Reducing socioeconomic disparities in STEM opportunities? Trends in access to advanced science and math courses in American high schools, 1992-2013

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Citation: Han, S.W., Kang, C., & Weis, L. (2024). Reducing socioeconomic disparities in STEM opportunities? Trends in access to advanced science and math courses in American high schools, 1992-2013. *Journal of Education for Students Placed at Risk (JESPAR)*, 1-38.
https://dx.doi.org/10.1080/10824669.2024.2398435

Abstract

High school science and math courses play a vital role in STEM opportunities and long-term labor market outcomes. Research on STEM inequality often focuses on gender and racial disparities, with less attention paid to socioeconomic inequalities in course-taking. Analyzing nationally representative data from 1992, 2004, and 2013 graduates, we find similar patterns of socioeconomic inequality in both science and mathematics subjects. Disparities persist in high-level courses, such as calculus, physics 2, chemistry 2, or biology 2, while gaps in mid-level courses, such as chemistry 1 and algebra 2, have lessened over time. Although both low- and high-SES students in the early 2010s take more advanced courses compared to their counterparts in the 1990s and early 2000s, high-SES students are more likely to do so. Moreover, even with efforts to increase and broaden access, disparities between socioeconomically advantaged and disadvantaged schools in advanced STEM course-taking have grown. Socioeconomic disparities in high school STEM courses continue to impact STEM opportunities for US students.

Keywords
Course-taking, science, math, high schools, SES, educational inequality, STEM

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This research was supported by the NSF, DGE#1660402, Effects of State Policy on High School Science, Technology, Engineering, and Mathematics (STEM) Opportunities and Outcomes for Low-Income Underrepresented Minorities, to Dr. Lois Weis (principal investigator) and Dr. Seong Won Han (co–principal investigator).

Acknowledgements:

We would like to acknowledge the generosity of Alan Schoenfeld, Jim Ryan, Phil Daro, and Amanda Simmons who guided and weighed in on our classification scheme. Their expertise in this area allowed us to make thoughtful decisions as we reduced the number of mathematics and science categories. Thanks to Margaret Eisenhart and her team, whose prior work on an NSF funded project with Lois Weis helped to highlight the importance of this subsequent study. We would also like to thank Barbara Means, Laura Perna, and Barbara Schneider for their feedback on our work. Thanks also to Dr. Jolene Jesse, our previous program officer, and to our current project program officer, Dr. Andrea Nixon, for her continuing support. Thanks also to Dr. Rachel Dominguez, project team member, for her participation in aspects of this manuscript. The paper is substantially improved by virtue of this collective attention. The opinions expressed are those of the authors and do not represent views of the National Science Foundation.

Conflict of Interest

The authors declare that they have no potential conflict of interest.

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INTRODUCTION

Educational attainment in STEM is one lever that can increase economic advantages and career opportunities for disadvantaged students (Arcidiacono, 2004). To be prepared for particular kinds of STEM majors in postsecondary education, it is critical for students to successfully reach a certain level of high school science and math courses, such as calculus or advanced physics (Adelman, 2006; Bottia et al., 2015; Bromberg & Theokas, 2016; Kaliski & Godfrey, 2014), although recent research challenges this, revealing that there is no consistent set of core-subject courses to STEM and that high grades across all subjects may hold more significance (Bowers et al., 2022).

Over the past three decades, educational policies in the United States have attempted to improve student achievement and reduce inequality through standards-based education reform and test-driven accountability policy (Domina et al., 2016; Domina & Saldana, 2012; National Science Board., 2012; Zhang, 2009). Recently, there has been a shift towards employing alternative approaches. California, for instance, approved the 2023 Mathematics Framework for California Public Schools, aiming at equity and excellence in math learning. It allows schools to choose between traditional or integrated pathways. Traditional follows the sequence of courses typically offered by many high schools (algebra 1- geometry-algebra 2-advanced courses (precalculus, statistics and probability, calculus, and AP probability and statistics)), while integrated blends standards from multiple domains, like algebra, geometry, and intermediate algebra in integrated math I (California Department of Education., 2013).

With the growing significance of science and math courses on educational attainment, numerous studies on STEM education have examined inequalities in high school math achievement and patterns of course-taking (e.g., Crosnoe & Schneider, 2010; Domina & Saldana, 2012; Riegle-Crumb, 2006; Riegle-Crumb & Grodsky, 2010; Rodriguez, 2018) and science achievement and patterns of course-taking (e.g., Posselt et al., 2012; Riegle-Crumb & Moore, 2014; Tyson et al., 2007). While many studies have investigated gender and racial/ethnic inequalities in science and math course-taking patterns (Bottia et al., 2021; Riegle-Crumb & Grodsky, 2010; Riegle-Crumb & Moore, 2014; Rodriguez & McGuire, 2019), surprisingly few studies, to date, have examined socioeconomic inequalities in science course-taking patterns (Bottia et al., 2022). High SES students make up a disproportionate percentage of those obtaining STEM degrees and pursuing STEM careers (Chen, 2009; Chen & Soldner, 2014). Completing advanced science and math courses remains one of the strongest predictors of students' pursuit of postsecondary STEM degrees (Adelman, 2006; Bottia et al., 2015; Tyson et al., 2007). Generally, low SES students are less likely to experience consistent upward moves in course-taking throughout their high school years (Eisenhart & Weis, 2022; Han et al., 2024; Han et al., 2023)~~(Han et al., 2023; Eisenhart & Weis, 2022)~~. As a consequence, their chances of enrolling in advanced courses are diminished (Domina & Saldana, 2012; Tyson et al., 2007).

Here we examine socioeconomic inequality in high school science and math course-taking. Specifically, we extend the research on inequality in high school course-taking by examining whether, and the extent to which, SES-based inequalities in science course-taking have changed over time. In addition, we extend prior research on mathematics course-taking patterns by examining a recent nationally representative high school cohort dataset and comparing science course-taking with mathematics course-taking. Particularly, we focused on inequalities in top science and mathematics course-taking patterns (i.e., calculus, biology 2, chemistry 2, or physics 2). We use three nationally representative high school cohort datasets, the National Educational Longitudinal Study of 1988 (NELS:88), the Educational Longitudinal Study of 2002 (ELS:2002), and the High School Longitudinal Study of 2009 (HSLS:09). While inequalities in course-taking patterns are stratified by race and gender as well as social class, here we focus specifically on changes in targeted SES-based inequalities in science and math course-taking patterns. Prior research has shown that SES-based inequalities in education have widened over the past two decades and continue to do so (Bowen et al., 2009; Gamoran, 2015; Reardon, 2011; Thomas & Bell, 2008).

Our contribution is twofold. First, our study addresses the above noted void in the literature by examining *trends* in SES-based inequalities in science course-taking patterns. Many studies have investigated disparities in science course-taking patterns by gender, race/ethnicity and sexual minority status, using mainly one cohort dataset (Bottia et al., 2021; Gottfried et al., 2015; Riegle-Crumb & Moore, 2014), but there is a dearth of research, to date, on changes in SES-based inequalities in science course-taking patterns over time specifically.

Second, our study empirically tests whether or not there is heterogeneity in SES-based inequality patterns across science and mathematics. One may assume that mathematics and science are neighboring disciplines and have similar course-taking patterns; students follow ~~hierarchal~~ hierarchical sequences from less to more difficult courses in both instances. Unlike mathematics, however, high school science coursework consists of a number of sub-disciplines (e.g., biology, chemistry, and physics). In this sense, completion of any given science course *does not necessarily* indicate readiness for another. For example, completion of chemistry 1 indicates that a student is ready for chemistry 2 in high school, but completion of chemistry 1 does not necessarily indicate readiness for physics 1. In science, one sub-discipline is not necessarily more difficult than another sub-discipline (Montgomery et al., 2010), although students' perceived difficulty varies across science sub-disciplines (Williams et al., 2003). Nor is learning from one sub-discipline necessarily a prerequisite for learning in another sub-discipline. Thus, individual schools or school systems may organize their science pathways differently (Montgomery et al., 2010). For example, a student can take either chemistry 1–physics 1 sequence, or alternatively, physics 1–chemistry 1 sequence.

Interdependence between math and science also varies, with advanced physics and chemistry requiring math completion (e.g., in AP physics 1, completion of geometry or concurrent enrollment into algebra 2 or an equivalent course), unlike other sciences such as AP biology (The College Board, n.d.). This leads to differing levels of math involvement and prerequisites among science disciplines, leading to variation in inequality across science subdisciplines. In this study, we examine *empirically* if, and the extent to which, inequalities in course-taking patterns vary across science and mathematics, and if so, for whom they vary.

1. LITERATURE REVIEW

While the importance of postsecondary credentials has been increasingly foregrounded for employment outcomes in the context of today's technology and knowledge-based economy (e.g., Hout, 2012), studies illuminate how families and students from advantaged backgrounds support their children's transition from K-12 to higher education through various mechanisms, perpetuating educational inequality in the United States (Andrew, 2017; Roksa et al., 2007). We explored four significant bodies of literature that informed our examination of trends in socioeconomic inequality in course-taking patterns: (a) the connection between family socioeconomic status (SES) and course-taking; (b) the influence of school SES (mainly defined by average student SES or average parental educational attainment levels in each school) on course-taking; (c) theories elucidating the persistent socioeconomic inequality in educational outcomes; and (d) the analysis of national trends in high school course-taking through utilization of large-scale national educational datasets.

2.1. Socioeconomic inequality in science and math course-taking

In the United States, while a larger number of students now pursue higher education, admissions, particularly at the most selective colleges and universities, have grown fiercely competitive (Roksa et al., 2007). This intensifying competition has heightened anxiety and fear among privileged students and families, who strive to secure admission to prestigious institutions in pursuit of enhanced long-term economic and social opportunities (Hout, 2012). Scholars closely examine the influence of high schools and the strategies employed by parents and students to position themselves for future advantages through attendance at particularly located postsecondary institutions (e.g., Weis et al., 2014; Crosnoe & Muller, 2014). Such meticulous management of academic preparation in high schools is crucial for understanding the persistent inequalities evident in course-taking patterns in the United States.

Research suggests that completion of advanced science and math courses can affect students' future educational attainments, facilitating their access to and graduation from particular located postsecondary destinations (Adelman, 2006). Furthermore, exposure to ~~a~~ more advanced math courses in high school has long-term labor market implications, particularly regarding overall employment and employment in STEM fields (Black et al., 2021). To be prepared for specific STEM majors in postsecondary education, successfully completing advanced math and science courses in high school—for example, calculus and advanced science courses (chemistry 2, physics 2, various advanced science topics), and Advanced~~ment~~ Placement (AP) and International Baccalaureate (IB) courses— is often crucial (Adelman, 2006; Hinojosa et al., 2016; Maltese & Tai, 2011; Tyson et al., 2007). However, recent research challenges this notion, indicating that there isn't a consistent set of core-subject courses to STEM, and high grades across all subjects may hold greater significance (Bowers et al., 2022).

A substantial body of important research has examined effects of student socioeconomic background and that of the school they attend as contextual variables in creating significant and persistent inequalities in educational outcomes (Crosnoe & Muller, 2014; Harris, 2010; Palardy, 2013). Previous studies documented that socioeconomically disadvantaged students are more likely to start high school in lower-level math courses compared to their more privileged peers and less likely to reach high-level math courses at the end of high school, even after taking into account their prior math and science learning experiences (Crosnoe & Schneider, 2010; Kelly, 2009; Riegle-Crumb, 2006). Prior research also indicates that inequalities in advanced science and mathematics course-taking affect students' postsecondary enrollment patterns as well as STEM pathways–from high school to college to career (Bottia et al., 2015; Posselt et al., 2012; Riegle-Crumb & King, 2010; Rodriguez, 2018; Sadler et al., 2014; Tyson et al., 2007).

Family SES directly and indirectly influences students' high school course-taking in science and mathematics. For example, socioeconomically privileged parents understand both what colleges are looking for and college admission processes. They activate their own cultural, social, and economic capital~~s~~ to create distinction wherever and whenever possible in the postsecondary admissions process, with the distinct goal of attaining entrance to particularly located high status postsecondary destinations (e.g., Weis et al., 2014; Crosnoe & Muller, 2014). To maintain their competitive edge in an increasingly competitive college admissions process and beyond, students from socioeconomically advantaged groups increasingly seek distinction, and are encouraged to seek distinction by their parents and the schools they attend, by taking the most challenging courses available (Nikischer, 2013; Weis et al., 2014). Additionally, socioeconomically advantaged students and parents often enroll in multiple math and science courses concurrently by recognizing the value placed on advanced math courses regardless of their eventual choice of STEM major or not. When completion in algebra 2 is near saturation, for instance, students from advantaged groups might complete the highest level of science courses as well as the highest level of math (i.e., calculus) (Domina & Saldana, 2012). Socioeconomically privileged parents also monitor grades of their children over their secondary school career, standing ready and willing to pay for private tutoring if students show any hint of failing, or simply falling behind in one or more courses (Weis et al., 2014).

2.2. School-level socioeconomic composition and educational inequality

Several studies have shown that various school-level factors contribute to stratification in students' math and science course-taking patterns (e.g., Kelly, 2009; Riegle-Crumb & Grodsky, 2010; Vaval et al., 2019). Attention has been given to the socioeconomic composition of schools as one of the mechanisms for perpetuating social reproduction and educational inequality (Chetty et al., 2022a, 2022b; Palardy, 2013; Rumberger & Palardy, 2005). With growing levels of income inequality in the United States, socioeconomic segregation in schools, patterns of friendship, and in neighborhoods, has increased (Mijs & Roe, 2021; Owens et al., 2016; Reardon & Owens, 2014). Prior studies found~~find~~ that the average socioeconomic level of students' schools, net of the effects of student background, influences their educational outcomes, including achievement in mathematics and science, high school graduation, and college enrollment (Konstantopoulos, 2006; Palardy, 2013; Rumberger & Palardy, 2005). Additionally, school socioeconomic composition in early educational trajectories has cumulative effects on students' later educational outcomes (Langenkamp & Carbonaro, 2018). However, another study found~~finds~~ that school SES effects on student achievement scores nearly vanish after controlling for a student's prior achievement (Armor et al., 2018).

School socioeconomic composition effects can be explained by several factors, such as school resources, teacher quality, school practices that emphasize academics, and peer influences, among others (Harris, 2010; Palardy, 2013; Rumberger & Palardy, 2005). Using a longitudinal national data set, NELS:88, Rumberger and Palardy (2005) found the average socioeconomic level of students' schools had as much impact on their achievement growth as their own socioeconomic status across various subjects, including mathematics, science, reading, and history, after accounting for other background factors. Moreover, they investigated three potential explanatory factors–structural features of schools, school resources, and school processes (policies and practices)–to understand why the impact of socioeconomic composition was consistent across both advantaged and disadvantaged students. They attributed this impact to four key school characteristics: the availability of rigorous courses, teacher expectations, the amount of homework assigned, and students' perceptions of safety.

Another possible explanatory factor linked to why school SES composition matters is in fact that students can gain valuable academic information from their friends, including the number of rigorous courses that students take (Crosnoe & Muller, 2014; Rumberger & Palardy, 2005). Using a nationally representative sample of seventh through twelfth grade from Add Health data, for example, Crosnoe and Muller (2014) found~~ind~~ that exposure to school-based socioeconomically advantaged groups differentiate students' enrollment in advanced coursework at the start of high school and that this initial disparity was firmly maintained across high school years. Their accompanying ethnographic data from a single high school reveal that students with socioeconomically advantaged parents value the diverse portfolios in coursework and have more information about the relative weights of grades, core courses, and electives in college going, whereas students with socioeconomically disadvantaged parents plan to drop out of math or science. When students receive academically relevant information from parents and peers with socioeconomically advantaged parents, students typically think that persisting in such advanced coursework is a necessity.

Beyond high school course-taking behaviors, cross-class friendships influence upward mobility later in life (Chetty et al., 2022a, 2022b). Chetty et al. (2022b) found that the social disconnection across socioeconomic lines is explained by differences in exposure to people with high SES in groups such as schools with resultant differences in the likelihood that an individual will interact with a high SES individual, given the opportunity. Despite the importance of cross-class friendship in schools, schools tend to become more socioeconomically segregated over the years (Chetty et al., 2022b; Konstantopoulos, 2006; Mijs & Roe, 2021; Owens et al., 2016), which serves to limit opportunities to build cross-class friendships in schools. This school segregation is attributable to rising income segregation between districts in the United States, particularly among affluent families (Mijs & Roe, 2021; Owens et al., 2016). This implies that inequalities between schools in completion of advanced math and science courses, net of student background characteristics, may be exacerbated over time.

Recent studies have also explored the interaction between family and school socioeconomic composition, investigating whether the effect of school socioeconomic composition varies across different student characteristics (Perry et al., 2022). Using Australian cross-sectional nationally representative data, Perry et al. (2022) found that the effect of school SES on the average student's achievement is greater when the student's SES is higher, a finding consistent across reading, math and science. It should be noted that this study did not take into account students' prior achievement due to limitations of cross-sectional data. Extending these studies using longitudinal datasets can enhance our theoretical understanding of how school SES influences student outcomes differently. Such research can contribute to debates on whether reducing school segregation can be beneficial and for whom.

2.3. Effectively maintained inequality (EMI) in high school course-taking

In addressing persistent educational inequalities, educational policies in the United States have sought to promote excellence and reduce educational disparities through standards-based reform and test-driven accountability over the past several decades. These efforts have included initiatives such as raising high school graduation requirements and introducing high school graduation tests, all aimed at equalizing learning opportunities, particularly in advanced science and math coursework (Domina et al., 2016; Domina & Saldana, 2012; National Science Board., 2012; Zhang, 2009). However, there have been recent shifts towards employing different approaches such as eliminating high school graduation test requirements and/or opening additional pathways beyond traditional standards-based course-taking sequences in California (Sublett & Rumberger, 2018).

In the last thirty years, course-credit graduation requirements in science and math increased over the past three decades (National Science Board., 2012). Bromberg and Theokas (2016) examined transcript data from the HSLS:09, which follows a nationally representative group of ninth graders from 2009 through 2013. They found that three in 10 graduates completed a minimum of three years of mathematics, including algebra 2, and three years of science, including biology and either chemistry or physics, which is aligned with entry requirements at many public four-year universities (Conforti, 2013; Rodriguez, 2018).

Some advocates for curricular intensification believe that increases in science and math requirements at high schools and accompanying push into advanced science and math courses will make students become academically more capable and reduce inequality in educational outcomes and attainments over time. But notions of *effectively maintained inequality* (EMI), would drive a hypothesis that inequality in the highest level of math and science courses will be maintained or exacerbated rather than diminished.

EMI (Lucas, 2001; S. Lucas & D. Byrne, 2017) theory observes that all educational outcomes have two dimensions: a quantitative dimension (e.g., the number of years of education obtained) and a qualitative dimension (e.g., the program of study pursued). EMI contends that if quantitative differences are common, the socioeconomically advantaged will work to obtain qualitative advantage. In other words, it is possible that even when quantitative outcomes are equalized, or quantitative advantage is impossible, socioeconomically advantaged individuals and/or families will strategically use their socioeconomic advantages so as to secure *qualitatively* different outcomes. In other words, they will activate and deploy a range of capitals at their disposal in a now intensified drive for *qualitative distinction*. Thus, the notion of EMI suggests that equalizing quantity will be insufficient to undermine educational inequality. When the locus of consequential inequality in education shifted from the quantitative to the qualitative dimension, it is important to focus on inequality in qualitative dimensions of education.

Applying this EMI theory of inequality to math and science course-taking patterns in education, the qualitative dimension can refer to more challenging curricular tracks and the level of math and science courses completed. For example, even when students earned the same credits in mathematics, the level of math completed varied from algebra 2, precalculus to calculus (Dalton et al., 2015). EMI implies that expanding access to advanced math and science courses may reduce inequalities in the sense of access to a *particular* set of courses (for example, algebra 2 or trigonometry) but will not, by itself, reduce consequential *qualitative* distinctions and associated inequalities, as those with privilege will increasingly drive for *distinction* in any given category given quantitative saturation at any given level (Lucas, 2009).

Drawing upon theories of maintained inequality and growing push for advanced science and math courses in high schools, a number of prior studies have investigated the extent to which inequalities in the most challenging high school coursework, such as highest-level math course (i.e., calculus) and AP courses, changed over time (Conger et al., 2009; Domina et al., 2016; Domina & Saldana, 2012; Klugman, 2013; Posselt et al., 2012). Using a dataset constructed from three nationally representative surveys, High School & Beyond 1980 (HS&B), NELS:88, and ELS:2002, for example, Domina and Saldana (2012) investigated the extent to which social class-based inequalities in math course-taking changed between 1982 and 2004. They found persistent social class-based inequalities in calculus completion but narrowed inequalities in lower-level math courses. While racial gaps in calculus completion were inconsistent, SES-based disparities remained significant, indicating the maintenance of inequalities over time. These studies provide supporting evidence of EMI theory (Lucas, 2009), suggesting that socioeconomically advantaged individuals strategically leverage their advantages to secure qualitative distinctions in math course-taking, particularly as the majority of students complete mid-level courses.

National reports have shown that the percentage of students who completed advanced math courses increased between 2004 and 2019 (National Center for Education Statistics., 2016, 2022). For example, around 2004, approximately 72% of high school graduates completed algebra 2 or a higher-level math course, with about 14% completing calculus (Domina &

Saldana, 2012). By 2019, about 85% of high school graduates successfully finished algebra 2, and 16% completed calculus (National Center for Education Statistics., 2022). The recent trend in advanced math course-taking suggests that about 9 out of ten students have enrolled in the class of algebra 2. It therefore seems plausible to consider that the nationwide increases in algebra 2 completion might influence SES-based inequalities in advanced math courses, such as calculus, among the recent high school cohort due to the increased eligibility of students for advanced math courses.

Recent studies have also examined changes in school-level inequalities in AP coursework, more broadly, including English, history and social science, math and computer science, and sciences, over time. Using a panel dataset of all California public high schools from 1997 and 2006, for example, Klugman (2013) examined inequalities in AP coursework along class lines. Klugman's research revealed that despite efforts to increase AP subject offerings and enrollments in schools serving disadvantaged populations, this had minimal impact on reducing inequalities in these outcomes. This was primarily because schools serving advantaged students experienced even greater increases in AP course offerings and enrollments, largely driven by proportionally higher demands from socioeconomically privileged families. As EMI theory points out, Klugman identified persistent or increasing school-level socioeconomic disparities in AP course offerings and enrollments over time.

Unlike high school math and AP course-taking more broadly (e.g., the number of enrollments in all AP courses), there is a dearth of research on patterns of SES-based inequality in science course-taking (Bottia et al., 2022). Drawing on nationally representative transcript data between 1982 and 2004, descriptive analyses in science course-taking show that completion in middle-level courses (chemistry 1 or physics 1, or chemistry 1 and physics 1) increased across all SES and racial/ethnic groups, except for Asians. Additionally, SES and racial/ethnic inequalities in enrollment at the highest level (i.e., chemistry 2, physics 2, or advanced biology) persisted or grew over the 22 years of study (Dalton et al., 2007). This descriptive approach cannot adequately assess the independent association between social background and science course-taking since students within each SES group vary in other aspects (Lucas & Byrne, 2017). To accurately assess socioeconomic inequality patterns in American high schools, it is essential to investigate patterns of social stratification in high school science course-taking after controlling for prior achievement, demographics, and school characteristics as linked to changes between cohorts. In other words, it's important to determine whether socioeconomically advantaged but academically equivalent students are more likely to complete advanced science courses.

2.4. Analyzing national trends in high school course-taking: Comparisons and insights from large-scale surveys

Research on the evolution of SES disparities in educational outcomes, including course-taking patterns, has expanded, utilizing longitudinal national and state-level data. Since 1982, the National Center for Education Statistics (NCES) has conducted high school transcript studies as part of the Longitudinal Studies Program and the National Assessment of Educational Progress (NAEP) High School Transcript Studies (HSTS) program. These studies align with major NCES data collection efforts. The first NCES-sponsored transcript study coincided with the HS&B program's initial follow-up survey in 1982. Subsequent studies in 1988, 2002, and 2009 collected post-high school transcripts. For instance, the NELS:88 1992 second follow-up included transcript collection~~ in 1992~~. The ELS:2002 conducted a transcript study in 2004/05, and the HSLS:09 had its own transcript study in 2013. Transcripts serve as official documentation of students' course enrollment, invaluable for analyzing course-taking trends, predicting educational trajectories, and establishing findings' national generalizability. Because high school courses vary in content and level, even among those with similar titles, a common course coding system, such as the Classification of Secondary School Courses (CSSC) – a general inventory of courses taught nationwide from grades 9 through 12–was used in NCES's high school transcript studies.

Because the high school transcript studies conducted by NCES have both similarities and dissimilarities of design and methodology that raise questions of comparability, it is important to ensure that comparability is maximized for inter-cohort comparisons. According to NCES guidelines about inter-cohort analysis, comparable analytic samples should be achieved across the high school transcript studies by taking into account differences in target populations and inclusion criteria across studies (Burns et al., 2011). NCES recommends that comparable analytic samples across cohorts can be achieved by *limiting samples to high school graduates* who received regular/standard or honors diplomas and imposing additional restrictions such as earned credit minimums (Burns et al., 2011, pp. 399-400). Following these guidelines, previous studies on course-taking across cohorts have primarily focused on on-time high school graduates (Domina & Saldana, 2012), posing challenges in including both on-time graduates and dropouts in inter-cohort comparisons.

Obtaining comparative measures across cohorts poses challenges, particularly in examining inequality in course-taking. It is crucial to investigate students' course-taking patterns while considering the opportunities available to them, such as on-site course offering. While HSLS:09 collected on-site course offering information through school counselor questionnaire and high school transcript school-level data, NELS:88 had substantial missing data on school-level course offering information. Moreover, school-level course-offering information from transcript data was only available for the High School Effectiveness Supplement (HSES) of NELS:88, complicating cross-cohort comparisons (Lee et al., 1998). Additionally, obtaining other comparative measures, such as standardized testing scores, across comprehensive subjects presents challenges. While mathematics standardized test scores are accessible across multiple high school cohorts, comprehensive assessment scores for other subjects, including reading, science, and social studies, are not available (Burns et al., 2011). Furthermore, the timing of standardized test scores varies across multiple high school cohorts; for example, mathematics standardized test scores are available in grade 10 in both NELS:88 and ELS:2002, while they are available in a different grade in HSLS:09.

In their examination of high school students' course-taking patterns using the NELS:88 transcript data, Burkam and Lee (2003) developed science and math course-taking classifications. Their aim was to extend beyond traditional metrics such as course credits or number of completed courses that have typically been used in this area of research. They introduced an 8-level index in mathematics, encompassing categories such as no mathematics, non-academic, low academic (e.g., prealgebra), middle academic 1 (e.g., algebra 1 and geometry), middle academic 2 (algebra 2), advanced 1 (trigonometry, probability, and statistics, among others), advanced 2 (e.g., precalculus), and advanced 3 (all calculus courses, including AP calculus). Additionally, they developed a 6-level index in science, including categories such as none, primary physical science (e.g., earth science), secondary physical science (e.g., environmental science, and introductory chemistry), general biology 1, chemistry 1 OR physics 1, chemistry 1 AND physics 1, and chemistry 2 or physics 2. These classifications served as the foundations for assessing high school course-taking patterns and were measured in national surveys and large-scale state-level analyses (Brown et al., 2018; Burkam & Lee, 2003; Dalton et al., 2007; Han et al., 2023; Posselt et al., 2012; Tyson et al., 2007). For instance, numerous studies have adopted a hierarchical sequence for mathematics courses, with a slight adjustment such as combining non-academic and low academic into one level: starting from no mathematics, progressing through below algebra 1 (or prealgebra), algebra 1, geometry, algebra 2, other advanced mathematics (e.g., trigonometry), precalculus, and concluding with calculus (e.g., Brown et al., 2018; Domina & Saldana, 2012; Posselt et al., 2012; Tyson et al., 2007).

However, several challenges in analyzing national high school transcript data should be noted. Firstly, it is challenging to incorporate new pathways such as integrated mathematics pathways in California, although NCES high school transcript raw data included multi-year integrated mathematics and offered a crosswalk framework enabling one-to-one matches in terms of course rigor and sequence. For example, integrated mathematics 1, 2 and 3 in California incorporates contents from algebra, geometry, statistics and probability, making it challenging to categorize this course within a specific traditional sequence (California Department of Education., 2013).

Secondly, mathematics follows a hierarchical structure where lower-level courses serve as preparation for higher ones such as algebra 1 – geometry - algebra 2 – advanced mathematics (e.g., precalculus and calculus) (see, for example, Brown et al., 2018). However, there is no consensus on the hierarchy for high school science course-taking. Science education encompasses diverse sub-disciplines such as biology, chemistry, and physics, with no necessarily inherent difficulty among them, and no prerequisite for learning one subdiscipline before another subdiscipline. Empirically, students often take biology followed by chemistry or physics (see, for example, Brown et al., 2018). Unlike the extensive research on mathematics course sequence, prior studies have primarily focused on completion of specific science courses like core lab science courses (biology, chemistry or physics) or physics only (e.g., Adelman, 2006; Maltese & Tai, 2011; Riegle-Crumb & Moore, 2014; Sadler & Tai, 2001). Only a few studies have explored the sequence of science course-taking (e.g., Posselt et al., 2012; Tyson, 2007). These studies typically construct the following sequence: no science, primary physical science, secondary physical science, general biology, chemistry 1 or physics 1, chemistry 1 *and* physics 1, and chemistry 2, physics 2 or advanced biology. Following empirical examination of course-taking patterns across grades, adjustment was made to some categories; for instance, chemistry 1 or physics 1 – chemistry 1 and physics 1 sequence was revised to chemistry 1 only – physics 1 only (e.g., Tyson, 2007). These studies have examined whether students' course-taking patterns or specific completion of science courses influence their STEM pathways.

Recently, scholars have begun utilizing a descriptive framework to visualize students' course-taking trajectories and analyze large-scale data, enabling the mapping of each student's complete course-taking patterns (see, for example, Bowers et al., 2022). These studies outline the entire progression trajectories of individual students from high school through college, taking into account all enrolled subjects, grades, and year simultaneously. They pose challenges to the literature on core-subject gateway courses, which traditionally focused solely on specific courses such as calculus or physics. Instead, they reveal that students generally perform well or are challenged in similar ways across subjects and courses (Bowers et al., 2022).

Building on EMI theories that predict persistent SES-based inequalities in course-taking patterns, we examine the following questions:

First, to what degree are individual SES and school-level SES associated with course-taking patterns in each cohort?

Second, have individual-level SES based inequalities in access to advanced math and science courses, such as calculus, biology 2, physics 2, or chemistry 2, decreased, even after controlling for student and school characteristics, including prior achievement and on-site course offerings?

Third, have school-level SES based inequalities in access to advanced math and science courses, calculus, biology 2, physics 2, or chemistry 2, changed over time?

2. METHODS

2.1. Data and sample

We utilized three nationally representative high school cohort datasets collected by the ~~National Center for Education Statistics (~~NCES~~)~~: NELS:88, ELS:2002, and HSLS:09. These datasets provide rich and elaborate information on student background, test scores, and high school transcript data for three cohorts of U.S. high school students educated between the 1990s and the early 2010s. The NELS:88 is based on a representative sample of 24,000 8th graders, but the study surveyed a "freshened" nationally representative sample of 10th graders in 1990 and followed them in 1992. The ELS:2002 includes a nationally representative sample of over 15,000 10th graders in 2002 and 12th graders in 2004. The most recent study, HSLS:09, is based on more than 23,000 9th graders surveyed in 2009 across the United States, with follow-ups in 2012, and 2014. It should be noted that the same high schools are not repeatedly sampled across the cohorts, suggesting the observations in each data~~-~~set are independent of the observations in the others.

As discussed above, it is critical to create comparable analytic samples and measures to conduct inter-cohort analyses using NCES high school cohort data. Following NCES guidelines (Burns et al., 2011, pp. 399-400), we limited our analytic sample to (a) 12th graders in 1992, 2004, and 2013, respectively, (b) high school graduates, and (c) those students who took any English credit.[1] In addition, our analytic sample was restricted to students who had complete transcript information from 9th grade through 12th grade to measure students' mathematics and science coursework pipelines. This allows us to eliminate the problem of differences in the excluded student population across studies (Burns et al., 2011, p. 399). Notably, this means that we were not able to meet the requirement of comparability across the three datasets if we included high school dropouts in this particular study. In preliminary analyse~~i~~s, we found that the high school dropouts in each cohort dataset tend to exhibit significantly lower SES than the high school graduates (see Appendix A). In addition, the percentage of students who ever dropped out of high school varied across the three datasets; 18.9% in NELS:88, 11.8% in ELS:2002, and 11.0% in HSLS:09. As dropouts tend not to meet coursework and performance standards for high school graduation established by the state or other approving authorities (Rosen et al., 2015), they have a lower probability of completing advanced math and science courses. Therefore, the exclusion of high school dropouts in our analytic sample can yield a smaller estimate of the SES gap in each cohort, suggesting that our findings should be interpreted with caution. Our analytic sample includes approximately ~~over~~ 85% of total students in the datasets.

[1] One of major issues in comparability of target populations across studies is related to differences in inclusion and exclusion with respect to students with disabilities and English language learners. Therefore, eliminating cases that lack of English course credits largely eliminates the problem of differences in the excluded student population across studies (Burnes et al., 2022, p. 400).

The total analytic sample sizes across the three cohorts were 36,800. The analytic sample sizes for NELS:88, ELS:2002, and HSLS:09 were 9,920, 10,730, and 16,150, respectively. The NCES provides weighting variables to account for the probabilities of participation in the base-year and follow-up surveys, as well as the nonresponse rates. The analyses used the appropriate transcript sample weights for each dataset to ensure that the estimates can be generalized to the 12th grade high school graduates of 1992, 2004, and 2013: we used *F3TRSCWT* for NELS, *F1TRSCWT* for ELS, and *W3HSTRANS* for HSLS.

2.2. Measures of High school math and science course-taking

To identify the highest-level math and science courses, we created measures of high school math and science course-taking pipelines. Math and science courses were classified based on the secondary school course classification system of NCES; the Classification of Secondary School Courses (CSSC) for NELS:88 and ELS:2002, and the School Codes for the Exchange of Data (SCED) for HSLS:09. Using raw course-level high school transcript data from ninth grade through twelfth grade in each dataset, we identified the highest math and science courses students completed. To make these course-taking variables comparable across the cohorts, we matched the course titles using the CSSC-SCED crosswalk provided by NCES. The coded math and science courses are ordered according to the difficulty level. Following previous approaches (Burkam & Lee, 2003; Domina & Saldana, 2012; McFarland, 2006; Schiller & Muller, 2003), we categorized a hierarchical order of the mathematics pipeline from less to more difficult courses; remedial, algebra 1, geometry, algebra 2, trigonometry, precalculus, and calculus.

Based on prior studies that investigated high school science course-taking patterns and their effects on educational outcomes (Brown et al., 2018; Burkam & Lee, 2003; Dalton et al., 2007; Posselt et al., 2012; Tyson et al., 2007), we categorized a hierarchical order of the science pipeline, as follows; low-level (i.e., students did not complete any science courses with a C or above), primary physical science (e.g., physical science and earth science), secondary physical science (e.g., general physics and introductory chemistry), secondary life science (e.g., biology),[2] chemistry 1, chemistry 1 and physics 1 (i.e., completed both chemistry 1 and physics 1), and chemistry 2, physics 2 or biology 2 (e.g., AP chemistry, AP physics, and AP biology). Because of a relative lack of consensus on a hierarchical order as regards the science pipeline, we empirically assessed the science pipeline by examining if students who completed higher-level courses in the science pipeline completed lower-level courses using our analytic sample. About 88% of students who completed chemistry 1, for example, completed secondary life science (e.g., biology). Despite the Physics First movement in science education, NCES high school cohort transcript study and other state-level analyses identified that many students peak at the "chemistry 1 only" level or students tend to take chemistry 1 first and then move to physics 1, whereas very few students move from physics 1 to chemistry 1 (Brown et al., 2018; Riegle-Crumb et al., 2006; Tyson et al., 2007). This suggests that students tend to take science courses from chemistry 1 – physics 1 sequence[3] in the science pipeline. In addition, a few studies confirmed the predictive validity of the science pipeline on educational attainment (Tyson et al., 2007). Prior studies demonstrated that advanced science course-taking in this science pipeline

[2] Primary physical science includes introductory physical science, earth science, and integrated science, among others. Secondary physical science includes conceptual biology, conceptual chemistry, conceptual physics, and astronomy, among others. Secondary life science includes biology-advanced studies (usually taken after a comprehensive initial study of biology), Anatomy, and microbiology, among others. Note that Burkam and Lee (2003) do not have a separate classification of "primary life science." Rather, basic biology I is included at the secondary physical science level.

[3] Following Burkam and Lee (2003), many studies categorized a hierarchal order of the science pipeline, as follows; low-level, primary physical science, secondary physical science, secondary life science, chemistry 1 *or* physics 1, chemistry 1 *and* physics 1, and chemistry 2, physics 2 or biology 2 (see, for example, Dalton et al., 2007; Posselt et al., 2012). Thus, we also tested the robustness of findings presented in the study using chemistry 1 or physics 1 – chemistry 1 and physics 1 sequence. Our findings are very consistent regardless of different chemistry 1 and physics 1 sequences.

has a positive effect on access to more selective 4-year institutions relative to noncompetitive 4-year institutions (by Barron’s profile of American colleges) (Posselt et al., 2012) and students’ STEM degree attainment (Tyson et al., 2007). Sadler et al. (2014) find that both chemistry and physics predict increased interest in STEM careers. The effect of chemistry on STEM career interest varies: there is non-significant difference between zero and one year of chemistry in predicting STEM career interest, while an increase from one year to two years boosts interest. For physics, no physics to one year and one year to two years both have significant impacts on STEM career interest.

2.3. Covariates

For cross-cohort comparisons, comparable measures across three studies were used in the study to take into account differences in individual and school characteristics. It should be noted that NCES high school cohort studies contained many comparable items across studies, but some items were available only in one study, which influence~~s~~d in/exclusion of measures in the study. Demographics, prior achievement, and high school characteristics were included in the models. Demographic variables included sex, race, and ~~socioeconomic status (~~SES~~)~~. In order to capture how students from different family socioeconomic backgrounds perform over time, a measure of family SES~~socioeconomic status~~ was constructed using common student background items across all three datasets: highest parental educational attainment (derived from fathers’~~s~~ and mothers’~~s~~ educational attainments), highest parental occupational prestige (derived from fathers’~~s~~ and mothers’~~s~~ occupational prestige scores) and family income (Burns et al., 2011). In terms of family income, we reco~~r~~ded the original ordinal indicator in each dataset by taking the midpoint of each income category. For the open-ended final category, we extrapolated from the next-to-last category using a modified formula suggested by Hout (2004). Next, we converted the dollar values from NELS:88 and ELS:2002 into equivalent dollars for students in the HSLS:2009 cohort using consumer price index (CPI) conversion factors to adjust for inflation. Using this converted set of income variables and all other measures, we constructed an SES composite variable across all three datasets. Because the value of SES may not have the same meaning across three waves, we standardized each individual's SES score in the national SES distribution relative to others in each dataset (Bai et al., 2021; Chetty et al., 2022a; Hanushek et al., 2022). Finally, following previous studies that examined SES-based inequalities in education (Lucas, 2017; Lucas & Irwin, 2018), we classified students into low-SES, middle-SES, and high-SES categories defined in terms of standard deviation units. Rather than using a gradational approach of family SES that assumes educational inequality on a unidimensional form in which families are arrayed on a continuum, this study used a categorical approach in SES that assumes *qualitative* differences of home environments across social groups (Jonsson et al., 2009). For each cohort, we defined low SES as at least one standard deviation below the SES mean, middle SES as the family SES index between the –1 standard deviation and + 1 standard deviation, and high SES as at least one standard deviation above the SES mean (Cowan et al., 2012; Crosnoe & Schneider, 2010).

The prior achievement score variable included ninth/tenth grade standardized math test scores as a proxy of students' achievement level at the beginning of high school. As HSLS:09 utilized different content and scaling of mathematics tests, and the timing to test was not the same as NELS:88 and ELS:2002, the achievement score from HSLS:09 is not comparable to the other two cohort data (Duprey et al., 2018). The HSLS math assessment, for example, was administered at grade 9 and 11, whereas math assessment was administered at grade 10 in NELS:88 and ELS:2002. Only standardized math test scores are available in all three datasets.[4]

We also included a school-level socioeconomic composition, ~~a~~the school mean SES. Prior studies indicate that certain students are afforded possibilities to take advanced math and science courses, whereas others are not, due to disparities in on-site course offerings among high schools (U.S. Department of Education and Office for Civil Rights 2018). Thus, it is crucial to control for the availability of on-site math and science courses. However, comparable measures of course offerings across the three datasets are lacking due to somewhat limited on-site course offerings, a consequence of variation in data collection methods across cohorts. For example, ELS:2002 and HSLS:09 obtained this information through high school transcripts, while NELS:88 relied on a school questionnaire. Notably, school-level course offering data were only accessible for the High School Effectiveness Supplement (HSES) of NELS:88, resulting in challenges regarding missing information (Lee et al., 1998). Prior studies examining course offerings and course-taking patterns using NELS:88 primarily relied on school questionnaire data. Despite differences in data sources, we included measures of course-offerings to examine students' course-taking patterns when such opportunities were available in their schools. Moreover, in our study, we controlled for the school mean ninth/tenth grade standardized math test score, urbanicity (urban, suburban, and rural), and school type (public, Catholic, and other private), that are also associated with on-site advanced course offerings (Iatarola et al., 2011; Klugman, 2013; Rodriguez, 2018; Rodriguez & Hernandez-Hamed, 2020).

[4] NELS:88 collected comprehensive standardized test scores compared to ELS:2002 and HLS:09. Using NELS:88 we estimated two models in preliminary analysis: (a) a model that included all comparable measures across three studies; and (b) a model that included additional covariates of prior achievement, reading and science standardized scores. We found that SES coefficients across these two models are very consistent.

2.4.Analysis

Before we examined inequalities in top science and mathematics course-taking, we conducted weighted descriptive statistics of course-taking patterns over time. We investigated the extent to which there are changes in the completion of advanced math and science courses between the 1992 and 2013 high school graduation cohorts and then conducted the Wilcoxon rank-sum test, a test of equality ~~tests on~~for unmatched data (that is, *k*-independent samples).

Next, to examine if SES-based inequalities in math and science course-taking have changed over time, we ran multi-level logistic regression models where students are nested within schools without and with covariate adjustment (see Appendix E). In ~~With~~ an effort to study social background effects on educational outcomes, Lucas and Byrne (2017) asserted that it is important to compare two individuals who are the same or very similar on everything else except socioeconomic background. Thus, we fitted multi-level multivariate models to describe trends in SES-based inequalities, estimating models where the first two levels are models with the multilevel models and the third level is models with fixed effects (McNeish & Wentzel, 2017):

$$\eta_{ijk} = \log\left(\frac{\varphi_{ijk}}{1-\varphi_{ijk}}\right)$$

$$= \beta_{0j} + \beta_K(Cohort\ indicators) + \beta_{1j}(SES\ indicators)$$

$$+ \beta_{2j}(SES$$

$$*\ Cohort\ indicators) + \beta_{Pj}(Other\ individual\ characteristics)$$

$$\beta_{oj} = \gamma_{00} + \gamma_{01}(School\ mean\ SES\ indicators) + \gamma_{0S}(Other\ school\ characteristics) + \mu_{0j}$$

$$\beta_K = \gamma_{10} + \gamma_{11}(School\ mean\ SES\ indicators)$$

$$\beta_{pj} = \gamma_{po} \text{ for } p \geq 1,$$

where η_{ijk} is the outcome variable for the *i*th student in the *j*th school Level 2 unit in the *k*ith Level 3 unit (cohort). It is worth noting that, for trends analysis, we included cohort indicators at Level 1 instead of employing three-level models, where students are nested within schools and within the cohort dataset (McNeish & Wentzel, 2017). This decision was made due to the limited size of Level 3 units (McNeish, 2023; McNeish & Kelley, 2019; McNeish & Wentzel, 2017). This approach is also typically favored when researchers lack theoretically meaningful predictors at the third level (McNeish & Kelley, 2019). It should be noted that we did not include two interaction terms simultaneously–the interaction between SES and cohort indicators, and the interaction between school mean SES and cohort indicators (see Appendix E for results).

When outcome variables are ordinal, such as a hierarchical course-taking sequence, the ordered logistic regression model is a popular analytical method, which is parsimonious.[5] The ordered logit model can provide a good summary of inequality in course-taking across all category ranges of sequences (see Kelly (2009) for B~~b~~lack-~~w~~White gaps in math course-taking sequence). However, this approach assumes the relationship between independent variables and student course taking is consistent across the course distribution, although the adjacent logit model allows the formulation of a model with selective constraints on coefficients (Allison, 1999). This assumption is not consistent with theories that explain SES-based inequality in

[5] A common example of ordinal dependent variable is educational attainment, in which only individuals who have completed high school are considered to be "at risk" of or eligible for completion of one or more years of college. Similarly, high school math and science course sequence variables are ordinal. Because students who completed a low level in the sequence (e.g., algebra 2) can move to precalculus with skipping trigonometry or other advanced math courses, the ordinal logit model (including the adjacent ordered logit model) can be criticized as inaccurate. Usually, the use of multinomial logistic model can be an alternative model, but there are no theoretical bases about courses that can be used as a reference when socioeconomically~~sociologically~~ advantaged students seek marks of distinction by taking the most challenging courses in science and math. While technically possible, the use of multinomial logit model remains impractical because it would require the comparison of seven outcomes for each subject and then the estimation of models using different reference groups for robustness of findings. Although the use of logistic regression model can be criticized as inaccurate, in the end, it was decided to use logit models that estimated predicted probabilities of completing the most challenging math and science courses in comparison to all others.

course taking, which suggest that the association between family SES and course-taking varies across the course distribution because students from socioeconomically advantaged groups increasingly seek distinction by taking the most challenging highest-level math and science courses whenever and wherever possible, given that a majority of students completed a particular set of mid-level courses (e.g., algebra 2). Furthermore, using logistic regression models prior studies have shown that SES-based inequalities persist at the highest level of math (i.e., calculus) between 1982 and 2004, while SES-based inequalities have narrowed in the lower level of mathematics courses (Domina & Saldana, 2012), suggesting that the relationship between SES and math courses is not the same across the hierarchical math course sequence. Thus, building on literature that examined inequalities in highest-level math courses (Domina & Saldana, 2012), we also estimated logistic regression models separately for the mid- and highest levels of courses and investigated whether SES-based inequalities vary across the level of difficulty in mathematics and science courses. For top math and science courses, we examined two outcomes: (a) calculus (all calculus courses such as AP calculus) and (b) chemistry 2, physics 2, or biology 2 (including AP/IB chemistry, AP/IB physics, or AP/IB biology). To compare inequalities in top math and science courses with inequalities in mid-level mathematics and science courses, we also examined two outcomes: (a) algebra 2 or above and (b) chemistry 1 or above. To check variation across highest-level science courses, we also estimated logistic regression models separately for biology 2, a less mathematized science course compared to chemistry 2 and physics 2 (see Appendix D).

In the multilevel logistic regression, we first fitted models by cohort and then compared SES and school mean SES coefficients across three time points. Next, we pooled three datasets (NELS:88, ELS:2002, and HSLS:09) and estimated two interaction models. Model 1 includes interaction terms between cohort indicators and individual-level SES and Model 2 includes interaction terms between cohort indicators and school-level SES. These two models answer the second and third research questions, respectively. Additionally, we estimated two sets of models: (a) one using ELS:2002 as a reference cohort (see Tables 3 and 4) and (b) one using NELS:88 as a reference cohort (see Appendix B). Consistent with the previous study (Domina & Saldana, 2012), we confirmed that there were no systematic differences in the distribution of the covariates —gender, race, ninth/tenth grade mathematics score, school location and type— between the three cohorts.

Finally, to address our research questions about trends in SES-based inequalities in course-taking, we used a postestimation strategy of computing adjusted marginal effect estimates from our statistical interactional model (Mood, 2010). Since the logistic regression model does not assume a linear relationship between dependent and independent variables, the difference in probability of completing math and science coursework by cohort and SES varies depending on what values the covariates have. In addition, the coefficient values of the interaction terms reflect the average of the effect sizes varied by the covariates (Ai & Norton, 2003). Therefore, for a more intuitive interpretation of the results than logged odds or odds ratios, we estimated marginal effects to show the cohort and SES subgroup changes in the probability of completing mathematics and science coursework after fixing the covariates to their mean values (Williams, 2012). This estimation strategy is a very useful tool in understanding and interpreting multiple interactions in logistic regression, allowing us to investigate whether SES inequalities have narrowed (or been maintained) in the odds of completing mid-level, and high-level science and math courses. If necessary, the Z-score formula[6] proposed by Paternoster et al. (1998) is used to verify that the effect sizes between the adjusted marginal effects differ significantly.

Since there were many cases with missing data for student background variables, such as ninth/tenth grade math achievement scores and SES, the multiple imputation by chained equations technique was used to replace missing values, to retain as many cases as possible (Royston, 2004). The missing distribution of each variable ranges from approximately less than 1% and 33%. The on-site course-offering variables in NELS:88 exhibited the highest missing percentage of missing data, an issue that has also been noted and discussed by other researchers (e.g., Lee et al., 1998). The missing distribution of SES ranges from approximately 5% to 15% across the three waves due to high levels of missing data in certain variables, such as income. To check out the robustness of our findings, we also conducted all analyses using composite measures of SES derived from the NCES data for each wave. Our results indicate that all findings remain robust across these alternative measures. The imputation model includes all the variables used in the analysis. In the imputation model, binary variables were modeled using logistic regression, ordinal variables modeled using ordered logistic regression, and continuous variables modeled using linear regression. We estimated the coefficients and standard errors from 20 imputed datasets to enhance our analysis's power (Graham et al., 2007). Imputed values compared reasonably to observed values, and results using listwise deletion were similar to those we present using multiple imputation (see Appendix E) (Manly & Wells, 2015). Specific details

[6] The numerator of this test is the estimated difference between the two coefficients in the subgroups ($b_i - b_j$), and the denominator is the square root of the sum of each standard error squared.

regarding the percentage of missing data and descriptive statistics for non-imputed and imputed variables can be found in Appendix C.

3. RESULTS

3.1. Descriptive trends in mathematics and science course-taking sequences

Table 1 provides descriptive trends in math and science course completion across three high school cohort datasets; NELS:88 (1992 cohort), ELS:2002 (2004 cohort), and HSLS:09 (2013 cohort). Note that our analytic sample includes only high school graduates to meet the NCES inter-cohort data analysis guideline. We calculated raw differences in the percentage of high school graduates who completed math and science courses between 1992 cohort and 2013 cohort and then tested if, overall, these changes in course completion rates across cohorts are statistically significant.

The high school cohort in the early 2010s completed more credits in advanced math and science courses when compared with the high school cohorts in the early 1990s. This trend occurs throughout advanced math and science course distribution. Specifically, the percentage of high school graduates who completed at least algebra 2 or above increased from about 69% to 86% over the study period. In the science course-taking pipeline, the percentage of high school graduates who completed chemistry 1 or above increased from about 60% to 74% over the study period.

The percentage of high school graduates who completed the highest-level math and science courses also increased over the study period. The percentage of high school graduates who completed calculus, for example, increased from about 11% to 16% over the study period.

Likewise, the percentage of students who completed chemistry 2, physics 2 or biology 2 increased from about 7% to 14% over the study period.

Across the study period, notable increases in students' enrollment in advanced math and science courses were observed, indicating that students in the early 2010s are more likely to complete higher-level science and math courses compared to their counterparts in the 1990s.

3.2. Association between individual SES, school mean SES, and course-taking patterns

Before examining if SES-based inequalities in course-taking patterns have changed, we explored the degree to which individual SES and school-level SES are associated with course-taking patterns in each cohort. To address this question, we initially constructed models by cohort and then conducted analyses by comparing SES coefficients and school mean SES coefficients across three distinctive time points, after including all individual- and school-level control variables. We fitted two models: (a) a model that includes both individual-level SES and school mean SES alongside all other control variables, including prior achievement scores; and (b) a model that includes the interaction between individual SES and school mean SES in addition to Model 1. High and middle SES backgrounds at individual and school levels are defined by being one standard deviation above, and between -1 and +1 standard deviation from the mean, respectively. Low SES backgrounds are defined as one standard deviation below the mean.

Not surprisingly, as shown in Model 1 of Table 2, students from families with higher SES are more likely to complete mathematics and science courses–algebra 2 or above, calculus, chemistry 1 or above, and physics 2, chemistry 2, or biology 2. Similarly, the socioeconomic composition of a school is also linked to students' course-taking patterns in these subjects, although this varies somewhat across cohort and subjects. For example, students at high SES schools are more likely to complete highest-level mathematics and science courses–calculus, physics 2, chemistry 2 or biology 2–compared to those at low SES schools. However, this positive link was mainly seen in the 2013 cohort, even after considering other individual and school background characteristics like prior achievement. Under equal conditions, no significant discrepancy is observed between students in middle SES schools and those in low SES schools. This suggests that the association between school mean SES and course-taking patterns is nonlinear.

Next, we examined whether the SES of a school affects students' course-taking in math and science differently for students from high SES families compared to those from low SES families. We did this by analyzing the interaction between individual SES and school SES (see Model 2 in Table 2). The coefficient of high school mean SES indicates the difference in the likelihood of completing mathematics and science courses between low school mean SES and high school mean SES for students from low SES families. Except for algebra 1 or above in the 1992 cohort, all of these coefficients are not statistically significant, implying there is no additional benefit for students from low SES families at high SES schools in the likelihood of completing these courses. In mathematics courses, however, the interaction terms between individual SES and school SES were positive and significant in the 1992 and 2004 cohorts. For example, in the 2004 cohort, students from middle SES families at high SES schools and students from high SES families at either middle or high SES schools were more likely to complete calculus. In the 2013 cohort, no significant interaction effects were observed. This means that in the earlier years, students from middle or high SES families at higher SES schools had higher chances of completing these courses compared to students from low SES families at low SES schools. The absence of these positive interactions in the 2013 cohort indicates a change in the pattern. Science course-taking patterns also exhibited a very similar change over time.

In sum, our analyses reveal that school SES matters more for students from middle or higher SES families than for students from low SES families in the earlier cohorts, but this was not held in the 2013 cohort.

4.3. Changes of SES inequality in taking mathematics and science coursework

Next, to examine if SES-based inequalities in math and science course-taking have changed over time, we estimated the pooled multilevel logit models (see Appendix E). To provide a more intuitive interpretation of changes in SES inequalities over the study period, Table 3 presents the results of the adjusted marginal effects that were obtained from the full multilevel logit models (i.e., include all other individual- and school-level characteristics and the interaction between cohort and SES in the estimation) for each outcome. Table 3 shows the changes in the probability of completing the mid- and highest-levels of math and science courses by SES subgroups over the 1992 and 2013 cohorts compared to the 2004 cohort (reference). The values of all covariates are fixed at their means. These marginal effect results show the degree to which SES-based inequalities in mid-level, and highest-level math and science courses have changed over the study period. In Figures 1 and 2, we also visualized the predicted probability of completing the mid-, and highest-level mathematics and science coursework by SES subgroup and cohorts, with all covariates being held to their mean values.

First, we assessed which SES group exhibits increases in the probability of completing courses over the study period. In mid-level mathematics, algebra 2 or above, as shown in Table 3 and Figure 1, when all other conditions are equal, the low SES students' predicted probability of completing algebra 2 or above increased by about 6 percentage points between the 1992 and 2004 cohorts and 19 percentage points between the 2004 and 2013 cohorts. However, for the high-SES students, there was no significant change between the 1992 and 2004 cohort and then about 12 percentage points increases in the predicted probability of completing algebra 2 or above between the 2004 and 2013 cohorts. Both low- and high-SES students in the early 2010s are more likely to complete a mid-level math course compared to their counterparts in the early 2000s, but low-SES students are more likely to do so. As shown in Figure 1, this suggests that disparities between high- and low-SES students' probability of completing mid-level mathematics coursework decreased over the three cohorts.

Not surprisingly, SES-based inequalities in the probability of completing mid-level science coursework, chemistry 1 or above, decreased over the three cohorts (see Table 3 and Figure 1). For low-SES students, the probability of completing chemistry 1 or above increased dramatically between the 1992 and 2004 high school graduation cohorts, compared to high-SES group. Meanwhile, all SES groups showed substantial increases in the probability of completing mid-level science coursework between the 2004 and 2013 cohorts.

Unlike mid-level mathematics and science courses, SES inequalities in the probability of *completing the most rigorous math and science courses* tend to persist or be slightly widened. Specifically, while holding all other factors constant, the predicted probability of all students completing calculus increased by approximately two, three, or four percentage points across all groups between the 1992 and 2004 cohorts. However, variations in changes across groups were observed in the recent cohort. For high and middle SES students, the predicted probability of completing calculus increased by 4 and 3 percentage points, respectively, between the 2004 and 2013 cohorts, whereas the predicted probability for low SES students remained steady over the same period. This suggests that SES-based inequalities in the probability of completing the highest-level mathematics coursework slightly widened in recent cohort.

Similarly, in highest-level science courses, all students in the early 2010s are more likely to complete physics 2, chemistry 2 or biology 2 compared to their counterparts in the 1990s and early 2000s, but SES-based inequalities persist over the study period. All students' predicted probabilities of completing highest-level science courses increased between the 1992 and 2004 cohorts, but there were no changes between the 2004 and 2013 cohorts for both low and high SES students. For middle-SES students, the predicted probabilities of completing highest-level science courses increased by 3 percentage points between the 2004 and 2013 cohorts.

Due to the variation in the level of mathematization and prerequisite of mathematics across highest science courses, we also investigated whether SES-based inequalities in the probability of completing biology 2 differed from those in other sub-science discipline courses (see Appendix D). There were no statistically significant increases in the predicted probability of completing biology 2 across all SES groups between the 1992 and 2004 cohorts, holding all other conditions constant. However, among low SES students' predicted probability of completing biology 2 decreased by 4 percentage points between the 2004 and 2013 cohorts, while the predicted probability for middle and high SES students remained unchanged between the 2004 and 2013 cohorts. There is no evidence to suggest that SES-based inequalities in the probability of completing biology 2 narrowed over the study period.

In sum, the findings from the adjusted marginal effect analysis, detailed in Table 3 and visually represented in Figures 1 and 2, reveal~~s~~ significant shifts in completion probabilities of mid- and highest-level math and science courses across socioeconomic subgroups over time. Notably, while disparities in mid-level mathematics narrowed, persistent inequalities were observed in the completion rates of rigorous math and science courses, particularly evident among low-SES students. Despite overall advancements, *SES-based inequalities in the probabilities of completing highest math and science courses have widened or maintained over the study period*, indicating ongoing challenges in equitable completion of advanced coursework.

4.4. School-level socioeconomic composition and inequality in taking mathematics and science coursework

Table 4 presents the results of the adjusted marginal effects that obtained from the full multilevel logit models for each outcome. Table 4 shows the changes in the probability of completing math and science courses by school-level socioeconomic composition over the 1992 and 2013 cohorts compared to the 2004 cohort (reference). The values of all covariates are fixed at their means. These marginal effect results show the degree to which school SES composition-based inequalities in course-taking have changed over the study period. In Figures 3 and 4, we also visualized the predicted probability of completing the mid-, and highest-level mathematics and science coursework by high, middle and low socioeconomic composition schools and cohorts, with all covariates being held to their mean values.

Consistent with prior research (Crosnoe & Muller, 2014), school-level socioeconomic composition is positively associated with course-taking patterns (see Appendix E). All else being equal, students in high SES schools—defined as one standard deviation above the mean of the school's SES— are more likely to complete science and mathematics courses compared to their counterparts in low-SES schools—defined as one standard deviation below the mean of the school's SES.

More importantly, as shown in Table 4 and Figures 3 and 4, our analyses reveal that trends in disparities between high and low socioeconomic composition schools in course-taking vary across mathematics and science, and difficulty levels in each subject. In mid-level math course, specifically algebra 2 or above, as depicted in Table 4 and Figure 2, the predicted probability of completion remained steady for students in low SES schools between 1992 and 2004, but increased by 18 percentage points between 2004 and 2013. For students in high SES schools, there was no statistically significant change between 1992 and 2004; however, this was followed by 12 percentage points increase between 2004 and 2013. This trend indicates a decrease in disparities between high and low SES schools in the predicted probability of completing mid-level mathematics coursework over the three cohorts.

For mid-level science course, specifically chemistry 1 or above, the analyses revealed that gaps between high and low-SES schools in the predicted probability of completing chemistry 1 have narrowed. All else being equal, students attending high SES schools did not show statistically significant increases in the predicted probability of completing chemistry 1 or above between the 1992 and 2004 cohorts. However, between the 2004 and 2013 cohorts, students from high SES schools exhibited statistically significant increases in the predicted probability of completing chemistry 1 or above, with increases of 10 percentage points. On the other hand, students at low SES schools showed statistically significant increases in the predicted probability of completing chemistry 1 or above across all three cohorts with increases 7 percentage points between the 1992 and 2004 cohorts and 10 percentage points between the 2004 and 2013 cohorts.

The differences between high- and low-SES schools in the predicted probability of completing highest-level mathematics and science courses have either widened or persisted over the study period time. All else being equal, students attending low SES schools did not show statistically significant increases in the predicted probability of completing calculus over the study period. In contrast, students from middle and high SES schools demonstrated consistent and significant increases in the predicted probability of completing calculus across three cohorts. For middle SES schools, the increase was a 2 percentage point between both the 1992 and 2004 cohorts, and the 2004 and 2013 cohorts. High SES schools showed a 2 percentage point increase between the 1992 cohorts and 2004 cohorts and a 7 percentage point increase between the 2004 and 2013 cohorts. This suggests that disparities between low and high SES schools in the predicted probability of completing calculus widened over the study period.

Holding all other factors constant, students from low, middle, and high SES schools showed statistically significant increases in the predicted probability of completing physics 2, chemistry 2, or biology 2 by approximately four or six percentage points between the 1992 and 2004 cohorts. However, there was no significant change in the predicted probability of completing these highest-level science courses for both low and high SES schools between the 2004 and 2013 cohorts. This indicates that disparities in the predicted probability of completing the highest-level science courses between low and high SES schools have persisted over the study period.

We also investigated whether school mean SES-based inequalities in the probability of completing biology 2 differed from those in other ~~sub-~~science sub-discipline courses (see Appendix D). Interestingly, similar to the findings in Table 4 and Figure 4, there is no indication that school mean SES-based inequalities in the probability of completing biology 2 have narrowed over the study period. There were no statistically significant changes observed in the likelihood of completing biology 2 across all schools over the study period, holding all other conditions constant. Despite variations in mathematization across science sub-disciplines, our analyses demonstrate that inequalities between high- and low-SES schools in the likelihood of completing highest-level science courses persist over the study period.

In sum, school-level socioeconomic composition is positively associated with course-taking patterns, with students in high SES schools more likely to complete math and science courses compared to those in low-SES schools. Disparities in mid-level math course completion between high and low SES schools decreased over the study period, with a substantial increase in completion rates observed in low SES schools. However, differences in completion rates of highest-level math and science courses widened or maintained over time, with significant increases observed in completion rates among students from high SES schools compared to those from low SES schools.

4. DISCUSSION AND CONCLUSION

Advanced course-taking patterns in high school play a significant role in shaping students' educational and occupational attainments. Despite recent findings that there isn't a consistent set of core-subject courses to STEM pathways (Bowers et al., 2022), many studies suggest that completion of advanced science and math courses can affect students' future educational attainments and long-term labor market outcomes (Adelman, 2006; Black et al., 2021; Hinojosa et al., 2016; Maltese & Tai, 2011; Tyson et al., 2007), as well as health at midlife (Carroll et al., 2017).

The share of high school students in advanced math has substantially increased over the past few decades. However, our analysis reveals shifts in completion probabilities of mid- and highest-level math and science courses across socioeconomic subgroups over time. While disparities in mid-level mathematics narrowed, persistent inequalities were observed in rigorous course completion rates, particularly among low-SES students. Similarly, disparities in mid-level math course completion between high and low SES schools decreased over the study period, with a substantial increase in completion rates observed in low SES schools. However, differences in completion rates of highest-level math and science courses widened or remained consistent over time, which has significant implications for promoting educational equity and fostering social mobility.

To enhance STEM opportunities, students who have relatively weak academic performance in mathematics tend to focus on science courses over mathematics (Weis et al., 2015; Eisenhart & Weis, 2022), while simultaneously attending and graduating from high schools that prioritize particular sciences over others. Specifically, they tend to prioritize relatively less mathematized science courses (e.g., biology) rather than highly mathematized science courses (e.g., physics). Such targeted moves towards less mathematized sciences is enabled and facilitated by teachers and counselors (Nikischer et al., 2016). Despite these efforts, our analyses indicate that SES-based inequalities have persisted even in a less mathematized science course, such as, in this case, biology 2. Our findings did not provide empirical evidence at a national level that the different degree of mathematization and mathematics prerequisite in science subdisciplines are related to SES-based inequalities in science course-taking patterns. Because we examined only three time points from early 1990s to 2010s, however, future studies should expand the study period and assess if the degree of mathematization in science disciplines is related to inequalities in science course-taking patterns.

Despite increases in math and science course completion across all SES groups, socioeconomically advantaged but academically equivalent students have a higher likelihood of completing advanced science and math courses, which are crucial for entry into more highly-ranked postsecondary institutions and/or STEM majors (Adelman, 2006; Black et al., 2021; Hinojosa et al., 2016; Maltese & Tai, 2011; Tyson et al., 2007). These findings provide supporting evidence for *effectively maintained inequality (EMI) in STEM opportunity in high school,* as proposed by Lucas (2001). *As less highly capitalized students increasingly evidence mid-level course completion in science and mathematics, more highly capitalized students continue to distinguish themselves relative to others by seeking and completing increasingly higher-level science and math courses.* Several qualitative studies reveal that how students from different family backgrounds perceive the value of advanced math and science courses can lead to subsequent decisions about high school course selection as related to college admissions and, ultimately, entrance to and graduation from prestigious STEM majors (Crosnoe & Muller, 2014; Weis et al., 2014). Students with college-educated parents prioritize both good grades and a targeted diverse portfolio and are more likely to take higher-level math and science courses, even if it jeopardizes their grades. Socioeconomically privileged parents closely monitor their children's grades throughout their secondary school career, readily investing in private tutoring if any academic struggles arise. In contrast, students with no college-educated parents tend to downgrade their coursework level, fearing that challenging courses could harm their college prospects by lowering their grades. Additionally, several studies show that students take advanced math and science courses with the expressed aim of making themselves more competitive in the college admissions process (Crosnoe & Muller, 2014; Grodsky & Riegle-Crumb, 2010; Weis et al., 2014). In line with these prior studies, therefore, our findings suggest that more highly capitalized students and families may work *with intention* to secure future postsecondary educational advantages by *taking both rigorous math and science courses*, thereby positioning themselves disproportionately to access selective and highly selective postsecondary institutions, attain four-year degrees, and, as relevant, enter prestigious STEM fields that have considerably larger economic returns compared to college selectivity (Arcidiacono, 2004). Evidence presented by qualitative researchers suggests that parents and students engage this strategy irrespective as to whether said students look to enter STEM majors at the postsecondary level and/or ultimately pursue a STEM career (Weis et al., 2014; Eisenhart & Weis, 2022).

Our findings underscore the need for policymakers and educational researchers to develop educational interventions/reforms that directly address the robust socioeconomic disparities in STEM educational opportunities and related outcomes. For instance, a report drawing upon nationally representative transcript data shows that about 45 percent of students did not earn credit in any science course in their senior year (Brown et al., 2018). Moreover, a recent multi-site longitudinal qualitative study (Eisenhart & Weis, 2022) reveals that in urban schools serving largely low-income and underrepresented minoritized students, school guidance counselors were overwhelmed with tasks related to accountability mandates and with students in crisis, with the consequent result that students who were *on track* to graduate were left entirely on their own to select their classes for senior year, and, at times, even earlier (Nikischer et al., 2016). As a result, high-achieving students who are interested in pursuing STEM fields beyond high school tended to enroll in non-college prep science and math classes, hoping for an easy year and a higher GPA in their senior year, or they did not take any science or math courses in their senior year at all (Eisenhart & Weis, 2022). Additionally, descriptive quantitative analysis using a nationally representative dataset indicates that high SES, white, and Asian students tend to consistently pursue upward course-taking patterns throughout high school, while students with relatively low family SES and minoritized students often experience nonlinear course-taking patterns, including downward moves, particularly from grade 11 to grade 12, limiting their opportunities in reaching to the highest-level math and science courses (Han et al., 2023). To narrow the gap in STEM learning opportunities and associated educational, social and occupational outcomes between socioeconomically advantaged and disadvantaged students, these students should be prepared for, scaffolded for, and guided to take rigorous STEM courses in their senior year.

Equally importantly, our findings highlight the need for policymakers and educational researchers to tackle disparities in STEM learning opportunities between schools in the United States. For example, only approximately 12% of high schools provide a comprehensive range of advanced coursework options, STEM-focused professional development for teachers, and utilize various informal STEM practices to enhance student interest in STEM. In contrast, the majority of high schools in the United States (about 54%) offer limited advanced STEM-related coursework and generally exhibit lower tendencies in implementing strategies to foster student interest in STEM, as well as in mandating STEM professional development for teachers (Vaval et al., 2019). Even after taking into account on-site course offerings, our study found persistent disparities in advanced math and science course-taking between high and low SES schools over time. This underscores and highlights the importance of policymakers prioritizing efforts to ensure equitable distribution of resources among schools, such as focusing on STEM-focused professional development for teachers, and opportunities for informal STEM engagement, in addition to providing authentic access to and scaffolding for advanced coursework options. This comprehensive approach is essential for promoting equity in STEM education and fostering opportunities for all students to succeed in these fields, with an eye towards equalizing future educational and occupational outcomes among students from advantaged and disadvantaged backgrounds.

It should be noted that our findings and implications for policies and practices need to be interpreted with caution due to several limitations in our study. First, our study was ~~in nature~~ descriptive in nature and described trends in SES-based inequalities in course-taking over three decades. Our study did not focus on mechanisms or specific policy changes that explain trends in SES-based inequalities. Therefore, our findings did not offer causal inferences about trends in inequalities. Second, our study was limited due to weaknesses of secondary datasets. Despite the importance of cross-social class friendships in educational and social mobilities (Chetty et al., 2022a, 2022b) as noted in literature review, for example, our study cannot examine or take account of cross-class friendships as one of the mechanisms for widening SES inequalities in course-taking due to the lack of information about friends' social class backgrounds in all three nationally representative high school cohort datasets. The study of social background effects on educational inequality and the test of EMI theory requires investigators to compare two people who are the same on everything else except socioeconomic background by including a set of covariates (Lucas & Byrne, 2017). In order to estimate SES-based inequalities among students with similar academic achievement levels, for example, it is critical to include comprehensive assessment scores for other subjects, such as reading, science, and social studies. In this study, covariate adjustment in prior achievement was somewhat limited due to the lack of comparability in standardized test scores across three studies. For cross-cohort comparison in our study, we included only comparable measures across three studies and employed analytic sample selection restriction, following the NCES guideline (Burns et al., 2011). Thus, our findings can be generalized only to high school graduates, as noted in our method section. It should be noted that our findings cannot be generalized to all high school students in each cohort, including high school dropouts, and our estimates of SES inequalities could be biased (possibly underestimated) due to the analytic sample restriction. In addition, our estimation could be biased due to omitted variables, particularly at school levels. In NCES high school cohort datasets, schools are not repeatedly sampled. Using state-level administrative data, longitudinal trends in school-level inequality in course-taking should be examined.

To tackle socioeconomic disparities in STEM opportunities in high school course-taking, we also need more studies on SES disparities in science achievement from Pre-K programs and elementary education through secondary education. While many studies have investigated socioeconomic disparities in reading and math achievement (e.g., Reardon, 2011), there is a lack of research on when SES disparities in science achievement and course-taking emerge and become well-established, and, as a consequence, unmovable. This line of inquiry can shed light on cumulative (dis)advantages (DiPrete & Eirich, 2006) in STEM opportunities; future study can help address when differences between socioeconomically advantaged and disadvantaged students became larger over time and at what point it becomes harder for those *left behind* to make up any relative loss, leading to persistent inequalities in high school science course-taking patterns and, in all likelihood, STEM educational and occupational outcomes of interest.

Future research is imperative to examine whether the influence of school SES composition effect on course-taking patterns and other broader educational outcomes (e.g., college enrollment rates, STEM major selection, and career trajectories) varies across different individual SES backgrounds and how such relationship evolves over time. Consistent with prior research in Australia (Perry et al., 2022), our study revealed that the effect of school SES on students' course-taking patterns is greater when the student's SES is higher. However, our study found changes in this effect in the recent cohort. This inquiry is particularly crucial given the increasing socioeconomic segregation between schools and districts in the United States (Mijs & Roe, 2021; Owens et al., 2016; Reardon & Owens, 2014). Therefore, exploring these dynamics further through longitudinal and comparative analyses across regions and school districts could provide valuable insights into the evolving relationship between individual and school-level SES and its implications for educational equity and policy interventions, such as effects of reduction in school SES segregation.

Furthermore, future research endeavors should consider integrating school-level variation in STEM learning opportunities, as suggested by Vaval et al (2019), to delve deeper into the examination of inequality in course-taking patterns. While our study employed a single regression framework to explore the associations between school characteristics (namely, school mean SES) and course-taking patterns, adopting multiple typologies of high school STEM learning opportunities, as proposed by Vaval et al (2019), could provide valuable insights into the heterogeneity of such opportunities. This approach could shed light on the types of resource allocation within high schools that may foster equity in STEM learning opportunities.

Future research is also needed to examine which STEM-related policies are effective in improving STEM opportunities specifically for low-income and underrepresented minoritized students. For example, prior studies examined effects of state policies on number of years completed in science and math (Kim et al., 2019; Teitelbaum, 2003), effects of inclusive-STEM-focused high schools on advanced STEM course-taking patterns (Weis et al., 2015; Means et al., 2016), and effects of state-level AP exam fee-reduction on low-income students (Rodriguez et al., 2022). To date, however, few studies have investigated effects of state policies as specifically related to the most rigorous high school math and science courses, such as physics 2, chemistry

2, biology 2 or AP/IB science-related courses, among low-income and underrepresented minoritized students. Future research is needed to compare the effects of STEM-related reform policies on these advanced high school math and science course-taking patterns and linked educational and occupational outcomes across states and within states over time. Such research should aim to assess which reforms are most effective in improving STEM opportunities and related outcomes for low-income and underrepresented minoritized students in the United States.

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Table 1. Descriptive Trends in Completed Highest Mathematics and Science Coursework Across Three Cohorts

Completed Highest Coursework	1992 cohort (%)	2004 cohort (%)	2013 cohort (%)	Δ 2013-1992 cohort (%)	Wilcoxon rank-sum test
Mathematics					
Calculus	10.73	12.39	15.88	5.15	
Precalculus	10.98	18.02	21.15	10.17	
Trigonometry	20.05	16.55	24.50	4.45	
Algebra 2	27.44	25.41	24.80	-2.64	z= –39.11***
Geometry	11.30	16.73	8.89	-2.41	
Algebra 1	9.91	5.56	3.04	-6.87	
Remedial	9.59	5.34	1.73	-7.86	
Science					
Chemistry 2, Physic 2, or Biology 2	6.89	11.97	14.47	7.58	
Physics 1 *and* Chemistry 1	17.27	19.28	23.89	6.62	
Chemistry 1	35.70	36.97	35.54	-0.16	
Secondary Life	35.34	26.53	22.68	-12.66	z= -31.38***
Secondary Physical	0.69	1.20	1.74	1.05	
Primary Physical	3.62	3.71	1.27	-2.35	
Low-Level	0.49	0.33	0.41	-0.08	

Note. Weighting is adjusted.

*** p<0.001

Table 2. Hierarchical Generalized Linear Analyses Predicting Completion of Mathematics and Science Courses by Cohort and Subjects

	Algebra 2 or above						Calculus						Chemistry 1 or above						Physics 2, Chemistry 2, or Biology 2					
	1992 cohort		2004 cohort		2013 cohort		1992 cohort		2004 cohort		2013 cohort		1992 cohort		2004 cohort		2013 cohort		1992 cohort		2004 cohort		2013 cohort	
Variables	M1	M2	M1	M2	M1	M2	M1	M2	M1	M2	M1	M2	M1	M2	M1	M2	M1	M2	M1	M2	M1	M2	M1	M2
Individual SES																								
Middle SES	0.71***	0.42*	0.32***	-0.09	0.30*	0.01	0.63**	0.26	0.13	-0.33	0.40*	0.08	0.84***	0.38	0.32***	-0.00	0.36***	0.25	0.65**	0.30	0.15	-0.30	0.40*	0.09
	(0.12)	(0.22)	(0.09)	(0.17)	(0.12)	(0.25)	(0.21)	(0.46)	(0.16)	(0.32)	(0.18)	(0.45)	(0.12)	(0.21)	(0.10)	(0.15)	(0.10)	(0.18)	(0.21)	(0.46)	(0.16)	(0.32)	(0.18)	(0.45)
High SES	1.09***	-0.32	0.79***	0.25	0.78**	-0.00	1.18***	-1.08	0.76***	-0.19	0.95***	0.90	1.53***	0.44	0.92***	0.90	1.29***	-0.20	1.23***	-0.96	0.77***	-0.16	0.96***	0.90
	(0.24)	(0.74)	(0.17)	(0.61)	(0.27)	(0.79)	(0.24)	(0.80)	(0.19)	(0.49)	(0.19)	(1.00)	(0.18)	(0.63)	(0.15)	(0.58)	(0.21)	(0.76)	(0.24)	(0.77)	(0.19)	(0.48)	(0.19)	(1.00)
School mean SES (Ref.: Low school mean SES)																								
Middle school mean SES	-0.14	-0.41	0.24	-0.12	-0.21	-0.48	-0.33	-0.84	-0.03	-0.50	0.27	-0.08	-0.14	-0.55**	0.13	-0.13	-0.16	-0.28	-0.29	-0.78	-0.07	-0.52	0.29	-0.05
	(0.16)	(0.21)	(0.18)	(0.22)	(0.20)	(0.28)	(0.23)	(0.46)	(0.21)	(0.35)	(0.20)	(0.45)	(0.14)	(0.21)	(0.18)	(0.22)	(0.20)	(0.25)	(0.24)	(0.45)	(0.20)	(0.34)	(0.20)	(0.45)
High school mean SES	1.14***	1.70**	0.98**	0.22	0.73*	0.12	-0.07	1.33	0.07	-1.48	0.57*	0.77	0.40	0.43	0.48	-0.48	0.20	0.13	0.04	1.48	0.06	-1.45	0.56*	0.78
	(0.30)	(0.63)	(0.30)	(0.50)	(0.35)	(0.77)	(0.31)	(1.12)	(0.28)	(0.76)	(0.28)	(0.76)	(0.24)	(0.55)	(0.29)	(0.57)	(0.31)	(0.56)	(0.31)	(1.09)	(0.27)	(0.76)	(0.28)	(0.75)
Interaction terms																								
Middle SES x Middle school mean SES		0.43		0.56**		0.39		0.60		0.60		0.43		0.66**		0.42*		0.16		0.57		0.57		0.42
		(0.26)		(0.20)		(0.28)		(0.54)		(0.39)		(0.49)		(0.25)		(0.19)		(0.22)		(0.53)		(0.39)		(0.49)
Middle SES x High school mean SES		-0.78		1.11*		0.67		-1.49		1.79*		-0.05		-0.06		1.24*		0.08		-1.52		1.75*		-0.06
		(0.62)		(0.53)		(0.74)		(1.16)		(0.78)		(0.74)		(0.57)		(0.55)		(0.49)		(1.13)		(0.78)		(0.74)
High SES x Middle school mean SES		1.42		0.77		0.82		2.39**		1.15*		0.29		1.12		0.14		1.57		2.33**		1.13*		0.29
		(0.79)		(0.64)		(0.83)		(0.85)		(0.54)		(1.02)		(0.66)		(0.60)		(0.80)		(0.82)		(0.53)		(1.03)
High SES x High school mean SES		1.32		0.88		1.68		0.62		2.10*		-0.53		1.22		0.72		1.57		0.53		2.06*		-0.53
		(1.01)		(0.78)		(1.16)		(1.29)		(0.87)		(1.16)		(0.83)		(0.78)		(0.93)		(1.26)		(0.87)		(1.16)
Individual-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*** *p*<.001, ** *p*<.01, * *p*<.05

Note. For each cohort, SES was categorized as follows: low SES was defined as at least one standard deviation below the SES mean, middle SES as within one standard deviation of the SES mean, and high SES as at least one standard deviation above the SES mean; the school mean SES groups were defined similarly, based on the school mean SES value. Additional covariates included in the analysis were sex, race/ethnicity, ninth/tenth grade mathematics achievement score, school mean mathematics score, coursework offering, school location, and type.

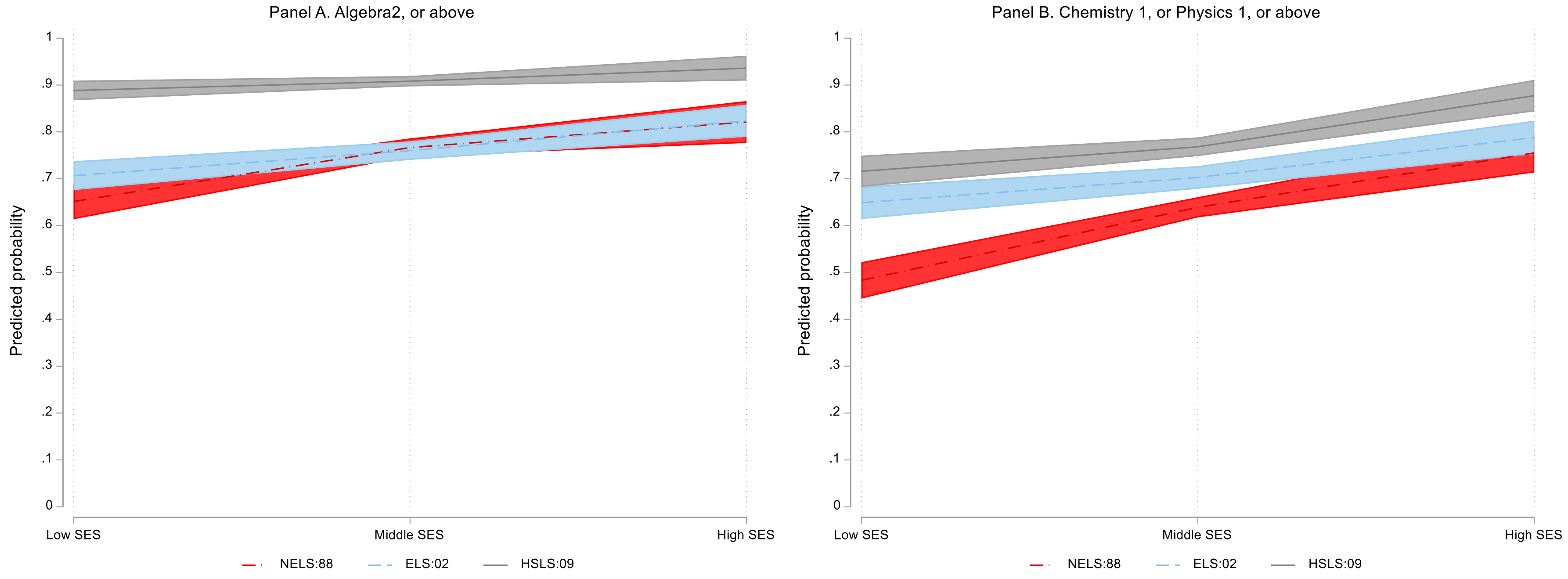
Table 3. Adjusted Marginal Effects of the Individual SES from Multilevel Logit Models Estimating Completing Mathematics, and Science Coursework

	Mathematics				Science			
	Mid-level or above		Highest-level		Mid-level or above		Highest-level	
	Algebra 2 or above		Calculus		Chemistry 1 or above		Physics 2, Chemistry 2, or Biology 2	
Groups[a]	1992 cohort	2013 cohort	1992 cohort	2013 cohort	1992 cohort	2013 cohort	1992 cohort	2013 cohort
Low SES	-0.06*	0.19***	-0.03**	0.01	-0.17***	0.07**	-0.04***	0.01
	(0.02)	(0.02)	(0.01)	(0.01)	(0.03)	(0.03)	(0.01)	(0.01)
Middle SES	0.00	0.16***	-0.02*	0.03***	-0.07***	0.07***	-0.04***	0.03**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
High SES	-0.01	0.12***	-0.04**	0.04**	-0.04	0.09***	-0.06***	0.02
	(0.03)	(0.02)	(0.01)	(0.01)	(0.03)	(0.02)	(0.01)	(0.02)

Note. [a]The reference group is the 2004 cohort. For each cohort, low SES was defined as at least one standard deviation below the SES mean, middle SES as the family SES index between –1 standard deviation and + 1 standard deviation, and high SES as at least one standard deviation above the SES mean. All other covariates, including sex, race/ethnicity, ninth/tenth grade mathematics achievement score, school mean SES, school mean mathematics score, coursework offering, school location, and type, were held at their mean values. Alongside the control variables, the interaction term between cohort and SES was included in the multilevel logit model. N= 36,800. Multilevel logistic regression model results are presented in Appendix E (Table E1).

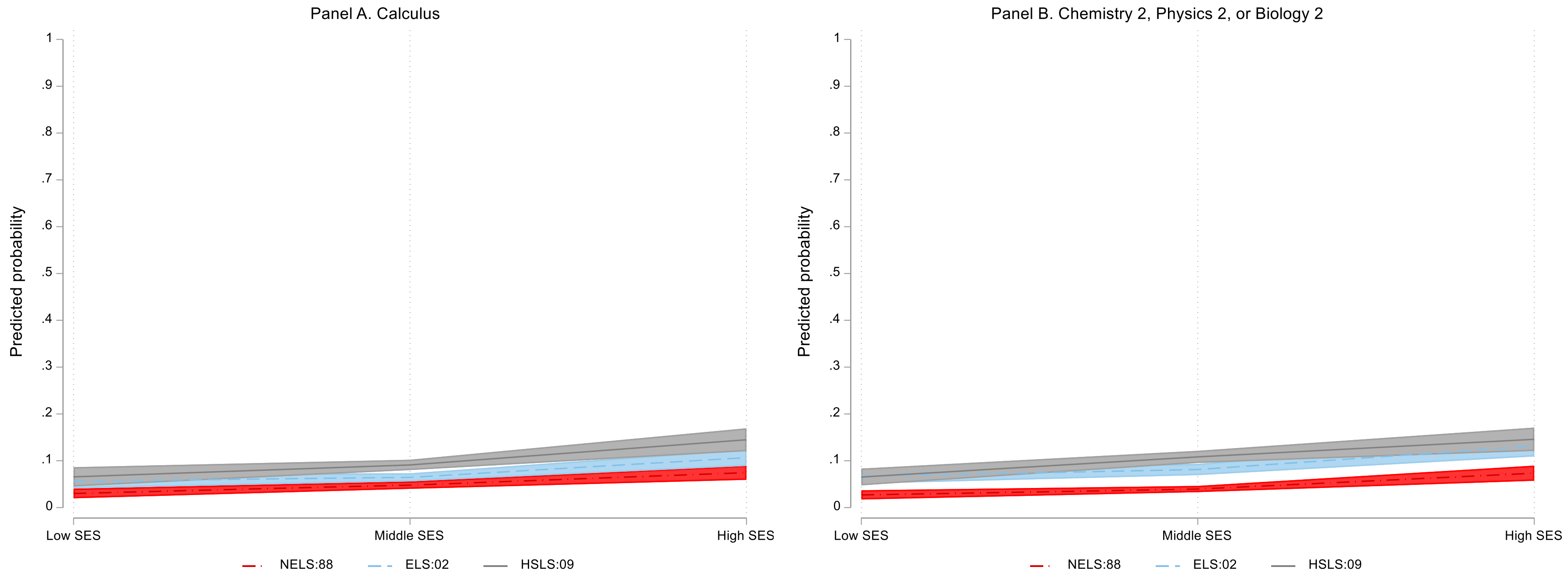
*** p<0.001, ** p<0.01, * p<0.05

Figure 1. Predicted Probability of Completing Mid-Level Mathematics, and Science Coursework by Individual SES Across Three Cohorts



All other covariates, including individual SES, sex, race/ethnicity, ninth/tenth grade mathematics achievement score, school mean SES, coursework offering, school mean mathematics score, school location, and type, were held at their mean values. Low SES was defined as at least one standard deviation below the SES mean, middle SES as the family SES index between –1 standard deviation and + 1 standard deviation, and high SES at least one standard deviation above the SES mean. Shaded area indicates 95% confidence interval. Multilevel logistic regression model results are presented in Appendix E.

Figure 2. Predicted Probability of Completing Highest-Level Mathematics, and Science Coursework by Individual SES Across Three Cohorts



All other covariates, including individual SES score, sex, race/ethnicity, ninth/tenth grade mathematics achievement score, school mean SES, coursework offering, school mean mathematics score, school location, and type, were held at their mean values. Low SES was defined as at least one standard deviation below the SES mean, middle SES as the family SES index between –1 standard deviation and + 1 standard deviation, and high SES as at least one standard deviation above the SES mean. Shaded area indicates 95% confidence interval. Multilevel logistic regression model results are presented in Appendix E (Table E1).

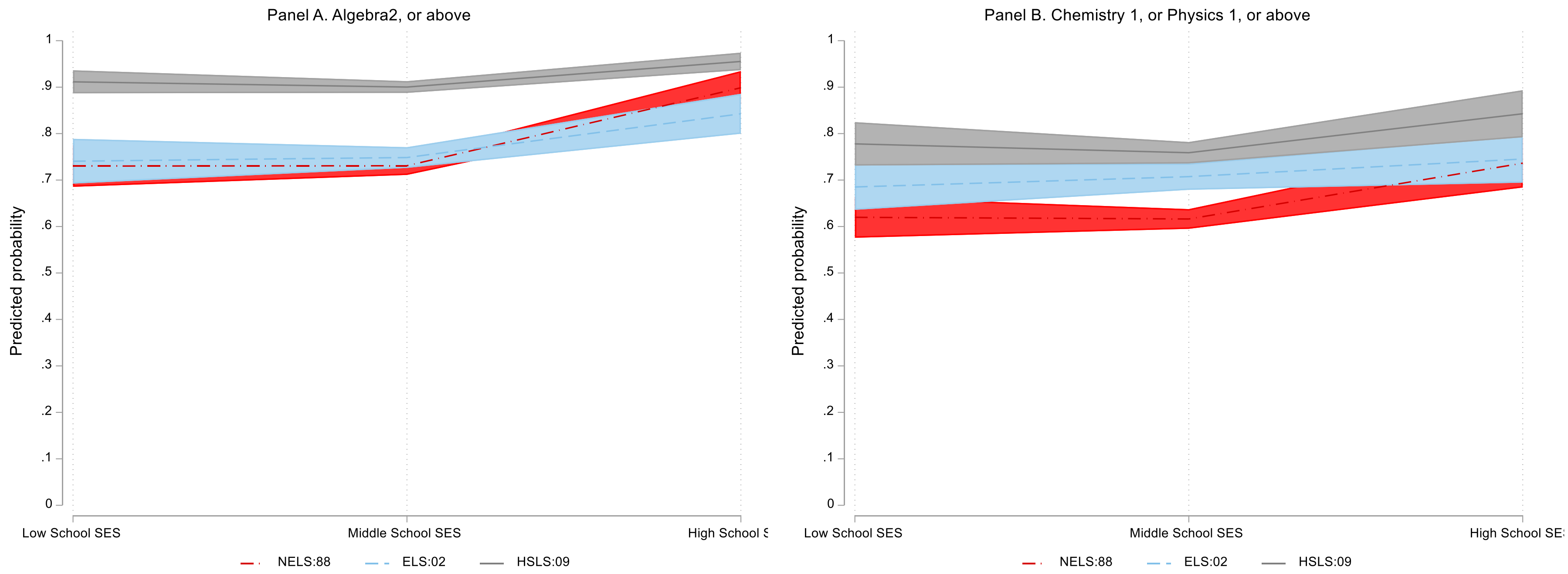
Table 4. Adjusted Marginal Effects of the School Mean SES from Multilevel Logit Models Estimating Completing Mathematics, and Science Coursework

	Mathematics				Science			
	Mid-level or above		Highest-level		Mid-level or above		Highest-level	
	Algebra 2 or above		Calculus		Chemistry 1, or above		Physics 2, Chemistry 2, or Biology 2	
Groups[a]	1992 cohort	2013 cohort	1992 cohort	2013 cohort	1992 cohort	2013 cohort	1992 cohort	2013 cohort
Low school mean SES	0.02	0.18***	0.00	0.00	-0.07*	0.10**	-0.04***	-0.00
	(0.04)	(0.03)	(0.01)	(0.01)	(0.03)	(0.04)	(0.01)	(0.02)
Middle school mean SES	-0.02*	0.16***	-0.02***	0.02**	-0.09***	0.06**	-0.04***	0.03**
	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
High school mean SES	0.05	0.12***	-0.02*	0.07***	-0.01	0.10**	-0.06*	0.02
	(0.03)	(0.02)	(0.01)	(0.01)	(0.04)	(0.03)	(0.01)	(0.02)

Note. [a]The reference group is the 2004 cohort. For each cohort, low school SES mean was defined as at least one standard deviation below the school mean SES, middle SES as the school mean SES index between –1 standard deviation and + 1 standard deviation, and high SES as at least one standard deviation above the mean value of the school mean SES. All other covariates, including sex, race/ethnicity, ninth/tenth grade mathematics achievement score, school mean mathematics score, coursework offering, school location, and type, were held at their mean values. Alongside the control variables, the interaction term between cohort and school mean SES was included in the multilevel logistic model. N= 36,800. Multilevel logistic regression model results are presented in Appendix E (Table E2).

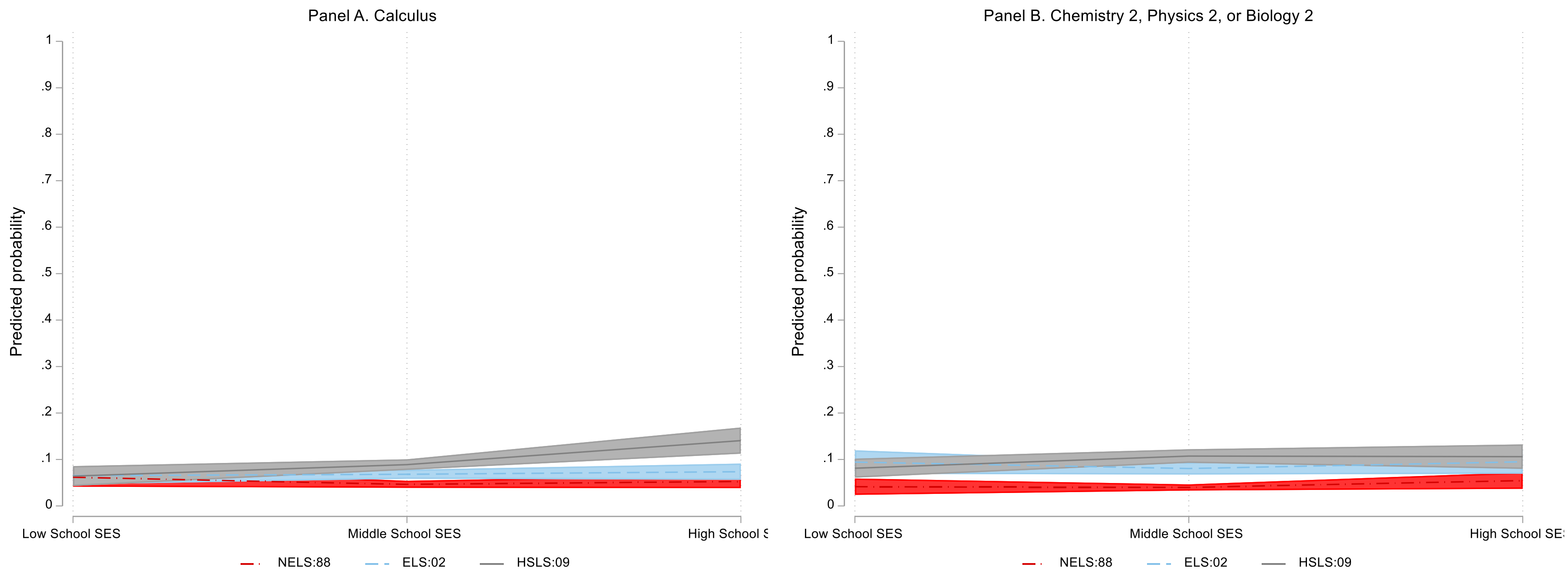
*** p<0.001, ** p<0.01, * p<0.05

Figure 3. Predicted Probability of Completing Mid-Level Mathematics, and Science Coursework by School Mean SES Groups Across Three Cohorts



All other covariates, including individual SES score, sex, race/ethnicity, ninth/tenth grade mathematics achievement score, school mean SES, coursework offering, school mean mathematics score, school location, and type, were held at their mean values. Low school SES mean was defined as at least one standard deviation below the school mean SES, middle SES as the school mean SES index between –1 standard deviation and + 1 standard deviation, and high SES as at least one standard deviation above the mean value of the school mean SES. Shaded area indicates 95% confidence interval. Full multilevel logistic regression model results are presented in Appendix E (Table E2).

Figure 4. Predicted Probability of Completing Highest-Level Mathematics, and Science Coursework by School Mean SES Groups Across Three Cohorts



All other covariates, including individual SES score, sex, race/ethnicity, ninth/tenth grade mathematics achievement score, school mean SES, coursework offering, school mean mathematics score, school location, and type, were held at their mean values. We defined low school SES mean as at least one standard deviation below the school mean SES, middle SES as the school mean SES index between the –1 standard deviation and + 1 standard deviation, and high SES as at least one standard deviation above the mean value of the school mean SES Shaded area indicates 95% confidence interval. Logistic regression model results are presented in Appendix E (Table E2).

Appendix A. Sensitivity Analysis of Dropout Students

Table A.1. Difference in SES Over Dropout Status for Each Cohort

	Dropout[a] Mean (Standard Error)	Non-dropout Mean (Standard Error)	*F*	*P*
1992 cohort	-.48 (.05)	.08 (.02)	578.56	.000
2004 cohort	-.44 (.02)	.06 (.01)	585.64	.000
2013 cohort	-.36 (.04)	.02 (.01)	219.90	.000

Note. [a]Students those who have experienced dropout at least one time during high school. All values are adjusted by weighting.

Appendix B. Replication of Tables 2 and 3, Using the 1992 Cohort as a Reference Group

Table B.1. Alternative Adjusted Marginal Effects of the Individual SES from Multilevel Logit Models Estimating Completing Mathematics, and Science Coursework

	Mathematics				Science			
	Mid-level or above		Highest-level		Mid-level or above		Highest-level	
	Algebra 2 or above		Calculus		Chemistry 1 or above		Physics 2, Chemistry 2, or Biology 2	
Groups[a]	2004 cohort	2013 cohort	2004 cohort	2013 cohort	2004 cohort	2013 cohort	2004 cohort	2013 cohort
Low SES	0.06*	0.25***	0.03**	0.04**	0.17***	0.24***	0.04***	0.04***
	(0.02)	(0.02)	(0.01)	(0.01)	(0.03)	(0.03)	(0.01)	(0.01)
Middle SES	-0.00	0.15***	0.02**	0.04***	0.07***	0.14***	0.04***	0.07***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
High SES	0.01	0.12***	0.03**	0.07***	0.04	0.13***	0.06***	0.08***
	(0.03)	(0.03)	(0.01)	(0.01)	(0.03)	(0.03)	(0.01)	(0.01)

Note. [a]The reference group is the 1992 cohort. For each cohort, low SES was defined as at least one standard deviation below the SES mean, middle SES as the family SES index between –1 standard deviation and + 1 standard deviation, and high SES as at least one standard deviation above the SES mean. All other covariates, including sex, race/ethnicity, ninth/tenth grade mathematics achievement score, school mean SES, school mean mathematics score, coursework offering, school location, and type, were held at their mean values. Alongside the control variables, the interaction term between cohort and SES was included in the multilevel logistic model. N= 36,800.

*** p<.001, ** p<.01, * p<.05

Table B.2. Alternative Adjusted Marginal Effects of the School Mean SES from Multilevel Logit Models Estimating Completing Mathematics, and Science Coursework

	Mathematics				Science			
	Mid-level or above		Highest-level		Mid-level or above		Highest-level	
	Algebra 2 or above		Calculus		Chemistry 1 or above		Physics 2, Chemistry 2, or Biology 2	
Groups[a]	2004 cohort	2013 cohort	2004 cohort	2013 cohort	2004 cohort	2013 cohort	2004 cohort	2013 cohort
Low school mean SES	-0.02	0.19***	0.00	0.00	0.07*	0.17***	0.06***	0.05***
	(0.03)	(0.03)	(0.01)	(0.01)	(0.03)	(0.03)	(0.02)	(0.01)
Middle school mean SES	0.02	0.18***	0.02***	0.04***	0.09***	0.15***	0.04***	0.08***
	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
High school mean SES	-0.05	0.06**	0.02*	0.09***	0.01	0.12**	0.04**	0.06***
	(0.03)	(0.02)	(0.01)	(0.01)	(0.04)	(0.04)	(0.01)	(0.01)

Note. [a]The reference group is the 1992 cohort. For each cohort, low school SES mean was defined as at least one standard deviation below the school mean SES, middle SES as the school mean SES index between –1 standard deviation and + 1 standard deviation, and high SES as at least one standard deviation above the mean value of the school mean SES. All other covariates, including sex, race/ethnicity, ninth/tenth grade mathematics achievement score, coursework offering, school mean mathematics score, school location, and type, were held at their mean values. Alongside the control variables, the interaction term between cohort and school mean SES was included in the multilevel logistic model. N= 36,800.

*** p<.001, ** p<.01, * p<.05

Appendix C. Missing Data Analyses

Table C.1. Missing Distribution of Variables Used in the Study

Variables	1992 cohort (%)	2004 cohort (%)	2013 cohort (%)	Total (%)
SES	14.97	5.69	4.66	7.74
Sex	4.27	4.35	.02	2.43
Race/ethnicity	4.91	0	4.4	3.26
Math achievement at 9th/10th grade	4.27	1.4	8.22	5.17
Algebra 2 or above	0	0	.04	.02
Calculus	0	0	.04	.02
Chemistry 1, or above	0	0	0	0
Physics 2, Chemistry 2, or Biology2	0	0	0	0
School mean SES	0	0	0	0
School mean achievement score	0	0	0	0
School location	1.50	0	0	.40
School type	1.51	0	0	.41
Algebra 2 coursework offer	3.62	4.59	13.98	15.73
Calculus coursework offer	33.26	4.59	13.98	16.44
Chemistry 1 coursework offer	29.44	4.73	13.98	15.45
Chemistry 2, Physics 2, or Biology 2 coursework offer	29.63	4.73	13.98	15.50
N	9,920	10,730	16,150	36,800

Table C.2. Descriptive Statistics of Variables used in the Study

	Unweighted		Weighted		Weighted & Imputed	
	Mean	*S.D.*	*Mean*	*S.D.*	*Mean*	*S.D.*
Cohort (Ref =NELS:88)						
ELS:02	.292	.454	.322	.467	.322	.467
HSLS:09	.439	.496	.382	.486	.382	.486
Highest Coursework						
Algebra 2 or above	.801	.400	.767	.423	.767	.423
Calculus	.164	.370	.132	.339	.132	.339
Chemistry or above	.710	.454	.679	.467	.679	.467
Chemistry 2, Physics 2, or Biology 2	.140	.347	.114	.318	.114	.318
SES (Ref =Low)						
Middle SES level	.710	.454	.713	.453	.711	.453
High SES level	.136	.343	.123	.328	.124	.329
Female (Ref =male)	.511	.500	.514	.500	.513	.500
Race/ethnicity (Ref =White)						
Black	.098	.297	.120	.325	.119	.324
Hispanic	.138	.345	.156	.363	.157	.364
Asian	.092	.290	.041	.197	.043	.202
Native	.059	.235	.051	.219	.050	.219
Prior math achievement score (Ref=The lowest 25%)						
25 to <50%	.251	.434	.255	.436	.252	.434
50 to <75%	.250	.433	.238	.426	.238	.426
75 to 100 (The highest 25%)	.252	.434	.235	.424	.233	.423
School mean SES (Ref =low school mean SES)						
Middle school mean SES	.709	.454	.743	.437	.743	.437
High school mean SES	.155	.362	.112	.315	.112	.315
School Type (Ref =public)						
Catholic	.118	.323	.051	.220	.051	.219
Other private	.078	.267	.038	.192	.038	.192
School location (Ref=urban)						
Suburban	.412	.492	.418	.493	.418	.493
Rural	.240	.427	.246	.430	.246	.431
Course offering						
Algebra 2	.994	.074	.994	.078	.995	.076
Calculus	.915	.280	.915	.279	.911	.278
Chemistry 1	.994	.080	.993	.082	.994	.074
Chemistry 2, Physics 2, or Biology 2	.848	.359	.857	.351	.882	.323

Note. *S.D.* = standard deviation

Appendix D. Changes in biology 2 course-taking patterns across three cohorts

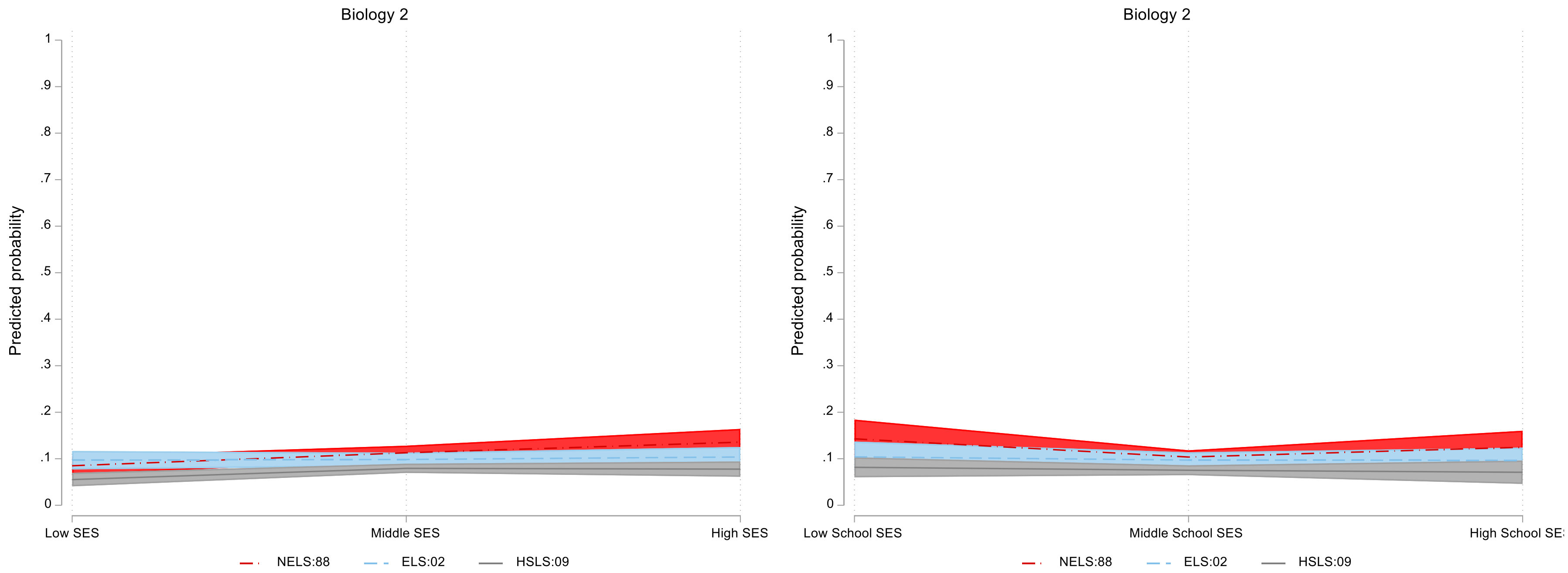
Table D1. Adjusted Marginal Effects of Individual- and School-Level SSES from the Multilevel Logit Models Estimating Completing Biology 2 Coursework

	Panel A: Individual SES					
	Low SES		Middle SES		High SES	
1992 cohort[a]	-.01	(.01)	.01	(.01)	.02	(.02)
2013 cohort[a]	-.04**	(.02)	-.01	(.01)	-.02	(.01)
	Panel B: School Mean SES					
	Low school mean SES[a]		Middle school mean SES[a]		High school mean SES[a]	
1992 cohort[a]	0.03	(0.03)	0.00	(0.01)	0.02	(0.02)
2013 cohort[a]	-0.02	(0.02)	-0.02	(0.01)	-0.02	(0.02)

Note. [a]The reference group is the 2004 cohort. For each cohort, low SES, and low school SES were refined as at least one standard deviation below the mean value, middle as the of their values between –1 standard deviation and + 1 standard deviation, and high as at least one standard deviation above the mean value. All other covariates, including sex, race/ethnicity, ninth/tenth grade mathematics achievement score, school mean mathematics score, school location, and type, were held at their mean values. Alongside the control variables, the interaction term between cohort and SES was included in the estimation of Panel A model, and the interaction between cohort and school mean SES was included in the estimation of Panel B in the multilevel logistic models. *N*= 36,800.

*** p<.001, ** p<.01, * p<.05

Figure D.1. Predicted probability of completing Biology 2 by SES group across three cohort



Note. All other covariates, including individual SES, sex, race/ethnicity, ninth/tenth grade mathematics achievement score, school mean SES, school mean mathematics score, coursework offering, school location, and type, were held at their mean values. Low SES was defined as at least one standard deviation below the SES mean, middle SES as the family SES index between –1 standard deviation and + 1 standard deviation, and high SES as at least one standard deviation above the SES mean. Shaded area indicates 95% confidence interval.

Appendix E. Comparison of multilevel logit models by application of weights and use of imputed datasets

Table E.1. Full results of interaction effect between individual SES and cohort on the likelihood of completing advanced mathematics and science coursework

	Algebra2 or above				Calculus				Chemistry 1, or above				Physics 2, Chemistry 2, or Biology 2			
Variables	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Individual Socio-economic Status (SES) (Ref.: Low SES)																
Middle SES	1.06***	1.14***	0.97***	0.35***	1.02***	1.26***	0.43†	0.16	1.07***	1.20***	0.84***	0.32***	1.11***	0.98***	0.46*	0.23
	(0.07)	(0.10)	(0.12)	(0.09)	(0.13)	(0.17)	(0.22)	(0.16)	(0.07)	(0.10)	(0.11)	(0.09)	(0.17)	(0.19)	(0.20)	(0.15)
High SES	2.25***	2.02***	1.53***	0.83***	2.03***	2.29***	0.90***	0.77***	2.22***	2.27***	1.55***	0.90***	2.17***	2.06***	1.14***	0.86***
	(0.12)	(0.20)	(0.20)	(0.16)	(0.15)	(0.19)	(0.24)	(0.18)	(0.11)	(0.16)	(0.19)	(0.15)	(0.18)	(0.21)	(0.22)	(0.17)
Cohort (Ref.: 1992 Cohort)																
2004 Cohort	0.46***	0.44***	0.49**	-0.36*	0.47**	0.72***	0.56*	-0.70**	0.78***	0.87***	0.89***	-0.91***	1.11***	0.97***	1.09***	-1.11***
	(0.10)	(0.12)	(0.15)	(0.14)	(0.17)	(0.21)	(0.28)	(0.24)	(0.10)	(0.13)	(0.15)	(0.15)	(0.20)	(0.23)	(0.25)	(0.26)
2013 Cohort	1.72***	1.80***	2.09***	1.55***	0.74***	1.05***	0.84*	0.17	1.32***	1.37***	1.38***	0.43**	1.21***	1.12***	1.08***	0.01
	(0.10)	(0.14)	(0.19)	(0.16)	(0.16)	(0.22)	(0.33)	(0.24)	(0.10)	(0.14)	(0.16)	(0.15)	(0.19)	(0.24)	(0.28)	(0.23)
Gender (Ref.: Male)			0.49***	0.44***			-0.02	-0.02			0.36***	0.35***			0.18**	0.17**
			(0.06)	(0.05)			(0.05)	(0.05)			(0.05)	(0.04)			(0.06)	(0.06)
Race/ethnicity (Ref.: White)																
Black			0.28*	0.16†			-0.38**	-0.30*			0.12	0.08			0.01	-0.06
			(0.11)	(0.09)			(0.14)	(0.12)			(0.08)	(0.07)			(0.17)	(0.16)
Latinx			-0.12	-0.12			-0.09	-0.13			-0.05	-0.05			-0.19	-0.22††
			(0.12)	(0.09)			(0.11)	(0.10)			(0.08)	(0.08)			(0.13)	(0.13)
Asian			0.85***	0.85***			1.28***	1.35***			0.80***	0.85***			1.20***	1.21***
			(0.13)	(0.12)			(0.11)	(0.10)			(0.12)	(0.11)			(0.10)	(0.10)
Native			0.03	0.01			-0.04	-0.06			-0.06	-0.07			0.00	0.01
			(0.11)	(0.10)			(0.13)	(0.12)			(0.10)	(0.10)			(0.13)	(0.12)
Prior math achievement score[a] (Ref.: The lowest 25%)																
25 to <50%			1.27***	1.23***			1.19***	1.17***			1.01***	0.98***			0.67***	0.96***
			(0.08)	(0.07)			(0.16)	(0.16)			(0.06)	(0.06)			(0.15)	(0.14)
50 to <75%			2.41***	2.34***			2.51***	2.38***			2.01***	1.97***			1.79***	1.92***
			(0.08)	(0.08)			(0.16)	(0.15)			(0.06)	(0.06)			(0.16)	(0.12)
75 to 100 (The highest 25%)			3.59***	3.37***			4.26***	4.08***			3.05***	2.97***			2.97***	3.12***
			(0.11)	(0.11)			(0.16)	(0.15)			(0.09)	(0.08)			(0.17)	(0.12)
School location (Ref.: Urban)																
Suburban			-0.11	0.09			0.12	0.13			-0.08	-0.07			-0.23*	-0.25*
			(0.10)	(0.10)			(0.09)	(0.09)			(0.10)	(0.10)			(0.11)	(0.11)
Rural			0.03	0.09			0.03	-0.00			-0.19	-0.21			-0.52***	-0.53***
			(0.13)	(0.12)			(0.11)	(0.11)			(0.13)	(0.13)			(0.12)	(0.12)
School mean SES (Ref.: Low school mean SES)															-	
Middle school mean SES			-0.12	-0.05			0.15	0.09			-0.06	-0.04			0.03	0.07
			(0.12)	(0.10)			(0.15)	(0.12)			(0.10)	(0.10)			(0.13)	(0.12)
High school mean SES			0.90***	1.01***			0.36*	0.36*			0.49**	0.50**			0.15	0.24
			(0.19)	(0.18)			(0.18)	(0.16)			(0.17)	(0.16)			(0.19)	(0.18)
School mean math achievement score			-0.03***	-0.03***			-0.02*	-0.02**			-0.03***	-0.03***			-0.01	-0.01
			(0.01)	(0.01)			(0.01)	(0.01)			(0.01)	(0.01)			(0.01)	(0.01)
School Type																

(Ref.: Public)																		
Catholic			1.47***	1.48***			0.43***	0.38**			0.84***	0.90***					0.01	-0.01
			(0.22)	(0.23)			(0.12)	(0.12)			(0.14)	(0.14)					(0.17)	(0.17)
Other private			0.52*	0.60**			0.49**	0.42*			0.78***	0.72***					-0.33	-0.37
			(0.21)	(0.18)			(0.18)	(0.16)			(0.19)	(0.18)					(0.31)	(0.29)
Coursework offering[b]			0.89	0.65			1.22***	0.95***			-0.36	-0.11					1.13***	1.14***
			(0.67)	(0.72)			(0.19)	(0.21)			(0.78)	(0.71)					(0.26)	(0.26)
Interaction terms[c]																		
Individual SES x Cohort (Ref.: Low SES, 1992 Cohort)																		
Middle SES x 2004 Cohort	-0.36***	-0.42***	-0.60***	0.37**	-0.34*	-0.51*	-0.26	0.36	-0.38***	-0.54***	-0.54***	0.52***	-0.50*	-0.28	-0.22	0.19
	(0.09)	(0.13)	(0.15)	(0.14)	(0.17)	(0.22)	(0.28)	(0.25)	(0.09)	(0.13)	(0.14)	(0.14)	(0.20)	(0.23)	(0.24)	(0.26)
Middle SES x 2013 Cohort	-0.39***	-0.58***	-0.79***	-0.10	-0.14	-0.44*	-0.16	0.24	-0.42***	-0.63***	-0.56***	0.03	-0.22	-0.07	0.23	0.40†
	(0.10)	(0.15)	(0.19)	(0.15)	(0.16)	(0.22)	(0.33)	(0.24)	(0.09)	(0.14)	(0.16)	(0.13)	(0.19)	(0.24)	(0.28)	(0.22)
High SES x 2004 Cohort	-0.58***	-0.27	-0.65*	0.30	-0.32†	-0.40	-0.08	0.26	-0.60***	-0.57**	-0.65**	0.66**	-0.64**	-0.32	-0.27	0.29
	(0.16)	(0.25)	(0.26)	(0.28)	(0.19)	(0.24)	(0.31)	(0.28)	(0.15)	(0.21)	(0.23)	(0.23)	(0.22)	(0.26)	(0.27)	(0.29)
High SES x 2013 Cohort	-0.51*	-0.27	-0.44	-0.13	-0.13	-0.39	0.08	0.22	-0.26	-0.27	-0.10	0.40	-0.49*	-0.28	0.04	0.18
	(0.22)	(0.31)	(0.35)	(0.32)	(0.18)	(0.25)	(0.35)	(0.27)	(0.18)	(0.26)	(0.27)	(0.24)	(0.22)	(0.27)	(0.31)	(0.25)
Intercept	0.18**	0.11	-0.56	1.61***	-3.35***	-3.84***	-6.34***	1.21***	-0.40***	-0.52***	0.30	1.66***	-4.08***	-4.20***	-6.11***	1.61***
	(0.07)	(0.09)	(0.79)	(0.11)	(0.13)	(0.16)	(0.50)	(0.10)	(0.07)	(0.09)	(0.85)	(0.09)	(0.17)	(0.19)	(0.50)	(0.12)
School-level intercept variance	1.10***	1.34***	1.62***	0.08	0.86***	0.99***	1.10***	-5.37***	1.22***	1.39***	1.74***	0.80	1.32***	1.41***	1.64***	-5.09***
	(0.06)	(0.09)	(0.12)	(0.79)	(0.05)	(0.08)	(0.10)	(0.38)	(0.06)	(0.08)	(0.10)	(0.78)	(0.08)	(0.10)	(0.12)	(0.43)

Note.
The clustered robust standard errors which account for the clustering at the school level are reported in parentheses. The models—(1) without weight (*N*=33,950), (2) with weight(*N*=33,950), (3) with weight and control variables(*N*=27,870), and (4) with weight, control variables, and imputed data (*N*=36,800)—are methodically delineated to showcase the variance in results contingent upon these adjustments.
*** p<.001, ** p<.01, * p<.05, †p<.10

[a]It indicates prior achievement score variable (ninth (HSLS:2009) or tenth grade (NELS:88 and ELS:2002) standardized math test scores) as a proxy of students' achievement level at the beginning of high school. As HSLS:09 utilized different content and scaling of mathematics tests, and the timing to test was not the same as NELS:88 and ELS:2002, the achievement score from HSLS:09 is not comparable to the other two cohort data. In ELS:2002, test specifications were adapted from frameworks utilized in the NELS:88. Mathematics assessments encompassed items spanning arithmetic, geometry, data/probability, and advanced topics. Compared to the NELS:88 assessments, the ELS:2002 math tests placed a heightened emphasis on practical applications and problem-solving (Ingels et al., 2004). In the HSLS, a framework was developed to gauge student achievement in algebra, track changes in this achievement over time, and explore its correlation with various individual, home, and school factors. This framework aligns a set of items with algebraic reasoning (Duprey et al., 2018). To ensure consistency and control for relative cohort positions within the model, we standardized starting mathematics achievement scores for each cohort to a mean of 0 and a standard deviation of 1. This approach allows for meaningful comparisons across cohorts by focusing on relative changes rather than absolute score levels.

[b]It indicates whether courses such as 'Algebra 2', 'Calculus', "Chemistry 1', or 'Physics 2, Chemistry 2, or Biology 2', respectively, were offered in schools, based on each model's estimation of coursework completion, with course offerings matched to each outcome in the estimation.

[c]To provide a clearer interpretation of the interactions between individual SES and cohort, we used a post-estimation approach to compute adjusted marginal effect estimates. This enabled us to demonstrate changes in the probability of completing mathematics and science coursework across different cohorts and SES subgroups, with covariates fixed at their mean values. The results are shown in Table 3.

Table E.2. Full results of interaction effect between school mean SES and cohort on the likelihood of completing advanced mathematics and science coursework

	Algebra2 or above				Calculus				Chemistry 1, or above				Physics 2, Chemistry 2, or Biology 2			
Variables	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
School mean SES (Ref.: Low school mean SES)																
Middle school mean SES	0.56***	0.61***	-0.08	0.00	0.56***	0.71***	-0.43	-0.33	0.55***	0.59***	-0.06	-0.02	0.68***	0.80***	-0.10	-0.05
	(0.11)	(0.13)	(0.20)	(0.16)	(0.15)	(0.18)	(0.27)	(0.21)	(0.12)	(0.12)	(0.15)	(0.14)	(0.20)	(0.24)	(0.29)	(0.26)
High school mean SES	2.65***	2.69***	1.43***	1.45***	1.93***	1.87***	-0.31	-0.19	2.23***	2.14***	0.67**	0.70**	1.83***	1.96***	0.26	0.32
	(0.18)	(0.23)	(0.33)	(0.28)	(0.18)	(0.21)	(0.31)	(0.25)	(0.16)	(0.19)	(0.24)	(0.22)	(0.22)	(0.27)	(0.35)	(0.32)
Cohort (Ref.: 1992 Cohort)																
2004 Cohort	0.23	0.18	-0.03	0.10	0.19	0.25	-0.12	0.07	0.50***	0.48**	0.35†	0.40*	0.95***	1.08***	1.04**	1.07***
	(0.14)	(0.19)	(0.27)	(0.23)	(0.19)	(0.23)	(0.32)	(0.26)	(0.15)	(0.16)	(0.20)	(0.19)	(0.23)	(0.28)	(0.32)	(0.30)
2013 Cohort	1.64***	1.75***	1.69***	1.72***	0.30	0.45††	-0.12	0.08	1.24***	1.26***	1.04***	1.06***	0.92***	1.11***	0.95**	0.95**
	(0.15)	(0.19)	(0.26)	(0.23)	(0.18)	(0.24)	(0.35)	(0.28)	(0.14)	(0.17)	(0.23)	(0.21)	(0.22)	(0.27)	(0.32)	(0.29)
Female (Ref.: Male)			0.49***	0.44***			-0.02	-0.01			0.36***	0.35***			0.18**	0.17**
			(0.06)	(0.05)			(0.05)	(0.05)			(0.05)	(0.04)			(0.06)	(0.06)
Race/ethnicity (Ref.: White)																
Black			0.27*	0.16††			-0.38**	-0.30*			0.12	0.08			0.02	-0.06
			(0.11)	(0.09)			(0.14)	(0.12)			(0.08)	(0.07)			(0.17)	(0.16)
Latinx			-0.11	-0.12			-0.08	-0.13			-0.04	-0.04			-0.19	-0.22††
			(0.12)	(0.09)			(0.11)	(0.10)			(0.08)	(0.08)			(0.13)	(0.13)
Asian			0.86***	0.86***			1.28***	1.36***			0.81***	0.87***			1.20***	1.21***
			(0.14)	(0.13)			(0.11)	(0.10)			(0.13)	(0.11)			(0.10)	(0.10)
Native			0.03	0.01			-0.04	-0.06			-0.06	-0.07			0.01	0.01
			(0.11)	(0.10)			(0.13)	(0.12)			(0.10)	(0.09)			(0.13)	(0.12)
Prior math achievement score[a] (Ref.: The lowest 25%)																
25 to <50%			1.26***	1.23***			1.19***	1.17***			1.01***	0.97***			0.67***	0.96***
			(0.08)	(0.07)			(0.16)	(0.16)			(0.06)	(0.06)			(0.15)	(0.14)
50 to <75%			2.40***	2.34***			2.51***	2.38***			2.01***	1.97***			1.79***	1.92***
			(0.08)	(0.08)			(0.16)	(0.15)			(0.06)	(0.06)			(0.16)	(0.11)
75 to 100 (The highest 25%)			3.58***	3.37***			4.26***	4.08***			3.05***	2.97***			2.98***	3.12***
			(0.11)	(0.11)			(0.16)	(0.15)			(0.09)	(0.08)			(0.17)	(0.12)
School location (Ref.: Urban)																
Suburban			-0.11	0.09			0.12	0.13			-0.08	-0.07			-0.22*	-0.25*
			(0.10)	(0.10)			(0.09)	(0.08)			(0.10)	(0.10)			(0.11)	(0.11)
Rural			0.01	0.08			0.01	-0.02			-0.20	-0.22††			-0.50***	-0.51***
			(0.13)	(0.12)			(0.11)	(0.11)			(0.13)	(0.13)			(0.12)	(0.12)
Individual SES (Ref.: Low SES)																
Middle SES			0.46***	0.43***			0.27*	0.34**			0.45***	0.47***			0.46***	0.46***
			(0.07)	(0.06)			(0.13)	(0.11)			(0.06)	(0.06)			(0.11)	(0.10)
High SES			1.06***	0.89***			0.89***	0.92***			1.20***	1.18***			1.06***	1.03***
			(0.12)	(0.12)			(0.14)	(0.12)			(0.11)	(0.10)			(0.12)	(0.11)
School mean math achievement score			-0.03***	-0.03***			-0.02*	-0.02**			-0.03***	-0.03***			-0.01	-0.01
			(0.01)	(0.01)			(0.01)	(0.01)			(0.01)	(0.01)			(0.01)	(0.01)
School type (Ref.: Public)																
Catholic			1.49***	1.50***			0.38**	0.34**			0.85***	0.90***			0.04	0.01
			(0.22)	(0.23)			(0.12)	(0.12)			(0.14)	(0.14)			(0.18)	(0.17)
Other private			0.53*	0.60**			0.47**	0.41*			0.79***	0.72***			-0.33	-0.37
			(0.21)	(0.18)			(0.17)	(0.16)			(0.19)	(0.17)			(0.31)	(0.29)
Coursework offering[b]			0.88	0.64			1.22***	0.96***			-0.35	-0.12			1.15***	1.15***

			(0.65)	(0.71)			(0.19)	(0.21)			(0.79)	(0.72)			(0.25)	(0.25)
Interaction terms[c] (Ref.: Low school mean SES, 1992 Cohort)																
Middle school mean SES x 2004 Cohort	0.04	0.03	0.15	0.05	0.13	0.10	0.55††	0.38	0.08	0.04	0.18	0.16	-0.22	-0.31	-0.15	-0.15
	(0.16)	(0.21)	(0.29)	(0.25)	(0.21)	(0.25)	(0.33)	(0.28)	(0.16)	(0.19)	(0.23)	(0.22)	(0.25)	(0.30)	(0.35)	(0.32)
Middle school mean SES x 2013 Cohort	-0.21	-0.43*	-0.20	-0.16	0.38††	0.17	0.87*	0.71*	-0.23	-0.45*	-0.09	-0.12	0.14	-0.04	0.43	0.40
	(0.16)	(0.21)	(0.28)	(0.25)	(0.20)	(0.25)	(0.36)	(0.29)	(0.16)	(0.20)	(0.25)	(0.23)	(0.24)	(0.29)	(0.34)	(0.32)
High school mean SES x 2004 Cohort	-0.59*	-0.67*	-0.59	-0.67††	-0.35	-0.13	0.45	0.33	-0.53*	-0.51††	-0.26	-0.32	-0.64*	-0.63†	-0.35	-0.31
	(0.25)	(0.33)	(0.43)	(0.38)	(0.24)	(0.29)	(0.37)	(0.32)	(0.23)	(0.28)	(0.32)	(0.30)	(0.29)	(0.34)	(0.40)	(0.37)
High school mean SES x 2013 Cohort	-0.78**	-0.81*	-0.91*	-0.63	0.18	0.30	1.31**	1.16***	-0.72**	-0.63*	-0.15	-0.17	-0.42	-0.53	-0.03	0.02
	(0.27)	(0.34)	(0.45)	(0.40)	(0.23)	(0.29)	(0.40)	(0.33)	(0.23)	(0.30)	(0.37)	(0.35)	(0.28)	(0.35)	(0.39)	(0.37)
Intercept	0.37***	0.34**	-0.22	-0.10	-3.01***	-3.34***	-5.68***	-5.53***	-0.15	-0.15	0.60	0.18	-3.71***	-4.03***	-6.04***	-6.13***
	(0.10)	(0.12)	(0.79)	(0.80)	(0.14)	(0.17)	(0.50)	(0.40)	(0.10)	(0.10)	(0.86)	(0.79)	(0.19)	(0.23)	(0.53)	(0.51)
School-level intercept variance	0.94***	1.19***	1.61***	-0.63	0.75***	0.92***	1.10***	1.16***	1.04***	1.26***	1.75***	-0.17	1.24***	1.34***	1.63***	0.02
	(0.05)	(0.07)	(0.12)	(0.40)	(0.05)	(0.07)	(0.10)	(0.33)	(0.05)	(0.07)	(0.10)	(0.35)	(0.07)	(0.09)	(0.12)	(0.37)

Note.

The clustered robust standard errors which account for the clustering at the school level are reported in parentheses. The models—(1) without weight (N=33,950), (2) with weight(N=33,950), (3) with weight and control variables(N=27,870), and (4) with weight, control variables, and imputed data (N=36,800)—are methodically delineated to showcase the variance in results contingent upon these adjustments.

*** $p<.001$, ** $p<.01$, * $p<.05$, $^{\dagger}p<.10$

[a]It indicates prior achievement score variable (ninth (HSLS:2009) or tenth grade (NELS:88 and ELS:2002) standardized math test scores) as a proxy of students' achievement level at the beginning of high school. As HSLS:09 utilized different content and scaling of mathematics tests, and the timing to test was not the same as NELS:88 and ELS:2002, the achievement score from HSLS:09 is not comparable to the other two cohort data. In ELS:2002, test specifications were adapted from frameworks utilized in the NELS:88. Mathematics assessments encompassed items spanning arithmetic, geometry, data/probability, and advanced topics. Compared to the NELS:88 assessments, the ELS:2002 math tests placed a heightened emphasis on practical applications and problem-solving (Ingels et al., 2004). In the HSLS, a framework was developed to gauge student achievement in algebra, track changes in this achievement over time, and explore its correlation with various individual, home, and school factors. This framework aligns a set of items with algebraic reasoning (Duprey et al., 2018). To ensure consistency and control for relative cohort positions within the model, we standardized starting mathematics achievement scores for each cohort to a mean of 0 and a standard deviation of 1. This approach allows for meaningful comparisons across cohorts by focusing on relative changes rather than absolute score levels.

[b]It indicates whether courses such as 'Algebra 2', 'Calculus', "Chemistry 1', or 'Physics 2, Chemistry 2, or Biology 2', respectively, were offered in schools, based on each model's estimation of coursework completion, with course offerings matched to each outcome in the estimation.

[c] To provide a clearer interpretation of the interaction between school mean SES and cohort, we used a post-estimation approach to compute adjusted marginal effect estimates. This enabled us to demonstrate changes in the probability of completing mathematics and science coursework across different cohorts and school mean SES subgroups, with covariates fixed at their mean values. The results are shown in Tables 4.