- Family SES indicators: parental education/schooling, occupational status, family income
- Students' educational outcomes: academic performance (i.e., test scores and GPAs), and educational attainment (i.e., enrollment in and completion of primary and secondary schooling)

[3] The following moderator analysis categorized countries into two types: developed (coded as 1) versus developing countries (coded as 0).

- Method[4] (e.g., difference-in-difference, instrument variables, twin studies, adoption studies, fixed effects)
- Model specifications: the number of causal inference methods employed (e.g., studies using a single causal inference method were coded as 1; studies using two causal inference methods were coded as 2, such as IV + FE)
- Results (e.g., a positive causal relationship between the years of education of adopted children and that of their birth parents (standardized effects = 0.13) and adoptive mothers (= 0.07))

Detailed information coded from each study is presented in Appendix Table 1. The first author coded relevant substantive and methodological information for the included 24 studies. To ensure the accuracy and reliability of the coding process, we employed a two-stage coding procedure. First, the first author thoroughly reviewed each study and coded the relevant details into the standardized coding sheet. Second, the second author independently coded the same studies again using the same protocol. Interrater reliability between the two coders was assessed using Cohen's kappa (κ) (McHugh, 2012), which yielded a score of 0.97, indicating a very high level of agreement.

Meta-analytic Approach

To calculate the overall effect sizes, a random-effects model, which accounts for both within-study and between-study variability, was used. The pooled Cohen's *d* effect sizes and associated 95% confidence intervals for the relationships between SES and academic achievement and educational attainment were reported. Cohen's *d* was used as the effect size measure because it is particularly well-suited for causal inference studies that compare treatment and control groups. It measures the standardized mean difference between two groups, making it an appropriate metric for quantifying the effect of SES (the "treatment") on educational outcomes (Kraft et al., 2018; Liebowitz & Porter, 2019; Rosenthal & DiMatteo, 2001). Furthermore, robust variance estimation (RVE) methods (Hedges et al., 2010; Tanner-Smith & Tipton, 2014) were employed to enhance the accuracy of the model estimates. These methods serve two key purposes. First, they account for varying levels of precision across different studies. Second, they address the non-independence of effect sizes within individual studies, functioning similarly to clustered standard errors. RVE automatically assigns greater weight to effect sizes that demonstrate higher precision (resulting from factors such as larger sample sizes, randomization level, and covariate predictive power), while reducing the influence of studies that contribute multiple effect size estimates (Liebowitz & Porter, 2019). This weighting system

[4] The following moderator analysis categorized the different types of causal inference methods used in the primary studies into five nominal categories. These categories were assigned values from 1 to 5, with the understanding that these numbers do not imply any hierarchical order or magnitude between the categories.

helps ensure a more balanced and accurate meta-analysis. Finally, STATA 17 software was used to conduct the meta-analysis of this study.

Results

This systematic review identified high-quality studies investigating causal relationships between SES and educational outcomes based on Fernandez-Castilla et al.'s (2024) SEMI checklist. The findings are organized into three dimensions: (1) the diverse causal strategies employed to address potential spurious associations between SES and educational outcomes; (2) the overall causal effect size in the relationship between SES and educational outcomes calculated from the publications over the past three decades; (3) the moderating influence on the strength of the SES-outcome relationship.

Research Questions

> **RQ1:** How do different causal methodological approaches address spuriousness in examining the relationship between family SES and educational outcomes in primary and secondary education?

This research question explores how different causal inference methods address spurious associations between SES and educational outcomes. The methods from the selected 24 primary studies are categorized into two main types. One focuses on controlling for spuriousness during data collection, including data collection in children-of-twin and adoption studies, while the other addresses spuriousness during data analysis through methods such as instrumental variables (IV), fixed-effects (FE) models, and difference-in-differences (DID) combined with IV or FE. Moreover, each method has distinct strengths and addresses specific challenges, which will be discussed along with their limitations.

Controlling for Spuriousness in the Data Collection Phase

Children-of-twin studies and adoption studies were included as they represent robust methodological strategies aimed at disentangling the effects of genetic (e.g., inherent abilities) and environmental factors (e.g., family SES) on educational attainment and achievement. Children-of-twin studies compare the offspring of identical twin parents. The children are biological cousins who share 25% of their genes (because their parents are identical twins), but they experience different parental environments (Bonjour et al., 2003; McAdams et al., 2021). This design helps control for genetic factors that run in extended families while examining how differences in parental characteristics (e.g., SES) affect child educational outcomes. Similarly, adoption studies compare the educational outcomes of adopted children with those of their adoptive and biological parents. Adopted children share genes with their biological parents but the environment with their adoptive parents (Haegeland et al., 2010; Sacerdote, 2002). By comparing the educational outcomes of adopted children with those of their adoptive and biological relatives, researchers can differentiate the influence of SES from that of genetic factors.

Therefore, these studies provide robust evidence of the causal effects of SES on educational outcomes to some extent by controlling for spuriousness in the data collection phase. To enhance the rigor and credibility of their findings, researchers often combine these studies with studies using other causal inference methods (e.g., FE) to strengthen the evidence base.

Controlling for Spuriousness in the Data Analysis Phase

In addition to children-of-twin and adoption studies, other causal inference methods, IV, FE, and DID, have been developed to control for unobserved confounders when examining the causal effects of family SES on educational outcomes.

Instrumental Variables (IV)

IV analysis is an econometric technique commonly used in education research to control for unobserved confounding. It isolates variation in SES that is uncorrelated with (orthogonal to) unobservable characteristics that might otherwise influence educational outcomes. For example, Cui et al. (2019) used China's compulsory schooling law (1986–1994) as an exogenous source of changes in mothers' education levels to control for unobserved environmental factors. Løken (2010) employed the Norwegian Oil Boom as an IV to explain parental income while controlling for parental abilities. The prevalence of IV studies in our review (14 primary studies) offered an opportunity to quantitatively assess their collective impact. The results revealed small but significant positive effects of SES on both educational attainment (Cohen's $d = 0.11$, $p < 0.05$) and academic achievement (Cohen's $d = 0.07$, $p < 0.05$) in primary and secondary education while using the IV approach (Table 3). It is crucial to interpret these meta-analytical findings cautiously due to the limited number of primary studies in each analysis, which may affect generalizability and potentially lead to effect size overestimation (Slavin & Smith, 2009). Nonetheless, these results underscore the utility of IV methods in educational research and call for further

Table 3 Results of meta-analyses on effects of family SES on educational outcomes

	No. of independent effect sizes(k)	Effect size		P	Heterogeneity	
		d	95% CI		Q (df)	τ^2
SES-educational attainment	50	0.08	[0.01, 0.15]	0.03*	94.27 (10)	0.01
SES-academic achievement	116	0.03	[−0.01, 0.07]	0.16	34.98 (13)	0.00
IV for academic achievement	60	0.07	[0.02, 0.12]	0.01*	7.54 (6)	0.00
IV for educational attainment	36	0.11	[0.01, 0.22]	0.04*	89.70 (7)	0.02

Note: *$p < .05$, d = mean weighted effect size in Cohen's d

studies employing rigorous IV designs to establish the causal pathways between SES and educational outcomes more definitively.

Fixed Effects (FE)

An FE method, controlling for time-invariant characteristics, is widely employed in the causal relationship between SES and educational outcomes. For example, Wang et al. (2020) used class fixed-effects models to control for unobserved class-level factors that could introduce spurious bias when estimating the causal effect of parental education on children's educational performance. These models work by accounting for time-invariant characteristics within each class, such as teaching quality, classroom environment, or peer influences, which could affect all students in a given class. Haegeland et al. (2010) used a children-of-twins design to separate genetic and environmental influences (e.g., parental education) as cousins whose parents are identical twins who share the same genetic relationship as siblings but are raised in different households. Grandparent fixed effects further controlled for time-invariant characteristics, enabling comparisons of children's educational outcomes based on variations in their parents' education levels.

Difference-in-Differences (DID)

The popularity of DID stems from its ability to simulate experimental conditions using observational data in policy or intervention evaluation settings. When it comes to exploring the causal link between SES and educational outcomes, the DID method is usually combined with IV or FE methods. For example, Piopiunik (2014) combined DID with IV to study how parental education affects their children's educational outcomes. He used education reforms that increased compulsory schooling from 8 to 9 years in West German states between 1946 and 1969 as an instrument to control parents' abilities.

Strengths and Limitations of Various Methods

In studying the causal relationship between SES and educational outcomes, methodologies including children-of-twin, adoption studies, IV analysis, FE models, and DID approaches each offer distinct advantages and constraints. Children-of-twin and adoption studies isolate genetic and environmental influences but face challenges. These include small samples due to the rarity of twins, incomplete control over familial factors, and sample selection issues as adoptive parents generally have higher SES than that of the broader population (Myers & Bölte, 2022; Sahu & Prasuna, 2016; Tan et al., 2020). To address these issues, hybrid designs, such as combining children-of-twin studies with FE models, have been used to account for unobserved time-invariant confounders (Haegeland et al., 2010). Moreover, IV analysis depends on valid instruments and strict assumptions (see IV details in Table 4). For instance, the recurrent use of "raising the minimum school leaving age" as an IV in two studies (Dickson et al., 2016; Silles, 2011) suggests its robustness to some extent, yet also highlights the need for diverse, context-specific instruments. FE models control for stable individual traits in panel data yet neglect time-varying confounders. At the same time, the DID approach simulates experimental conditions using observational data and is particularly useful in policy evaluations, but it relies on the parallel trends assumption and may be susceptible to selection bias.

In conclusion, this systematic review highlights the varying approaches to addressing spuriousness in the causal effects of SES on educational outcomes. By categorizing methods into those that control for spuriousness during data collection and those that focus on data analysis, researchers are able to discern the unique strengths and challenges of each methodology. Understanding these differences is crucial in selecting the most appropriate method depending on the research context, while also recognizing their limitations in providing a comprehensive picture of the influence of family SES on educational outcomes.

RQ2: Does the body of causal evidence suggest a causal relationship between family SES and students' educational outcomes in primary and secondary education, and if so, what is the strength of the causal relationship?

Focusing on the causal relationship between SES and educational attainment, the meta-analysis in this study yielded a pooled effect size of 0.08 standard deviations, as measured by Cohen's *d* (Cohen, 2013; Sawilowsky, 2009). The result indicated that family SES had a small but statistically significant effect on educational attainment in primary and secondary education, according to Cohen's rules of thumb ($d<0.2$ for small, $0.2\leq d<0.5$ for medium, and $d\geq 0.5$ for large effect sizes). This implies that, while family SES influenced educational attainment, this influence was relatively small when examined through the lens of causal studies. Regarding the relationship between family SES and academic achievement, the meta-analysis in this study revealed an overall effect size of Cohen's $d=0.03$ ($p=0.16$). This result suggested an even smaller effect of family SES on achievement than its effect on educational attainment, and the effect was not statistically significant at the conventional level ($p<0.05$) (Table 3).

RQ3: How does the relationship between family SES and students' educational outcomes vary across countries, different indicators of family SES, and various causal inference research designs?

Indicators of Family SES

In the context of academic achievement, this study investigated three key components of SES: parental education, occupational status, and family income. The meta-regression analysis revealed no statistically significant differences in the effects of these indicators (all $ps>0.05$, Table 5). This suggested that different indicators of SES have comparable effects when examined through causal inference methods. For educational attainment, the analysis in this study focused on two components of SES: parental education and family income. We were unable

Table 4 IV studies

	Study	Country	SES	Educational outcome (achievement = 1, attainment = 2)	Sample size	Method
1	Chevalier et al., 2013	UK	Maternal school leaving age	1	8661	IV (raising of school leaving age + month of birth + paternal union status + father workers in a manual job)
1	Chevalier et al., 2013	UK	Maternal school leaving age	1	8137	IV (raising of school leaving age + month of birth + paternal union status + father workers in a manual job)
1	Chevalier et al., 2013	UK	Paternal school leaving age	1	8661	IV (raising of school leaving age + month of birth + paternal union status + father workers in a manual job)
1	Chevalier et al., 2013	UK	Paternal school leaving age	1	8137	IV (raising of school leaving age + month of birth + paternal union status + father workers in a manual job)
1	Chevalier et al., 2013	UK	Paternal log earnings	1	8661	IV (raising of school leaving age + month of birth + paternal union status + father workers in a manual job)
1	Chevalier et al., 2013	UK	Paternal log earnings	1	8137	IV (raising of school leaving age + month of birth + paternal union status + father workers in a manual job)
2	Cui et al., 2019	China	Maternal years of schooling	1	12,887	IV (maternal reform exposure status)
2	Cui et al., 2019	China	Maternal years of schooling	2	6410	IV (maternal reform exposure status)
2	Cui et al., 2019	China	Maternal years of schooling	2	6370	IV (maternal reform exposure status)
2	Cui et al., 2019	China	Maternal years of schooling	1	5230	IV (maternal reform exposure status)

Table 4 (continued)

	Study	Country	SES	Educational outcome (achievement = 1, attainment = 2)	Sample size	Method
3	Gayle et al., 2018	USA	Father has a high school education	1	1332	IV (the sibling sex composition)
3	Gayle et al., 2018	USA	Father has a college education (Incomplete)	1	1332	IV (the sibling sex composition)
3	Gayle et al., 2018	USA	Father has a college education	1	1332	IV (the sibling sex composition)
3	Gayle et al., 2018	USA	Mother has a high school education	1	1332	IV (the sibling sex composition)
3	Gayle et al., 2018	USA	Mother has a college education (incomplete)	1	1332	IV (the sibling sex composition)
3	Gayle et al., 2018	USA	Mother has a college education	1	1332	IV (the sibling sex composition)
3	Gayle et al., 2018	USA	Maternal labor income	1	1332	IV (the sibling sex composition)
3	Gayle et al., 2018	USA	Paternal labor income	1	1332	IV (the sibling sex composition)
4	Løken, 2010	Norway	Family income (1973–1988)	1	330,918	IV (the oil shock in Norway in the 1970s and 1980s)
4	Løken, 2010	Norway	Family income (1968–1970)	1	330,918	IV (the oil shock in Norway in the 1970s and 1981s)
4	Løken, 2010	Norway	College mother	1	330,918	IV (the oil shock in Norway in the 1970s and 1982s)
4	Løken, 2010	Norway	College father	1	330,918	IV (the oil shock in Norway in the 1970s and 1983s)
5	Cheng, 2017	China	Parental years of education	1	3155	IV (deviations of cohort graduation rates from predicted education trends) + FE
6	Piopiunik, 2014	Germany	Maternal (with a basic school degree) schooling	1	2981	DID + IV (compulsory schooling reforms—introduction of the compulsory ninth grade)

Table 4 (continued)

	Study	Country	SES	Educational outcome (achievement = 1, attainment = 2)	Sample size	Method
6	Piopiunik, 2014	Germany	Paternal (with a basic school degree) schooling	1	3108	DID + IV (compulsory schooling reforms—introduction of the compulsory ninth grade)
6	Piopiunik, 2014	Germany	Maternal (with a basic school degree) schooling	1	2755	DID + IV (compulsory schooling reforms—introduction of the compulsory ninth grade)
6	Piopiunik, 2014	Germany	Paternal (with a basic school degree) schooling	1	2799	DID + IV (compulsory schooling reforms—introduction of the compulsory ninth grade)
7	Bastian & Michelmore, 2018	USA	Family income from age 0 to 5	1	3495	IV (Earned Income Tax Credit exposure)
7	Bastian & Michelmore, 2018	USA	Family income from age 6 to 12	1	3495	IV (Earned Income Tax Credit exposure)
7	Bastian & Michelmore, 2018	USA	Family income from age 13 to 18	1	3495	IV (Earned Income Tax Credit exposure)
7	Bastian & Michelmore, 2018	USA	Family income from age 0 to 5	1	2506	IV (Earned Income Tax Credit exposure)
7	Bastian & Michelmore, 2018	USA	Family income from age 6 to 12	1	2506	IV (Earned Income Tax Credit exposure)
7	Bastian & Michelmore, 2018	USA	Family income from age 13 to 18	1	2506	IV (Earned Income Tax Credit exposure)
8	Dumas & Lambert, 2011	Senegal	Paternal highest education level	1	2234	IV (primogeniture status of the parent, the presence of education and health infrastructures accessible to the parents in their childhood)

Table 4 (continued)

	Study	Country	SES	Educational outcome (achievement = 1, attainment = 2)	Sample size	Method
8	Dumas & Lambert, 2011	Senegal	Maternal highest education level	1	2234	IV (primogeniture status of the parent, the presence of education and health infrastructures accessible to the parents in their childhood)
8	Dumas & Lambert, 2011	Senegal	Paternal highest education level	1	2592	IV (primogeniture status of the parent, the presence of education and health infrastructures accessible to the parents in their childhood)
8	Dumas & Lambert, 2011	Senegal	Maternal highest education level	1	2592	IV (primogeniture status of the parent, the presence of education and health infrastructures accessible to the parents in their childhood)
9	Tsai et al., 2011	Taiwan	Maternal schooling years	2	196,156	IV (1968 Educational Reform in Taiwan)
9	Tsai et al., 2011	Taiwan	Paternal schooling years	2	196,156	IV (1968 Educational Reform in Taiwan)
9	Tsai et al., 2011	Taiwan	Maternal schooling years	2	232,857	IV (1968 Educational Reform in Taiwan)
9	Tsai et al., 2011	Taiwan	Maternal schooling years	2	232,759	IV (1968 Educational Reform in Taiwan)
9	Tsai et al., 2011	Taiwan	Maternal schooling years	2	169,911	IV (1968 Educational Reform in Taiwan)
9	Tsai et al., 2011	Taiwan	Maternal schooling years	2	140,027	IV (1968 Educational Reform in Taiwan)
9	Tsai et al., 2011	Taiwan	Maternal schooling years	2	139,272	IV (1968 Educational Reform in Taiwan)

Table 4 (continued)

	Study	Country	SES	Educational outcome (achievement = 1, attainment = 2)	Sample size	Method
9	Tsai et al., 2011	Taiwan	Maternal schooling years	2	109,362	IV (1968 Educational Reform in Taiwan)
9	Tsai et al., 2011	Taiwan	Maternal schooling years	2	103,300	IV (1968 Educational Reform in Taiwan)
9	Tsai et al., 2011	Taiwan	Maternal schooling years	2	102,892	IV (1968 Educational Reform in Taiwan)
9	Tsai et al., 2011	Taiwan	Maternal schooling years	2	67,510	IV (1968 Educational Reform in Taiwan)
9	Tsai et al., 2011	Taiwan	Paternal schooling years	2	232,857	IV (1968 Educational Reform in Taiwan)
9	Tsai et al., 2011	Taiwan	Paternal schooling years	2	232,759	IV (1968 Educational Reform in Taiwan)
9	Tsai et al., 2011	Taiwan	Paternal schooling years	2	169,911	IV (1968 Educational Reform in Taiwan)
9	Tsai et al., 2011	Taiwan	Paternal schooling years	2	140,027	IV (1968 Educational Reform in Taiwan)
9	Tsai et al., 2011	Taiwan	Paternal schooling years	2	139,272	IV (1968 Educational Reform in Taiwan)
9	Tsai et al., 2011	Taiwan	Paternal schooling years	2	109,362	IV (1968 Educational Reform in Taiwan)
9	Tsai et al., 2011	Taiwan	Paternal schooling years	2	103,300	IV (1968 Educational Reform in Taiwan)
9	Tsai et al., 2011	Taiwan	Paternal schooling years	2	102,892	IV (1968 Educational Reform in Taiwan)
9	Tsai et al., 2011	Taiwan	Paternal schooling years	2	67,510	IV (1968 Educational Reform in Taiwan)

Table 4 (continued)

	Study	Country	SES	Educational outcome (achievement = 1, attainment = 2)	Sample size	Method
10	Dahl & Lochner, 2012	USA	Family income	2	8608	IV (simulated changes in the EITC)
10	Dahl & Lochner, 2012	USA	Family income	2	5019	IV (simulated changes in the EITC)
11	Dickson et al., 2016	UK	Maternal schooling years	2	3931	IV (policy of raising of the minimum school leaving age)
11	Dickson et al., 2016	UK	Maternal schooling years	2	3837	IV (policy of raising of the minimum school leaving age)
11	Dickson et al., 2016	UK	Paternal schooling years	2	3931	IV (policy of raising of the minimum school leaving age)
11	Dickson et al., 2016	UK	Paternal schooling years	2	3837	IV (policy of raising of the minimum school leaving age)
12	Duncan et al., 2011	USA, Canada	Family income	2	8073	IV (study program type)
12	Duncan et al., 2011	USA, Canada	Log family income	2	8073	IV (study program type)
12	Duncan et al., 2011	USA, Canada	Family income	2	8073	IV (study sites)
12	Duncan et al., 2011	USA, Canada	Log family income	2	8073	IV (study sites)
13	Silles, 2011	UK	Paternal schooling years	2	7366	Full sample IV (the raising of the minimum school leaving age)
13	Silles, 2011	UK	Maternal schooling years	2	7366	Full sample IV (the raising of the minimum school leaving age)
13	Silles, 2011	UK	Paternal schooling years	2	3472	Discontinuity sample IV (the raising of the minimum school leaving age)
13	Silles, 2011	UK	Maternal schooling years	2	3472	Discontinuity sample IV (the raising of the minimum school leaving age)
14	Naoi et al., 2021	Japan	Family income	2	373	IV (unexpected changes in CAP payments)

Table 5 Results of moderator analyses

Moderators	SES-attainment					SES-achievement				
	k	*β*	*SE*	95% CI	*P*	*k*	*β*	*SE*	95% CI	*P*
Country										
Developing vs. developed countries	50	0.01	0.14	[−0.27, 0.29]	0.93	116	0.15	0.28	[−0.39, 0.70]	0.58
Indicators of SES										
Education vs. income	50	0.30	0.12	[0.07, 0.53]	0.01*	108	−0.28	0.25	[−0.77, 0.21]	0.26
Education vs. occupational status	-	-	-	-	-	88	−0.18	0.47	[−1.10, 0.73]	0.70
Income vs. occupational status	-	-	-	-	-	34	0.11	0.09	[−0.06, 0.28]	0.20
Causal inference research designs										
Causal inference methods	50	0.03	0.05	[−0.08, 0.13]	0.63	116	−0.13	0.11	[−0.35, 0.08]	0.21
Sample sizes	50	0.00	0.00	[−0.00, 0.00]	0.05	116	−0.00	0.00	[−0.00, 0.00]	0.36
Model specifications	50	−0.17	0.21	[−0.58, 0.24]	0.42	116	0.01	0.34	[−0.65, 0.67]	0.98

*$p < .05$; k represents the number of independent effect sizes

to include occupational status due to a lack of primary causal inference studies related to this indicator in the context of primary and secondary education. The findings revealed a significant difference between these two indicators, with parental education demonstrating a stronger effect on students' educational attainment than that of family income ($\beta = 0.30$, $p < 0.05$).

Countries: Developed Versus Developing

Additionally, this study examined the effects of SES on educational outcomes in both developed and developing countries (Table 6). The results showed that the effect of SES on academic achievement was stronger in developing countries ($\beta = 0.06$, $p < 0.05$) compared to developed countries ($\beta = 0.01$), where the relationship was not statistically significant. In terms of educational attainment, the effects of SES were similar in both contexts ($\beta = 0.09$ vs $\beta = 0.08$), although the relationship was more reliable in developing countries. However, since the effect sizes for the relationship between SES and educational outcomes in developing countries were primarily derived from only three studies (i.e., Wang et al. (2020), Cui et al. (2019), and Tsai et al. (2011)), these significant effects should be interpreted with caution. Furthermore, a moderator analysis was conducted to compare the effects of SES in developed versus developing countries. The results in Table 5 indicated no significant differences in these effects for both academic achievement ($\beta = 0.14$, $p = 0.60$) and educational attainment ($\beta = 0.024$, $p = 0.868$) in these different contexts. Overall, these findings suggested that parental education was a stronger predictor of educational attainment than family income, and that, while the magnitude of SES effects may vary, the underlying mechanisms of socioeconomic influence on educational outcomes remain surprisingly consistent across global contexts.

Table 6 Results of meta-analyses on effects of family SES on educational outcomes for developed and developing countries

	No. of independent effect sizes(k)	Effect size		P	Heterogeneity	
		d	95% CI		Q (df)	τ^2
Developed countries						
SES-educational attainment	42	0.09	[−0.04, 0.21]	0.17	40.54 (7)	0.03
SES-academic achievement	68	0.01	[−0.03, 0.06]	0.56	26.28 (10)	0.00
Developing countries						
SES-educational attainment	8	0.08	[0.04, 0.11]	0.00***	4.13 (2)	0.00
SES-academic achievement	48	0.06	[0.04, 0.09]	0.00***	0.49 (2)	0.00

****p < .001*, d = mean weighted effect size in Cohen's d

Causal Inference Research Design: Methodologies, Samples, and Model Specifications

The primary studies synthesized in this meta-analysis employed a diverse range of methodologies, model specifications, and sample characteristics, potentially contributing to heterogeneity in the observed relationships between family SES and educational outcomes (Table 5). To address this potential source of variation and assess the robustness of our findings, we conducted a comprehensive moderator analysis. When all moderators were simultaneously included in the meta-regression model, the results revealed that none of these factors, methodologies, sample sizes, or model specifications had a statistically significant effect on the effect sizes reported in the studies ($ps > 0.05$). The consistency of results across different methodological approaches, sample sizes, and model complexities suggests that our overall findings are robust and not artifacts of specific research designs.

Discussion

Why Researchers Use Particular Methods to Make Causal Inferences on the SES-Educational Outcome Relationship

- This systematic review has identified five primary methods commonly used in establishing causality between SES and educational outcomes: (1) children-of-twin studies, (2) adoption studies, (3) IV, (4) fixed-effects models, and (5) the DID approach with IV or FE. These methods have been categorized into two broader groups based on how they address spuriousness: those controlling for spuriousness in the data collection phase (children-of-twin and adoption studies) and those doing so during the data analysis phase (IV, FE, and DID). The choice of these methods may be driven by two crucial factors: the nature of the research question or hypothesis and practical constraints of data availability.

Regarding the first reason for choosing a method, the method should align with the research question or hypothesis and address the specific SES variable in the context of its relationship with student educational outcomes. For example, adoption studies and children-of-twins designs provide distinct strategies for isolating the non-genetic effects of parental education. By comparing adoptees' outcomes to both their biological parents (who contribute genes but no rearing environment) and adoptive parents (who contribute environment but no direct genes), these studies directly partition genetic and environmental transmission. Children-of-twin design holds genetic transmission constant (via the monozygotic twin parents' identical DNA) while varying environmental factors. When parents are identical twins, their children are genetic cousins (sharing ~25% of genes) but are raised in separate households. Differences in cousins' educational outcomes can then be attributed to environmental SES effects (Björklund et al., 2006; Haegeland et al., 2010). These methods are particularly useful when isolating the causal impact of parental education on children's educational outcomes beyond genetic influences.

In contrast, when investigating the causal effects of parental income or occupational status on children's educational outcomes, the concern regarding genetic transmission is less pronounced. Instead, the main spuriousness issues stem from family characteristics and environments correlated with parental occupational status and family income. Specifically, higher-income families can invest more in education, live in better neighborhoods, send their children to higher-quality schools, and provide other privileges (Duncan et al., 2014; Reardon, 2013). Children's educational outcomes are shaped by these family investments and environments, not just family income per se. Similarly, higher occupational status parents often have greater knowledge and professional skills to support their children's development. Their behaviors, values, and connections also influence children's educational outcomes, above and beyond just occupation status (Chetty et al., 2011; Erola et al., 2016). It is important to note that these methods are not exclusively used for studying income and occupation effects, but are valuable across all SES variables. Moreover, concerning the second reason for choosing a method, the choice may be influenced by the data constraints and research context. Specifically, children-of-twin studies require a sufficient number of twins and adoptees. FE models benefit from greater within-group variation over time. IV relies on the availability of credibly exogenous sources of variation in the SES factor. For example, a study by Carneiro et al. (2013) exploited distance to college as an instrument for examining the effect of parental education on children's educational outcomes. However, this IV strategy relies on specific geographic variances in access to schooling that may not transfer to other settings. Similarly, policy changes (e.g., compulsory schooling laws) provide quasi-experimental variation in parental education, but are not universal across nations and time periods (Currie & Moretti, 2003). Hence, these methods are context-specific and not always available in different studies.

Overall, these approaches help to account for the potential confounders and provide a more accurate and robust assessment of the relationship between SES and educational outcomes. However, the optimal methodology emerges from the interplay between research questions or hypotheses and data availability.

How Family SES Influences Educational Outcomes

The results of meta-analysis showed that family SES had a small yet measurable effect on educational attainment (Cohen's $d = 0.08$, $p < 0.05$), but its association with academic achievement was not statistically significant ($d = 0.03$, $p = 0.17$) (Table 3). These findings represent a paradigm shift in understanding socioeconomic influences on education, suggesting that traditional sociocultural explanations may have overestimated the direct causal impact of SES on educational outcomes. The results of this study align with previous causal research indicating that relations between SES and educational outcomes are much smaller in magnitude than the correlational estimates would imply (Bastian & Michelmore, 2018; O'Connell & Marks, 2022; Tsai et al., 2011). The divergence between correlational and causal findings suggests that many previously observed relations between SES and educational outcomes may have been confounded by other variables, particularly genetic factors. For example, Holmlund et al. (2011) indicated that removing genetic transmission reduced the apparent influence of parental education. Moreover, Marks and O'Connell (e.g., Marks & O'Connell, 2023; Marks & O'Connell, 2021; O'Connell & Marks, 2022) have argued that the intergenerational transmission of abilities, rather than sociological processes tied to SES, is more important for students' academic success.

Furthermore, our moderator analysis revealed no significant differences between parental education, occupational status, and family income in terms of their effects on academic achievement ($ps > 0.05$). However, for educational attainment, parental education showed a significantly stronger effect than that of family income, while occupational status could not be examined due to insufficient primary studies ($p < 0.05$). These findings can be explained by the different nature of these outcomes (academic achievement versus educational attainment). Academic achievement is often measured using standardized tests or grades, which capture performance at specific points in time. In contrast, educational attainment represents a cumulative process that unfolds over several years, allowing for the compounding effects of various SES factors, particularly parental education, to manifest more prominently (Alexander et al., 2007; Dubow et al., 2009). This may be attributed to factors like role modeling, educational expectations, and familiarity with educational systems (Bukodi & Goldthorpe, 2013; Carneiro et al., 2013; Davis-Kean, 2005), which may be more directly linked to parental education than to other SES indicators.

Second, the relationship between SES and educational outcomes remained consistent across different research designs and country contexts. Despite variations in institutional structures and educational systems between developed and developing countries (Soyyiğit, 2019; Vasilyeva et al., 2020), our analysis found no significant differences in results across methodologies, sample sizes, model specifications, or country development levels (all $ps > 0.05$). This consistency strengthens the credibility of our findings, suggesting that the casual SES effects represent genuine relationships rather than artifacts of particular research methods or contexts.

Limitations and Future Studies

It is important to consider some limitations when interpreting the findings of this systematic review. First, this study exclusively focused on English-language publications. This constraint potentially overlooks valuable insights from research conducted and reported in other languages. Future systematic reviews could expand their scope to include studies published in diverse languages, which may enhance the robustness of our results pertaining to the effects of SES on educational outcomes. Second, while this systematic review provides valuable insights into the causal relationship between family SES and educational outcomes, it leaves several critical areas unexplored. This study did not examine whether SES effects change over time or trace the dynamic trajectory of its effect on educational outcomes. Future studies could focus on the dynamic understanding of how SES interacts with educational outcomes across different cohorts and life stages.

Conclusion

Being the first systematic review to provide systematic evidence on the causal relationship between family SES and educational outcomes, this study makes three theoretical and practical contributions. First, it contributes to the ongoing debate on the influence of family SES on students' educational outcomes. The findings of small causal effects ($d = 0.03$ for academic achievement and $d = 0.08$ for educational attainment) challenge the view that positions SES as central to educational stratification. These results suggest that existing theories may overemphasize the direct causal role of SES, neglecting alternative factors such as the transmission of cognitive ability (Marks & O'Connell, 2023; O'Connell & Marks, 2022), and thus invite a critical re-examination of the theoretical foundations underpinning research on the relation between SES and educational outcomes. Furthermore, the moderator analyses in this study revealed that parental education had a stronger effect on educational attainment than that of family income. Additionally, the lack of significant differences in the effects of SES between developed and developing countries, and across various causal inference research designs (i.e., sample size effects, model specification, and methodologies), challenges assumptions about the context-dependent nature of SES influences. These findings suggest a need to differentiate between various components of SES in theoretical frameworks and point towards the existence of more universal mechanisms in the relationship between SES and educational outcomes. Overall, these findings collectively call for a more sophisticated theoretical understanding of how family SES shapes educational outcomes. Third, the findings cast doubt on the likelihood that equalizing SES conditions alone can substantially reduce gaps in educational outcomes. The small causal effects observed in this study provide an explanation for the limited success, or even failure, of policy interventions targeting SES in reducing socioeconomic inequalities over the past few decades (Schnepf et al., 2019).

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Data Availability There are no primary data collected in this systematic review.

Declarations

Conflict of Interest The authors declare no competing interests.

References

Alexander, K. L., Entwisle, D. R., & Olson, L. S. (2007). Lasting consequences of the summer learning gap. *American Sociological Review, 72*(2), 167–180.

Angrist, J. D., & Pischke, J.-S. (2010). The credibility revolution in empirical economics: How better research design is taking the con out of econometrics. *Journal of Economic Perspectives, 24*(2), 3–30.

Bailey, M. J., & Dynarski, S. M. (2011). Inequality in postsecondary education. In G. J. Duncan, & R. J. Murnane (Eds.), *Whither Opportunity?: Rising Inequality, Schools, and Children's Life Chances* (pp. 117–132). Russell Sage.

Bastian, J., & Michelmore, K. (2018). The long-term impact of the earned income tax credit on children's education and employment outcomes. *Journal of Labor Economics, 36*(4), 1127–1163.

Betts J. R., & Tang Y. E. (2014). *A meta-analysis of the literature on the effect of charter schools on student achievement*. Natl. Charter School Res. Proj., Cent. Reinventing Public Educ., Bothell, Univ. Wash.

Betts, J. R., & Tang, Y. E. (2016). A meta-analysis of the literature on the effect of charter schools on student achievement. *Society for Research on Educational Effectiveness*.

Björklund, A., Lindahl, M., & Plug, E. (2006). The origins of intergenerational associations: Lessons from Swedish adoption data. *The Quarterly Journal of Economics, 121*(3), 999–1028.

Bloom, B. S., Engelhart, M. D., Furst, E. J., Hill, W. H., & Krathwohl, D. R. (1956). *Taxonomy of educational objectives: The classification of educational goals. Handbook 1: Cognitive domain* (pp. 1103–1133). New York: Longman.

Bonjour, D., Cherkas, L. F., Haskel, J. E., Hawkes, D. D., & Spector, T. D. (2003). Returns to education: Evidence from UK twins. *American Economic Review, 93*(5), 1799–1812.

Brüderl, J., & Ludwig, V. (2015). Fixed-effects panel regression. In H. Best, & C. Wolf (Eds.), *The Sage handbook of regression analysis and causal inference*, (pp. 327–357). Sage.

Bukodi, E., & Goldthorpe, J. H. (2013). Decomposing 'social origins': The effects of parents' class, status, and education on the educational attainment of their children. *European Sociological Review, 29*(5), 1024–1039.

Calvin, C. M., Deary, I. J., Webbink, D., Smith, P., Fernandes, C., Lee, S. H., Luciano, M., & Visscher, P. M. (2012). Multivariate genetic analyses of cognition and academic achievement from two population samples of 174,000 and 166,000 school children. *Behavior Genetics, 42*, 699–710.

Carneiro, P., Meghir, C., & Parey, M. (2013). Maternal education, home environments, and the development of children and adolescents. *Journal of the European Economic Association, 11*(suppl_1), 123–160.

Chetty, R., Friedman, J. N., Hilger, N., Saez, E., Schanzenbach, D. W., & Yagan, D. (2011). How does your kindergarten classroom affect your earnings? Evidence from Project STAR. *The Quarterly Journal of Economics, 126*(4), 1593–1660.

Chevalier, A., Harmon, C., O'Sullivan, V., & Walker, I. (2013). The impact of parental income and education on the schooling of their children. *IZA Journal of Labor Economics*, *2*, 1–22.

Cohen, J. (2013). *Statistical power analysis for the behavioral sciences*. Academic press.

Conn, K. M. (2017). Identifying effective education interventions in sub-Saharan Africa: A meta-analysis of impact evaluations. *Review of Educational Research, 87*(5), 863–898.

Crawford, C., Goodman, A., & Joyce, R. (2011). Explaining the socio-economic gradient in child outcomes: The inter-generational transmission of cognitive skills. *Longitudinal and Life Course Studies, 2*(1), 77–93.

Cui, Y., Liu, H., & Zhao, L. (2019). Mother's education and child development: Evidence from the compulsory school reform in China. *Journal of Comparative Economics, 47*(3), 669–692.

Currie, J., & Moretti, E. (2003). Mother's education and the intergenerational transmission of human capital: Evidence from college openings. *The Quarterly Journal of Economics, 118*(4), 1495–1532.

Dahl, G. B., & Lochner, L. (2012). The impact of family income on child achievement: Evidence from the earned income tax credit. *American Economic Review, 102*(5), 1927–1956.
Davis-Kean, P. E. (2005). The influence of parent education and family income on child achievement: The indirect role of parental expectations and the home environment. *Journal of Family Psychology, 19*(2), 294.
Dickson, M., Gregg, P., & Robinson, H. (2016). Early, late or never? When does parental education impact child outcomes? *The Economic Journal, 126*(596), F184–F231.
Dubow, E. F., Boxer, P., & Huesmann, L. R. (2009). Long-term effects of parents' education on children's educational and occupational success: Mediation by family interactions, child aggression, and teenage aspirations. *Merrill-Palmer Quarterly (Wayne State University Press), 55*(3), 224.
Dumas, C., & Lambert, S. (2011). Educational achievement and socio-economic background: Causality and mechanisms in Senegal. *Journal of African Economies*, *20*(1), 1–26.
Duncan, G. J., Morris, P. A., & Rodrigues, C. (2011). Does money really matter? Estimating impacts of family income on young children's achievement with data from random-assignment experiments. *Developmental Psychology, 47*(5), 1263.
Duncan, G. J., Magnuson, K., & Votruba-Drzal, E. (2014). Boosting family income to promote child development. *The Future of Children*, *24*(1), 99–120.
Erola, J., Jalonen, S., & Lehti, H. (2016). Parental education, class and income over early life course and children's achievement. *Research in Social Stratification and Mobility, 44*, 33–43.
Erola, J., Lehti, H., Baier, T., & Karhula, A. (2022). Socioeconomic background and gene–environment interplay in social stratification across the early life course. *European Sociological Review, 38*(1), 1–17.
Fernández-Castilla, B., Said-Metwaly, S., Kreitchmann, R. S., & Van Den Noortgate, W. (2024). What do meta-analysts need in primary studies? Guidelines and the SEMI checklist for facilitating cumulative knowledge. *Behavior Research Methods, 56*(4), 3315–3329.
García, S., & Saavedra, J. E. (2017). Educational impacts and cost-effectiveness of conditional cash transfer programs in developing countries: A meta-analysis. *Review of Educational Research, 87*(5), 921–965.
Gayle, G. L., Golan, L., & Soytaş, M. A. (2018). Intergenerational mobility and the effects of parental education, time investment, and income on children's educational attainment. *Federal Reserve Bank of St. Louis Review*, *100*(3), 281–295.
Gibbs, C., Ludwig, J., & Miller, D. L. (2011). *Does Head Start do any lasting good?* (NBER Working Paper No. w17452). National Bureau of Economic Research.
Gregg, P., Macmillan, L., & Nasim, B. (2012). The impact of fathers' job loss during the recession of the 1980s on their children's educational attainment and labour market outcomes. *Fiscal Studies, 33*(2), 237–264.
Guskey, T. R. (2007). Closing achievement gaps: Revisiting Benjamin S. Bloom's "Learning for Mastery." *Journal of Advanced Academics, 19*(1), 8–31.
Haegeland, T., Kirkebøen, L. J., Raaum, O., & Salvanes, K. G. (2010). *Why children of college graduates outperform their schoolmates: A study of cousins and adoptees*. (NHH Dept. of Economics Discussion Paper No. 22/2010). Norwegian School of Economics.
Hanushek, E. A., Peterson, P. E., Talpey, L. M., & Woessmann, L. (2019). The achievement gap fails to close. *Education Next, 19*(3), 8–17.
Hanushek, E. A., Light, J. D., Peterson, P. E., Talpey, L. M., & Woessmann, L. (2022). Long-run trends in the US SES—Achievement gap. *Education Finance and Policy, 17*(4), 608–640.
Harwell, M., Maeda, Y., Bishop, K., & Xie, A. (2017). The surprisingly modest relationship between SES and educational achievement. *The Journal of Experimental Education*, *85*(2), 197–214.
Hedges, L. V., Tipton, E., & Johnson, M. C. (2010). Robust variance estimation in meta-regression with dependent effect size estimates. *Research Synthesis Methods, 1*(1), 39–65.
Holmlund, H., Lindahl, M., & Plug, E. (2011). The causal effect of parents' schooling on children's schooling: A comparison of estimation methods. *Journal of Economic Literature, 49*(3), 615–651.
Hu, Y., Behrman, J. R., & Zhang, J. (2021). The causal effects of parents' schooling on children's schooling in urban China. *Journal of Comparative Economics, 49*(1), 258–276.
Kenny, D. A. (1975). Cross-lagged panel correlation: A test for spuriousness. *Psychological Bulletin, 82*(6), 887.
Kim, S. W., Cho, H., & Kim, L. Y. (2019). Socioeconomic status and academic outcomes in developing countries: A meta-analysis. *Review of Educational Research, 89*(6), 875–916.

Klungel, O., Uddin, M. J., de Boer, A., Belitser, S., Groenwold, R., & Roes, K. (2015). Instrumental variable analysis in epidemiologic studies: An overview of the estimation methods. *Pharmaceutica Analytica Acta, 6*(353), 2.

Kraft, M. A., Blazar, D., & Hogan, D. (2018). The effect of teacher coaching on instruction and achievement: A meta-analysis of the causal evidence. *Review of Educational Research, 88*(4), 547–588.

Lechner, M. (2011). The estimation of causal effects by difference-in-difference methods. *Foundations and Trends® in Econometrics, 4*(3), 165–224.

Lee, J. J., Wedow, R., Okbay, A., Kong, E., Maghzian, O., Zacher, M., Nguyen-Viet, T. A., Bowers, P., Sidorenko, J., & KarlssonLinnér, R. (2018). Gene discovery and polygenic prediction from a genome-wide association study of educational attainment in 1.1 million individuals. *Nature genetics, 50*(8), 1112–1121.

Liebowitz, D. D., & Porter, L. (2019). The effect of principal behaviors on student, teacher, and school outcomes: A systematic review and meta-analysis of the empirical literature. *Review of Educational Research, 89*(5), 785–827.

Liu, J., Peng, P., & Luo, L. (2020). The relation between family socioeconomic status and academic achievement in China: A meta-analysis. *Educational Psychology Review*, *32*, 49–76.

Liu, J., Peng, P., Zhao, B., & Luo, L. (2022). Socioeconomic status and academic achievement in primary and secondary education: A meta-analytic review. *Educational Psychology Review, 34*(4), 2867–2896.

Løken, K. V. (2010). Family income and children's education: Using the Norwegian oil boom as a natural experiment. *Labour Economics*, *17*(1), 118–129.

Lucas, S. R. (2001). Effectively maintained inequality: Education transitions, track mobility, and social background effects. *American Journal of Sociology, 106*(6), 1642–1690.

Malanchini, M., Allegrini, A. G., Nivard, M. G., Biroli, P., Rimfeld, K., Cheesman, R., von Stumm, S., Demange, P. A., van Bergen, E., & Grotzinger, A. D. (2024). Genetic associations between noncognitive skills and academic achievement over development. *Nature Human Behaviour, 8*(10), 2034–2046.

Marks, G. N. (2016). The relative effects of socio-economic, demographic, non-cognitive and cognitive influences on student achievement in Australia. *Learning and Individual Differences, 49*, 1–10.

Marks, G. N., & O'Connell, M. (2023). The importance of parental ability for cognitive ability and student achievement: Implications for social stratification theory and practice. *Research in Social Stratification and Mobility, 83*, 100762.

Marks, G. N., & O'Connell, M. (2021). Inadequacies in the SES–achievement model: Evidence from PISA and other studies. *Review of Education, 9*(3), e3293.

McAdams, T. A., Rijsdijk, F. V., Zavos, H. M., & Pingault, J.-B. (2021). Twins and causal inference: Leveraging nature's experiment. *Cold Spring Harbor Perspectives in Medicine, 11*(6), a039552.

McHugh, M. L. (2012). Interrater reliability: The kappa statistic. *Biochemia Medica, 22*(3), 276–282.

Michelmore, K. (2013). *The effect of income on educational attainment: Evidence from state earned income tax credit expansions*. SSRN Electronic Journal.

Morgan, S. L., & Winship, C. (2014). *Counterfactuals and causal inference: Methods and principles for social research*. Cambridge University Press.

Murnane, R. J., & Willett, J. B. (2010). *Methods matter: Improving causal inference in educational and social science research*. Oxford University Press.

Myers, L., & Bölte, S. (2022). Guest editorial: Overview, implications, and directions of twin design research exploring neurodevelopmental conditions. *JCPP Advances, 2*(4), e12121.

Naoi, M., Akabayashi, H., Nakamura, R., Nozaki, K., Sano, S., Senoh, W., & Shikishima, C. (2021). Causal effects of family income on educational investment and child outcomes: Evidence from a policy reform in Japan. *Journal of the Japanese and International Economies*, *60*, 101122.

Nguyen, T. T., Tchetgen, E. J. T., Kawachi, I., Gilman, S. E., Walter, S., Liu, S. Y., Manly, J. J., & Glymour, M. M. (2016). Instrumental variable approaches to identifying the causal effect of educational attainment on dementia risk. *Annals of Epidemiology, 26*(1), 71–76.

O'Connell, M., & Marks, G. N. (2022). Cognitive ability and conscientiousness are more important than SES for educational attainment: An analysis of the UK Millennium Cohort Study. *Personality and Individual Differences, 188*, 111471.

OECD. (2017). PISA 2015 technical report. Retrieved from https://www.oecd.org/pisa/data/2015-technical-report/PISA2015_TechRep_Final.pdf

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., & Brennan, S. E. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *International Journal of Surgery, 88*, 105906.
Pan, W., & Ost, B. (2014). The impact of parental layoff on higher education investment. *Economics of Education Review, 42*, 53–63.
Papaioannou, D., Sutton, A., Carroll, C., Booth, A., & Wong, R. (2010). Literature searching for social science systematic reviews: Consideration of a range of search techniques. *Health Information & Libraries Journal, 27*(2), 114–122.
Piopiunik, M. (2014). Intergenerational transmission of education and mediating channels: Evidence from a compulsory schooling reform in Germany. *The Scandinavian Journal of Economics*, *116*(3), 878–907.
Pronzato, C. (2012). An examination of paternal and maternal intergenerational transmission of schooling. *Journal of Population Economics, 25*, 591–608.
Reardon, S. F. (2013). The widening income achievement gap. *Educational Leadership, 70*(8), 10–16.
Rege, M., Telle, K., & Votruba, M. (2011). Parental job loss and children's school performance. *The Review of Economic Studies, 78*(4), 1462–1489.
Rodriguez-Hernandez, C. F., Cascallar, E., & Kyndt, E. (2020). Socio-economic status and academic performance in higher education: A systematic review. *Educational Research Review, 29*, 100305.
Rosenthal, R., & DiMatteo, M. R. (2001). Meta-analysis: Recent developments in quantitative methods for literature reviews. *Annual Review of Psychology, 52*(1), 59–82.
Ruiz-Valenzuela, J. (2020). Job loss at home: Children's school performance during the Great Recession. *Series, 11*(3), 243–286.
Sacerdote, B. (2002). The nature and nurture of economic outcomes. *American Economic Review, 92*(2), 344–348.
Sahu, M., & Prasuna, J. G. (2016). Twin studies: A unique epidemiological tool. *Indian Journal of Community Medicine, 41*(3), 177–182.
Sawilowsky, S. S. (2009). New effect size rules of thumb. *Journal of Modern Applied Statistical Methods, 8*, 597–599.
Scheeren, L., Das, M., & Liefbroer, A. C. (2017). Intergenerational transmission of educational attainment in adoptive families in the Netherlands. *Research in Social Stratification and Mobility, 48*, 10–19.
Schnepf, S. V., Klinger, D. A., Volante, L., & Jerrim, J. (2019). Cross-national trends in addressing socioeconomic inequality in education. In L. Volante, S. Schnepf, J. Jerrim, & D. Klinger (Eds.), *Socioeconomic inequality and student outcomes: Cross-national trends, policies, and practices*, (pp. 207–223). Springer.
Selvitopu, A., & Kaya, M. (2021). A meta-analytic review of the effect of socioeconomic status on academic performance. *Journal of Education, 203*(4), 768–780.
Silles, M. A. (2011). The effect of schooling on teenage childbearing: Evidence using changes in compulsory education laws. *Journal of Population Economics, 24*, 761–777.
Sirin, S. R. (2005). Socioeconomic status and academic achievement: A meta-analytic review of research. *Review of Educational Research, 75*(3), 417–453.
Slavin, R., & Smith, D. (2009). The relationship between sample sizes and effect sizes in systematic reviews in education. *Educational Evaluation and Policy Analysis, 31*(4), 500–506.
Song, Q., & Tan, C. Y. (2022). The association between family socioeconomic status and urban–rural and high-school attainment gaps: A logistic regression analysis of the China Family Panel Studies data. *British Educational Research Journal, 48*(6), 1102–1124.
Soyyiğit, S. (2019). A comparative analysis of causality between institutional structure and economic performance for developed and developing countries. *Montenegrin Journal of Economics*, *15*(3), 37–51.
Steinmayr, R., Meiṅer, A., Weideinger, A. F., & Wirthwein, L. (2014). *Academic achievement*. Oxford University Press.
Stevens, A. H., & Schaller, J. (2011). Short-run effects of parental job loss on children's academic achievement. *Economics of Education Review, 30*(2), 289–299.
Sullivan, A. (2001). Cultural capital and educational attainment. *Sociology, 35*(4), 893–912.
Tan, T. X., Yi, Z., & Camras, L. A. (2020). High family SES and youth adjustment: The case of Chinese youth who were adopted from orphanages into American families. *Children and Youth Services Review, 110*, 104784.

Tsai, W.-J., Liu, J.-T., Chou, S.-Y., & Grossman, M. (2011). *Intergenerational transfer of human capital: Results from a natural experiment in Taiwan* (NBER Working Paper No. w 16876). National Bureau of Economic Research.
Vasilyeva, T., Bilan, S., Bagmet, K., & Seliga, R. (2020). Institutional development gap in the social sector: Crosscountry analysis. *Economics & Sociology*, *13*(1), 271–294.
Wang, W., Dong, Y., Liu, X., Bai, Y., & Zhang, L. (2020). The effect of parents' education on the academic and non-cognitive outcomes of their children: Evidence from China. *Children and Youth Services Review, 117*, 105307.
Zhao, N., Valcke, M., Desoete, A., & Verhaeghe, J. (2012). The quadratic relationship between socioeconomic status and learning performance in China by multilevel analysis: Implications for policies to foster education equity. *International Journal of Educational Development, 32*(3), 412–422.

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No.	Study	Country	SES (Detail)	Academic achievement (Detail)	Sample size	Method (causal)	Estimates	Standard error
1	Cui et al., 2019	China	Maternal schooling years	Math test scores	6,410	IV	0.127	0.06
1	Cui et al., 2019	China	Maternal schooling years	Word test scores	6,370	IV	0.062	0.06
2	Dahl & Lochner, 2012	US	Family income	Combined math and reading scores	8,608	IV	0.061	0.0231
2	Dahl & Lochner, 2012	US	Family income	Reading recognition scores	8,608	IV	0.0359	0.0195
2	Dahl & Lochner, 2012	US	Family income	Reading comprehension scores	8,608	IV	0.0613	0.0273
2	Dahl & Lochner, 2012	US	Family income	Math scores	8,608	IV	0.0582	0.0273
2	Dahl & Lochner, 2012	US	Family income	Normalized average of math and reading scores	5,019	IV	0.0889	0.0598
3	Dickson et al., 2017	UK	Maternal schooling years	English language GCSE	3,931	IV	0.802	0.394
3	Dickson et al., 2017	UK	Maternal schooling years	Mathematics GCSE	3,837	IV	1.135	0.477
3	Dickson et al., 2017	UK	Paternal schooling years	English language GCSE	3,931	IV	1.199	0.434
3	Dickson et al., 2017	UK	Paternal schooling years	Mathematics GCSE	3,837	IV	1.770	0.524
4	Duncan et al., 2010	US, Canada	Family income	Parent or teacher report or test scores (Picture vocabulary test, bracken basic concept scale, math, reading)	8,073	IV	0.003	0.043
4	Duncan et al., 2010	US, Canada	Log family income	Parent or teacher report or test scores (Picture vocabulary test, bracken basic concept scale,	8,073	IV	0.032	0.411

				math, reading)				
4	Duncan et al., 2010	US, Canada	Family income	Parent or teacher report or test scores (Picture vocabulary test, bracken basic concept scale, math, reading)	8,073	IV	0.062	0.035
4	Duncan et al., 2010	US, Canada	Log family income	Parent or teacher report or test scores (Picture vocabulary test, bracken basic concept scale, math, reading)	8,073	IV	0.539	0.316
5	Hægeland et al., 2010	Norway	Maternal years of schooling	Scores of Mathematics, Norwegian or English	588	(Grandparent) FE	0.037	0.003
5	Hægeland et al., 2010	Norway	Paternal years of schooling	Scores of Mathematics, Norwegian or English	588	(Grandparent) FE	0.043	0.003
5	Hægeland et al., 2010	Norway	Log family income	Scores of Mathematics, Norwegian or English	588	(Grandparent) FE	0.133	0.014
5	Hægeland et al., 2010	Norway	Maternal years of schooling	Scores of Mathematics, Norwegian or English	588	(Grandparent) FE	0.051	0.003
5	Hægeland et al., 2010	Norway	Paternal years of schooling	Scores of Mathematics, Norwegian or English	588	(Grandparent) FE	0.041	0.003
5	Hægeland et al., 2010	Norway	Log family income	Scores of Mathematics, Norwegian or English	588	(Grandparent) FE	0.121	0.014
5	Hægeland et al., 2010	Norway	Maternal years of schooling	Scores of Mathematics, Norwegian or English	588	Adoptee	0.022	0.011
5	Hægeland et al., 2010	Norway	Paternal years of schooling	Scores of Mathematics, Norwegian or English	588	Adoptee	0.019	0.014
5	Hægeland et al., 2010	Norway	Log family income	Scores of Mathematics,	588	Adoptee	0.081	0.092

				Norwegian or English				
5	Hægeland et al., 2010	Norway	Maternal years of schooling	Scores of Mathematics, Norwegian or English	588	Twin mothers, grandparent FE	-0.004	0.021
5	Hægeland et al., 2010	Norway	Paternal years of schooling	Scores of Mathematics, Norwegian or English	588	Twin mothers, grandparent FE	0.034	0.015
5	Hægeland et al., 2010	Norway	Log family income	Scores of Mathematics, Norwegian or English	588	Twin mothers, grandparent FE	0.272	0.107
5	Hægeland et al., 2010	Norway	Maternal years of schooling	Scores of Mathematics, Norwegian or English	588	Twin fathers, grandparent FE	0.091	0.017
5	Hægeland et al., 2010	Norway	Paternal years of schooling	Scores of Mathematics, Norwegian or English	588	Twin fathers, grandparent FE	0.042	0.022
5	Hægeland et al., 2010	Norway	Log family income	Scores of Mathematics, Norwegian or English	588	Twin fathers, grandparent FE	0.022	0.122
6	Rege et al., 2011	Norway	Plant Closure in Father's Plant non-booming municipality (Father job loss)	GPA of the 11 graduating subjects	10,344	FE (Industry and school)	-0.1207	0.0272
6	Rege et al., 2011	Norway	Plant Closure in Father's Plant booming municipality (Father job loss)	GPA of the 11 graduating subjects	10,344	FE (Industry and school)	0.0051	0.033
7	Ruiz-Valenzuela, 2020	Spain	Father job loss	Student's average scores of 3 years	890	FE	-0.147	0.062
8	Sacerdote, 2002	UK	Paternal occupation Level	Southgate reading score	128	Adoptee	0.314	0.194

8	Sacerdote, 2002	UK	Paternal schooling years	Southgate Reading score	81	Adoptee	0.159	0.300
8	Sacerdote, 2002	UK	Paternal occupation level	NFER reading test	107	Adoptee	0.334	0.081
8	Sacerdote, 2002	UK	Paternal schooling years	NFER reading test	81	Adoptee	0.110	0.338
8	Sacerdote, 2002	UK	Paternal occupation level	NFER math test	107	Adoptee	0.600	0.132
8	Sacerdote, 2002	UK	Paternal schooling years	NFER math test	81	Adoptee	0.084	0.449
8	Sacerdote, 2002	US	SES index from CAP (including salary and status)	PIAT reading score	117	Adoptee	0.008	0.0046
8	Sacerdote, 2002	US	Maternal schooling years	PIAT reading score	180	Adoptee	-0.108	0.281
9	Silles, 2011	UK	Paternal schooling years	Math score percentile ranking	7,366	IV	0.637	2.551
9	Silles, 2011	UK	Paternal schooling years	Math score percentile ranking	7,366	IV	0.556	2.447
9	Silles, 2011	UK	Paternal schooling years	Math score percentile ranking	7,366	IV	-1.573	2.466
9	Silles, 2011	UK	Maternal schooling years	Math score percentile ranking	7,366	IV	-2.907	2.047
9	Silles, 2011	UK	Maternal schooling years	Math score percentile ranking	7,366	IV	0.736	1.930
9	Silles, 2011	UK	Maternal schooling years	Math score percentile ranking	7,366	IV	1.882	1.959
9	Silles, 2011	UK	Paternal schooling years	Math score percentile ranking	3,472	IV	3.542	2.615
9	Silles, 2011	UK	Paternal schooling years	Math score percentile ranking	3,472	IV	4.476	2.483
9	Silles, 2011	UK	Paternal schooling	Math score percentile ranking	3,472	IV	3.036	2.445

			years					
9	Silles, 2011	UK	Maternal schooling years	Math score percentile ranking	3,472	IV	-1.552	2.420
9	Silles, 2011	UK	Maternal schooling years	Math score percentile ranking	3,472	IV	3.622	2.270
9	Silles, 2011	UK	Maternal schooling years	Math score percentile ranking	3,472	IV	3.106	2.244
10	Wang et al., 2020	China	Paternal education level	Chinese score	16,104	FE (Class fixed effects)	0.077	0.011
10	Wang et al., 2020	China	Paternal education level	Math score	16,098	FE (Class fixed effects)	0.072	0.011
10	Wang et al., 2020	China	Paternal education level	English score	16,100	FE (Class fixed effects)	0.081	0.011
10	Wang et al., 2020	China	Paternal education level	Self-reported academic achievement	16,457	FE (Class fixed effects)	0.127	0.013
10	Wang et al., 2020	China	Maternal education level	Chinese score	16,104	FE (Class fixed effects)	0.024	0.011
10	Wang et al., 2020	China	Maternal education level	Math score	16,098	FE (Class fixed effects)	0.030	0.011
10	Wang et al., 2020	China	Maternal education level	English score	16,100	FE (Class fixed effects)	0.042	0.011
10	Wang et al., 2020	China	Maternal education level	Self-reported academic achievement	16,457	FE (Class fixed effects)	0.088	0.013
10	Wang et al., 2020	China	Paternal education level	Chinese score	15,294	FE (Class fixed effects model after considering student ability)	0.068	0.011
10	Wang et al., 2020	China	Paternal education level	Math score	15,289	FE (Class fixed effects model after considering student ability)	0.063	0.012
10	Wang et al., 2020	China	Paternal education level	English score	15,289	FE (Class fixed effects model after considering student ability)	0.076	0.011

10	Wang et al., 2020	China	Paternal education level	Self-reported academic achievement	15,624	FE (Class fixed effects model after considering student ability)	0.119	0.014
10	Wang et al., 2020	China	Maternal education level	Chinese score	15,294	FE (Class fixed effects model after considering student ability)	0.018	0.011
10	Wang et al., 2020	China	Maternal education level	Math score	15,289	FE (Class fixed effects model after considering student ability)	0.022	0.012
10	Wang et al., 2020	China	Maternal education level	English score	15,289	FE (Class fixed effects model after considering student ability)	0.034	0.011
10	Wang et al., 2020	China	Maternal education level	Self-reported academic achievement	15,624	FE (Class fixed effects model after considering student ability)	0.075	0.014
11	Naoi et al., 2021	Japan	Family income	Japanese test score	373	IV	-0.0491	0.1035
11	Naoi et al., 2021	Japan	Family income	Math test score	373	IV	0.1003	0.1171
11	Naoi et al., 2021	Japan	Family income	Combined test score	373	IV	0.0256	0.0762
12	Tsai et al., 2011	Taiwan	Maternal schooling years	Chinese February competency test scores	196,156	IV	0.019	0.01
12	Tsai et al., 2011	Taiwan	Maternal schooling years	English February competency test scores	196,156	IV	0.028	0.02
12	Tsai et al., 2011	Taiwan	Maternal schooling years	Math February competency test scores	196,156	IV	0.080	0.02
12	Tsai et al., 2011	Taiwan	Maternal schooling years	Social science February competency test scores	196,156	IV	0.067	1.97
12	Tsai et al., 2011	Taiwan	Maternal schooling years	Natural science February competency test scores	196,156	IV	0.034	0.09

12	Tsai et al., 2011	Taiwan	Maternal schooling years	Total February competency test scores	196,156	IV	0.209	0.08
12	Tsai et al., 2011	Taiwan	Paternal schooling years	Chinese February competency test scores	196,156	IV	0.009	0.01
12	Tsai et al., 2011	Taiwan	Paternal schooling years	English February competency test scores	196,156	IV	0.081	0.02
12	Tsai et al., 2011	Taiwan	Paternal schooling years	Math February competency test scores	196,156	IV	0.094	0.02
12	Tsai et al., 2011	Taiwan	Paternal schooling years	Social science February competency test scores	196,156	IV	-0.090	0.01
12	Tsai et al., 2011	Taiwan	Paternal schooling years	Natural science February competency test scores	196,156	IV	0.047	0.08
12	Tsai et al., 2011	Taiwan	Paternal schooling years	Total February competency test scores	196,156	IV	0.110	0.07
12	Tsai et al., 2011	Taiwan	Maternal schooling years	Chinese July JCEE scores	232,857	IV	-0.243	4.05
12	Tsai et al., 2011	Taiwan	Maternal schooling years	English July JCEE scores	232,759	IV	-1.476	0.17
12	Tsai et al., 2011	Taiwan	Maternal schooling years	Math (b) July JCEE scores	169,911	IV	0.661	0.22
12	Tsai et al., 2011	Taiwan	Maternal schooling years	History July JCEE scores	140,027	IV	0.378	0.08
12	Tsai et al., 2011	Taiwan	Maternal schooling years	Geography July JCEE scores	139,272	IV	0.296	0.11
12	Tsai et al., 2011	Taiwan	Maternal schooling years	Math (a) July JCEE scores	109,362	IV	-0.535	0.12
12	Tsai et al., 2011	Taiwan	Maternal schooling years	Chemistry July JCEE scores	103,300	IV	-0.248	0.08
12	Tsai et al., 2011	Taiwan	Maternal schooling years	Physics July JCEE scores	102,892	IV	0.143	0.19
12	Tsai et al., 2011	Taiwan	Maternal schooling	Biology July JCEE scores	67,510	IV	-0.067	0.08

			years					
12	Tsai et al., 2011	Taiwan	Paternal schooling years	Chinese July JCEE scores	232,857	IV	0.643	5.36
12	Tsai et al., 2011	Taiwan	Paternal schooling years	English July JCEE scores	232,759	IV	2.681	0.18
12	Tsai et al., 2011	Taiwan	Paternal schooling years	Math (b) July JCEE scores	169,911	IV	1.071	0.19
12	Tsai et al., 2011	Taiwan	Paternal schooling years	History July JCEE scores	140,027	IV	0.314	0.08
12	Tsai et al., 2011	Taiwan	Paternal schooling years	Geography July JCEE scores	139,272	IV	0.078	0.11
12	Tsai et al., 2011	Taiwan	Paternal schooling years	Math (a) July JCEE scores	10,362	IV	1.017	0.09
12	Tsai et al., 2011	Taiwan	Paternal schooling years	Chemistry July JCEE scores	103,300	IV	1.131	0.09
12	Tsai et al., 2011	Taiwan	Paternal schooling years	Physics July JCEE scores	102,892	IV	1.284	0.18
12	Tsai et al., 2011	Taiwan	Paternal schooling years	Biology July JCEE scores	67,510	IV	0.817	0.08
13	Elstad & Bakken, 2015	Norway	Full sample log family income	GPA score (Oral and written Norwegian, mathematics, science and environment, oral and written English, social studies, physical education, religion and ethics, arts and craft, music, and home economics)	230,517	Sibling FE	0.059	0.018
13	Elstad & Bakken, 2015	Norway	Full sample relative income (Percentiles)	GPA score (Oral and written Norwegian, mathematics, science and environment, oral and written	230,517	Sibling FE	-0.0001	0.0003

				English, social studies, physical education, religion and ethics, arts and craft, music, and home economics)				
13	Elstad & Bakken, 2015	Norway	Income below 60% of median (Absolute income)	GPA score (Oral and written Norwegian, mathematics, science and environment, oral and written English, social studies, physical education, religion and ethics, arts and craft, music, and home economics)	11,515	Sibling FE	0.17	0.041
13	Elstad & Bakken, 2015	Norway	Income 60-90% of median (Absolute income)	GPA score (oral and written Norwegian, mathematics, science and environment, oral and written English, social studies, physical education, religion and ethics, arts and craft, music, and home economics)	60,787	Sibling FE	-0.044	0.053
13	Elstad & Bakken, 2015	Norway	Income 90-120% of median (Absolute income)	GPA score (Oral and written Norwegian, mathematics, science and environment, oral and written English, social studies, physical education, religion and ethics, arts and craft, music, and home economics)	86,179	Sibling FE	-0.012	0.046

13	Elstad & Bakken, 2015	Norway	Income 120%+ of median (Absolute income)	GPA score (Oral and written Norwegian, mathematics, science and environment, oral and written English, social studies, physical education, religion and ethics, arts and craft, music, and home economics)	72,036	Sibling FE	0.048	0.026
13	Elstad & Bakken, 2015	Norway	Income below 60% of median (Relative income)	GPA score (Oral and written Norwegian, mathematics, science and environment, oral and written English, social studies, physical education, religion and ethics, arts and craft, music, and home economics)	11,515	Sibling FE	0.008	0.0045
13	Elstad & Bakken, 2015	Norway	Income 60-90% of median (Relative income)	GPA score (Oral and written Norwegian, mathematics, science and environment, oral and written English, social studies, physical education, religion and ethics, arts and craft, music, and home economics)	60,787	Sibling FE	-0.0009	0.0007
13	Elstad & Bakken, 2015	Norway	Income 90-120% of median (Relative income)	GPA score (Oral and written Norwegian, mathematics, science and environment, oral and written	86,179	Sibling FE	0	0.0004

				English, social studies, physical education, religion and ethics, arts and craft, music, and home economics)				
13	Elstad & Bakken, 2015	Norway	Income 120%+ of median (Relative income)	GPA score (Oral and written Norwegian, mathematics, science and environment, oral and written English, social studies, physical education, religion and ethics, arts and craft, music, and home economics)	72,036	Sibling FE	0.0009	0.0006
14	Sabates & Duckworth, 2010	UK	Maternal schooling years	Math score	1,180	FE (Mixed effect---random and fixed effects)	0.029	0.011
14	Sabates & Duckworth, 2010	UK	Maternal schooling years	Reading score	1,180	FE (Mixed effect---random and fixed effects)	-0.01	0.094
14	Sabates & Duckworth, 2010	UK	Maternal schooling years	Boy math score	588	FE (Mixed effect---random and fixed effects)	0.036	0.016
14	Sabates & Duckworth, 2010	UK	Maternal schooling years	Girl math score	587	FE (Mixed effect---random and fixed effects)	0.021	0.014

```
* Replication file for: Effects of family socioeconomic status on educational
outcomes in primary and secondary education: A systematic review of the causal
evidence
* Version: Stata 17.0

* Required packages
fre from http://fmwww.bc.edu/repec/bocode/f
gtools from http://github.com/mcaceresb/stata-gtools
R libraries: haven, ggplot2, estimatr
labmask from http://www.stata-journal.com/software/sj8-2/
missings from http://fmwww.bc.edu/repec/bocode/m
rsource from http://fmwww.bc.edu/RePEc/bocode/r
schemepack from http://fmwww.bc.edu/repec/bocode/s
vioplot from http://fmwww.bc.edu/RePEc/bocode/v

* Please set your directory in line 16 and line 116
cd "[set directory]"
set scheme gg_tableau

***************************************************************************

// Source: authors' own data extraction
ssc install metafunnel
ssc install schemepack, replace

********SES-academic achievement************

clear
// import delimited "data/extraction_data.xlsx"

import excel "data/Achievement data.xlsx", sheet("data") firstrow clear

destring Estimates Standarderror, force replace

save "data/dataone.dta", replace

*****************************************************************
*main effects
*****************************************************************
clear
use "data/dataone.dta"

* average effect size and standard errors across studies
collapse Estimates Standarderror (sum) sample_size, by(study)

* set meta analysis variables
meta set  Estimates Standarderror, random studylab(study) studysize(sample_size)

* forest plot
meta forest _id _plot _esci _weight, xline(0, lw(thin) lc(cranberry)) ///
            sort(es) ciopts(lc(black) mlc(black) mfc(black) lw(medium)) ///
            markeropts(mc("31 119 180")) omarkeropts(mc(cranberry)) ///
            body(size(huge)) coltit(size(huge)) plotr(c(white) ic(white)) ///
            xlabel(-1(1)5, labs(medlarge)) xmtick(-1(0.5)5) xscale(line) ///
            name(forest, replace) tdistribution

graph export "out/forest.pdf", replace

********************************************************************
*moderator analysis
********************************************************************
clear
use "data/dataone.dta"
```

```
*developed versus developing countries
reg Estimates developing_versus_developed, robust cl(study)
mixed Estimates developed_versus_developing || study:

*indicators of SES
reg Estimates education_versus_income, robust cl(study)
mixed Estimates education_versus_income || study:

reg Estimates education_versus_income, robust cl(study)
mixed Estimates education_versus_income || study:

reg Estimates income_versus_occuptaion, robust cl(study)
mixed Estimates education_versus_income || study:

*causal inference research designs
reg Estimates causal_inference_methods sample_size model_speficications, robust
cl(study)
mixed Estimates causal_inference_methods sample_size model_speficications ||
study:


********SES-educational attainment************

clear
// import delimited "data/extraction_data.xlsx"

import excel "data/Attainment data.xlsx", sheet("data") firstrow clear

destring Estimates Standarderror, force replace

save "data/dataone.dta", replace

*****************************************************************
*main effects
*****************************************************************
clear
use "data/dataone.dta"

* average effect size and standard errors across studies
collapse Estimates Standarderror (sum) sample_size, by(study)

* set meta analysis variables
meta set  Estimates Standarderror, random studylab(study) studysize(sample_size)

* forest plot
meta forest _id _plot _esci _weight, xline(0, lw(thin) lc(cranberry)) ///
            sort(es) ciopts(lc(black) mlc(black) mfc(black) lw(medium)) ///
            markeropts(mc("31 119 180")) omarkeropts(mc(cranberry)) ///
            body(size(huge)) coltit(size(huge)) plotr(c(white) ic(white)) ///
            xlabel(-1(1)5, labs(medlarge)) xmtick(-1(0.5)5) xscale(line) ///
            name(forest, replace) tdistribution

graph export "out/forest.pdf", replace

********************************************************************
*moderator analysis
********************************************************************
clear
use "data/dataone.dta"

*developed versus developing countries
reg Estimates developing_versus_developed, robust cl(study)
mixed Estimates developed_versus_developing || study:
```

```
*indicators of SES
reg Estimates education_versus_income, robust cl(study)
mixed Estimates education_versus_income || study:

*causal inference research designs
reg Estimates causal_inference_methods sample_size model_speficications, robust cl(study)
mixed Estimates causal_inference_methods sample_size model_speficications || study:
```

No.	Study	Country	SES (Detail)	Academic achievement (Detail)	Sample size	Method (causal)	Estimates	Standard error
1	Chevalier et al., 2013	UK	Maternal school leaving age	Sons stay in post-compulsory schooling	8,661	IV	0.011	0.037
1	Chevalier et al., 2013	UK	Maternal school leaving age	Daughters stay in post-compulsory schooling	8,137	IV	0.001	0.034
1	Chevalier et al., 2013	UK	Paternal school leaving age	Sons stay in post-compulsory schooling	8,661	IV	0.028	0.036
1	Chevalier et al., 2013	UK	Paternal school leaving age	Daughters stay in post-compulsory schooling	8,137	IV	0.07	0.035
1	Chevalier et al., 2013	UK	Paternal log earnings	Sons stay in post-compulsory schooling	8,661	IV	0.157	0.066
1	Chevalier et al., 2013	UK	Paternal log earnings	Daughters stay in post-compulsory schooling	8,137	IV	-0.031	0.06
2	Cui et al., 2019	China	Maternal years of schooling	Children's school enrollment	12,887	IV	0.05	0.017
2	Cui et al., 2019	China	Maternal years of schooling	Children's school enrollment (16–19 years)	5,230	IV	0.11	0.037
3	Gayle et al., 2018	US	Maternal labor income	Children have a high school education	1,332	IV	-0.0277	0.0087
3	Gayle et al., 2018	US	Paternal labor income	Children have a high school education	1,332	IV	0.0011	0.0025
4	Løken, 2010	Norway	Family income (1973–1988)	Children's level of education	330,918	IV	-0.4286	0.3143
4	Løken, 2010	Norway	Family income (1968–1970)	Children's level of education	330,918	IV	0.0279	0.0122
4	Løken, 2010	Norway	College mother	Children's level of education	330,918	IV	1.3844	0.0746
4	Løken, 2010	Norway	College father	Children's level of education	330,918	IV	1.5791	0.0904
5	Michelmore, 2013	US	Family income (Maximum	Children's high school graduation	81,724	DDD, FE	0.003	0.003

			federal and state EITC benefit)					
5	Michelmore, 2013	US	Family income (Maximum federal and state EITC benefit)	Children's high school graduation	51,374	DDD, FE	0.005	0.003
5	Michelmore, 2013	US	Family income (Maximum federal and state EITC benefit)	Children's high school graduation	97,123	DDD, FE	0.015	0.004
6	Cheng, 2017	China	Parental years of education	Children completed junior high school	3,155	IV, FE	0.0594	0.00716
6	Cheng, 2017	China	Parental years of education	Children completed senior high school	3,155	IV, FE	0.0676	0.00956
7	Piopiunik, 2014	Germany	Mother with a secondary school degree	Sons obtain at least a middle school degree	4,647	DID	0.078	0.039
7	Piopiunik, 2014	Germany	Father with a secondary school degree	Daughters obtain at least a middle school degree	4,677	DID	0.003	0.035
7	Piopiunik, 2014	Germany	Mother with a secondary school degree	Sons obtain at least a middle school degree	4,486	DID	-0.01	0.034
7	Piopiunik, 2014	Germany	Father with a secondary school degree	Daughters obtain at least a middle school degree	4,511	DID	-0.021	0.031
7	Piopiunik, 2014	Germany	Maternal (With a basic school degree) schooling	Sons obtain at least a middle school degree	2,981	DID, IV	0.335	0.155
7	Piopiunik, 2014	Germany	Paternal (With a basic school degree) schooling	Daughters obtain at least a middle school degree	3,108	DID, IV	0.037	0.106
7	Piopiunik, 2014	Germany	Maternal (With a basic school degree) schooling	Sons obtain at least a middle school degree	2,755	DID, IV	0.056	0.139
7	Piopiunik,	Germany	Paternal	Daughters obtain at	2,799	DID, IV	-0.117	0.099

	2014		(With a basic school degree) schooling	least a middle school degree				
8	Akee et al., 2010	US	Mother has a high school degree/GED	Years of completed child's education at age 21	1,045	DID	0.557	0.399
8	Akee et al., 2010	US	Mother has a high school degree/GED	The probability of a child being a high school graduate by age 19	1,060	DID	0.103	0.051
8	Akee et al., 2010	US	Mother has a high school degree/GED	Children have a high school or a general equivalency degree	1,060	DID	0.079	0.034
8	Akee et al., 2010	US	Father has a high school degree/GED	Years of completed children's education at age 21	1,045	DID	−0.164	0.396
8	Akee et al., 2010	US	Father has a high school degree/GED	The probability of a child being a high school graduate by age 19	1,060	DID	0.001	0.067
8	Akee et al., 2010	US	Father has a high school degree/GED	Children have a high school or a general equivalency degree	1,060	DID	0.026	0.044
8	Akee et al., 2010	US	Mother has more than a high school degree	Years of completed children's education at age 21	1,045	DID	0.924	0.367
8	Akee et al., 2010	US	Mother has more than a high school degree	The probability of a child being a high school graduate by age 19	1,060	DID	0.117	0.058
8	Akee et al., 2010	US	Mother has more than a high school degree	Children have a high school or a general equivalency degree	1,060	DID	0.129	0.045
8	Akee et al., 2010	US	Father has more than a high school degree	Years of completed children's education at age 21	1,045	DID	0.757	0.306
8	Akee et al., 2010	US	Father has more than a high school degree	The probability of a child being a high school graduate by age 19	1,060	DID	0.053	0.056
8	Akee et al., 2010	US	Father has more than a high school degree	Children have a high school or a general equivalency degree	1,060	DID	0.051	0.04
9	Bastian &	US	Family	Children graduate	3,495	IV	-0.0001	0.0013

	Michelmore, 2018		income from age 0 to 5	from high school				
9	Bastian & Michelmore, 2018	US	Family income from age 6 to 12	Children graduate from high school	3,495	IV	-0.0017	0.001
9	Bastian & Michelmore, 2018	US	Family income from age 13 to 18	Children graduate from high school	3,495	IV	0.0021	0.0011
9	Bastian & Michelmore, 2018	US	Family income from age 0 to 5	Children complete the highest grade	2,506	IV	0.0024	0.0061
9	Bastian & Michelmore, 2018	US	Family income from age 6 to 12	Children complete the highest grade	2,506	IV	-0.0009	0.0059
9	Bastian & Michelmore, 2018	US	Family income from age 13 to 18	Children complete the highest grade	2,506	IV	0.0101	0.0045
10	Salminen & Lehti, 2023	Finland	Family income	Children's general secondary enrollment	624,658	FE	0.0061	0.0069
11	Dumas & Lambert, 2011	Senegal	Paternal education	The probability of children having ever been going to school	2,234	IV	0.0794	0.019
11	Dumas & Lambert, 2011	Senegal	Maternal education	The probability of children having ever been going to school	2,234	IV	0.0011 6	0.0191
11	Dumas & Lambert, 2011	Senegal	Paternal education	Children's final level of education	2,592	IV	0.423	0.102
11	Dumas & Lambert, 2011	Senegal	Maternal education	Children's final level of education	2,592	IV	0.219	0.0956

Table X.

The quality assessment of included studies

	Cui et al., 2019	Dahl &Lochner, 2012	Dickson et al., 2017	Duncan et al., 2010	Hægeland et al., 2010	Rege et al., 2011	Ruiz-Valenzuela, 2020	Sacerdote, 2002	Silles, 2011	Wang et al., 2020	Naoi et al., 2021	Tsai et al., 2021	Elstad&Bakken, 2015	Sabates&Duckworth,2010	Chevalier et al., 2013	Gayle et al., 2018	Løken, 2010	Michelmore, 2013	Cheng, 2017	Piopiunik&Marc, 2011	Akee et al., 2010	Bastian& Michelmore, 2018	Salminen and Lehti, 2023	Dumas& Lambert, 2010
Title and abstract																								
1. The key concepts, constructs, and variables under investigation are clearly mentioned in the title and/or abstract.																								
	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
2. The abstract gives relevant details about the study objectives, methods, and results.																								
	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Background																								
3. Relevant literature (including reviews and meta-analyses) is summarized and clearly cited.																								
	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Methods																								
4. The sample size, including that of the entire sample and each subsample, is reported. The number of missing values is given for each variable, and the sample size used for each analysis is reported. In the case of longitudinal studies, the sample size at each time point is reported.																								
	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
5. Statistics describing participant characteristics (e.g., proportion identifying as men, mean age, proportion of sample by race/ ethnicity), study context and procedures that may (substantially) influence the studied effects are reported.																								
	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
6. Other publications based on the same data, or a portion thereof, are clearly cited.																								
	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

7. There is a description of how each variable is operationally defined and measured.																							
Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
8. Details of how the measurement tools are administered and scored are provided, together with a measure of reliability on the current sample.																							
Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
9. Details of the type of study design (e.g., correlational, comparative, or experimental) are provided, possibly together with a bibliographic source for further details.																							
Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
10. Details of the study procedures are provided, including where, how, and when data are collected.																							
Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
11. There is a description of how data categories are defined or how continuous variables are categorized. When reporting data from a subsample, details on subsample descriptions and selection criteria subsample are provided.																							
Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
12. Details of the data-analytic methods used are provided (e.g., statistical tests, model fitted, estimation procedure, software, options chosen, significance level, whether the test is two-sided or one-sided, degrees of freedom, how cluster data are handled if needed, and whether missing data imputation methods were used and which ones).																							
Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
13. A risk of bias assessment tool is consulted to ensure the inclusion of all methodological details required for evaluating the study's risk of bias.																							
Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Results																							
14. For categorical variables, frequencies of all categories are reported for the final sample and relevant subgroups, after removing dropouts. When studying the association between categorical variables, a cross-tabulation is provided with disaggregated frequencies.																							
Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
15. For quantitative variables, means and standard deviations are provided for the whole sample and relevant subgroups.																							
Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
16. For nested data structures, information on the intraclass correlation coefficient, the between-clusters variance, and the pooled within-cluster variance is reported.																							
NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
17. The correlation matrix between all quantitative variables under investigation is reported. When missing data are imputed, correlations based on the original incomplete data are provided.																							

Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
18. For longitudinal studies, the timing of measurements and the correlation between subsequent measures are reported, also for any relevant subgroup																							
NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
19. Test statistics and associated p-values (and degrees of freedom where relevant) are reported, also for negative findings.																							
Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
20. Effect sizes related to the research questions are presented along with (references to) the corresponding formulas used for their calculation.																							
Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
21. The results are reported in sufficient detail and clarity, following the description of the analyses in the methods-section (e.g., following the same order).																							
Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
22. The results presented in the text align with those depicted in the tables and figures.																							
Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
23. Tables and figures are appropriately labeled, understandable and referred to in the text.																							
Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Open science practices																							
24. A statement indicating the availability and location of raw study data (and if applied of the protocol or registered report) is provided.																							
Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
25. If a protocol or registered report was developed before the investigation, it is clarified how the investigation deviates from the initial planning.																							
NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
26. A codebook explaining the variables in the dataset is provided.																							
NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
27. Relevant codes/syntax that reproduce the analyses are provided.																							
NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	Y	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
28. Additional information or materials that could enhance understanding of methods or results are included in appendices or supplementary materials.																							
Y	Y	Y	N	Y	Y	Y	Y	Y	Y	Y	N	N	N	N	N	Y	Y	N	N	Y	Y	N	Y

Note: Y = Yes; N = No; NA = Not applicable.