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The importance of STEM: High school knowledge, skills and occupations in an era of growing inequality

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Abstract

Science, Technology, Engineering and Mathematics (STEM) jobs have grown in importance in the labor market in recent decades, and they are widely seen as the jobs of the future. Using data from the U.S. Census and American Community Survey, we first investigate the role of employment in STEM occupations when it comes to recent changes in the occupational employment distribution in the U.S. labor market. Next, with data from the High School and Beyond sophomore cohort (Class of 1982) recent midlife follow-up, we investigate the importance of high school students' mathematics and science coursework, knowledge, and skills for midlife occupations. The Class of 1982 completed high school prior to technological changes altering the demand for labor. We find that individuals who took more advanced levels of high school mathematics coursework enjoyed occupations with a higher percentile rank in the average wage distribution and were more likely to hold STEM-related occupations. Findings suggest that the mathematics coursework enabled workers to adapt and navigate changing labor market demands.

Keywords

STEM occupations; employment polarization; wage inequality; education

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1. Introduction

Science, Technology, Engineering and Mathematics (STEM) jobs have grown in importance in the labor market in recent decades, and they are widely seen as the jobs of the future. Policy makers around the world try to entice pupils to enroll more in high school courses that prepare them for the increasing STEM skill requirements of work, and more and more schools establish STEM programs. However, to date, we know little about how the formal educational processes in schools – the curriculum to which students are exposed – prepares individuals for the STEM skill requirements of the labor market. This study examines whether high school coursework in mathematics and science (which we refer to as STEM training) as well as non-STEM coursework, fosters people’s adaptability to the increased STEM skill requirements over the long run.

Before investigating how coursework in school affects later labor market outcomes, we first put STEM jobs in the context of recent changes in the U.S. labor market. The structure of jobs in the U.S. has polarized over the past four decades, with the share of employment in in high skill and low skilled occupations increasing relative to that in middle skilled workers (Acemoglu and Autor, 2011). Although STEM occupations are generally considered to be high skill jobs that demand specialized training (Xie et al., 2016), there are also a number of STEM occupations that are middle-skill jobs (Rothwell, 2013). Recent work suggests that the labor market outcomes of those in the middle of the wage distribution strongly depends on the workers’ skills, with more able workers better adapting to the changing labor markets (Cortes, 2016), but a question remains about which specific skills this includes. We document that STEM occupations in the middle of the occupational wage distribution had countervailing effects on the general evolution of employment in that area of the wage distribution, and that they are important for positive employment developments more generally. Our results thus suggest that STEM skills are the skills that help workers to adjust.

Next, we analyze the relation between school coursework and labor market success later in life. Although research shows the knowledge and skills that U.S. students develop in their coursework at school are related to their labor force outcomes in the short-run (c.f. Altonji, 1995, Arum and Shavit, 1995, Carbonaro, 2007, Altonji et al., 2012), we know little about what happens in school that might contribute to their ability to adapt over the long-run in a rapidly changing knowledge-based economy (Powell and Snellman, 2004). This study examines whether high school STEM training helps workers adapt to the changing labor market over the long run.

We focus on advanced math and science course-taking in schools and argue that they matter the most for the adaptability of workers to the changing skill requirements of work in recent decades. Recent research suggests that technology shifted the task composition of occupations toward analytical and interactive tasks that are complementary to computers’ capabilities, and away from routine cognitive and routine manual tasks for which computers tend to substitute (Autor et al., 2003; Spitz-Oener, 2006; Spitz-Oener, 2008, among others). Employees possessing computer-complementary skills enjoy higher demand and positive wage developments because computers both raise the demand for their skills and increase their marginal product. Workers in STEM jobs possess the computer (technology)-complementary skills that have experienced increasing demand and increasing marginal products in recent decades.

Why might mathematics coursework be important for later access to STEM jobs? Beginning with Algebra 1, students are introduced to abstract mathematical concepts and complex reasoning that form the building blocks of advanced mathematics and science curriculum (Heppen et al., 2012). Geometry introduces supporting concepts, and Algebra 2 provides the knowledge and skills for advanced knowledge and skills tested on college entrance exams, and for supporting persistence to a baccalaureate degree (Adelman, 1999, 2006). Students who progress through calculus, either in high school or early in college, typically have the foundational knowledge to succeed in science, engineering, and statistics fields in higher education (Sadler and Tai, 2007). Thus, one reason for focusing on mathematics coursework is that students are exposed to abstract concepts and obtain skills in these courses that allow them to tackle workforce challenges that demand flexible STEM knowledge and skills that can be applied across STEM fields. Each level of mathematics course may contribute different but complementary skills and knowledge to form an increasingly advanced foundation of expertise as the student transitions from Algebra 1 as far as calculus (or more). Or it may be that the levels simply reflect the number of years in high school similar abstract concepts were reinforced, with more years of reinforcement simply representing a higher “dose” of exposure to abstract advanced curriculum. We control for the number of mathematics and science credits a student accumulated by the end of high school in order to test whether we still find an independent effect of the specific advanced courses. This is consistent with the hypothesis that the more advanced coursework contributes to increasingly advanced knowledge of concepts and skills rather than just a higher dose of mathematics.

We use longitudinal data from the High School and Beyond sophomore (HS&B:SO) cohort, including a recent midlife follow-up. The HS&B began in 1980 as a nationally representative sample of high school sophomores in over 1000 public and private high schools in the United States. Against the background of recent technological changes and the topic of this study, this is a particularly interesting cohort. The HS&B:SO cohort—the Class of 1982—graduated from high school the month that the *New York Times* featured a National Science Foundation report stating that “technology could transform society” (Reinhold, 1982). This was a year before the influential *A Nation at Risk* (Gardner et al., 1983) report declared that schools should teach more rigorous coursework, especially in mathematics and science, to meet national workforce challenges. The Class of 1982 completed high school at a time when personal computers were just released and their diffusion at workplaces was still scarce, with no one realizing how large and profound the impact of this technology on job content and skill requirements in the labor market would be.

For these reasons, we argue that at the beginning of the 1980s students chose their high school coursework with very limited knowledge of future labor market demands. However, their high school coursework and the knowledge and skills that they developed may have helped them to adapt to the labor market challenges that they would face during their adult years. The relatively rapid shifts in the occupational structure during this period provides an excellent opportunity to observe how individuals adjust their labor force participation to the polarization.

The HS&B:SO database enables us to estimate whether high school academic achievement predicts individuals' labor market outcomes over the long run, holding constant their family background, fixed high school characteristics, and subsequent degree attainment. With a focus on how individuals' mathematics and science training predicts their labor force outcomes, the nationally representative HS&B:SO data provide an opportunity to better understand the relationship between two key institutions that structure inequality in our society: education and workforce. Specifically, we focus on high school coursework that develops knowledge and skills in mathematics and science, and employment in a STEM occupation, wages, and occupational upgrading between 1991 and 2013. The results indicate that an individual's high school mathematics coursework is an important predictor of their labor market success, even net of students' high school mathematics test scores and their background. These results suggest a role for rigorous mathematical preparation for all students to best prepare them for the changing labor market.

2. Background and related literature

2.1. Workforce polarization and STEM STEM

Many studies document the profound changes in occupational employment in the United States and other countries in recent decades (Autor et al., 2003; Goos and Manning, 2007; Acemoglu and Autor, 2011; Goos et al., 2009; Goos et al., 2014; Harrigan et al., 2020, among others).[1] In addition, skill requirements have changed within occupations (Spitz-Oener, 2006; Atalay et al., 2020; Deming and Kahn, 2018).

Efforts to link specific skills of workers to their occupations and to the polarization of the workforce have had limited success. While it is clear that recent technological changes have altered the demand for skills, we know little about the origins of those skills (Liu and Grusky, 2013). We focus on STEM fields and argue that if growth of occupations is connected to computerization then it should be evident in the STEM fields (Rothwell, 2013). We thereby follow policy reports and academic work that has long focused on the STEM fields as key drivers of innovation and economic growth in the context of the United States maintenance of a competitive economic advantage globally (National Academy of Sciences et al., 2007, 2010; Bush, 1945; Grogger and Hanson, 2015; Hanson and Slaughter, 2013, 2016) and more generally on global economic development (Goldin and Katz, 2008; Schofer et al., 2000).[2]

[1]For a criticism, see Hunt and Nunn (2019). Work in sociology includes Oesch and Menes (2011); Oesch(2013); Murphy and Oesch(2018); Fernandez-Macias (2012); Hurley and Fernandez-Macias (2008).

[2]Many aspects of STEM employment have recently received attention in the literature. Kerr and Kerr (2013), for example, illustrate the role played by immigration in the evolution of employment in STEM occupations, and Kerr et al (2016) put STEM employment in

Indeed, more nuanced versions of the now standard polarization figures illustrate the connection between STEM and STEM-related fields and the changing structure of employment. Fig. 1 uses data from the U.S. Census and the American Community Survey (ACS), and begins by replicating earlier work by Acemoglu and Autor(2011) depicting the change in the share of U.S. employment from 1980 to 2019 broken down by occupation (excluding employment in agriculture).[3] The occupations are ranked on the horizontal axis according to the mean wage of workers in the occupation in 1980. The vertical axis shows the change in employment share from 1980 to 2019 at each occupational wage percentile. Below the 26th percentile, employment growth by occupation was declining nearly monotonically, with employment growth positive below the 9th percentile and negative thereafter. Above the 26th percentile, growth in employment shares increases relatively monotonically, with occupations above the 55th percentile increasing as a share of total U.S. employment. Overall, the figure shows the pronounced polarization of employment in the U.S. labor market, with the declining share of middle-wage occupations offset by the increase in employment in high and low-wage occupations. The red circles in Fig. 1 depict the distribution of STEM occupations across occupational wage percentiles, and the radiuses of the circles represent how many STEM occupations are in each percentile. When we examine STEM occupations, more specifically, we see that, although STEM occupations are primarily higher-wage occupations, there are also a non-trivial number of STEM occupations in the middle of the occupational wage distribution.

Next, we examine the evolution of employment in STEM occupations along the occupational wage distribution. To do so, we break down total employment changes by terciles of the average occupational wage distribution and consider STEM occupations relative to other occupations, by decade. Fig. 2 Panel A shows the result for the first tercile, i.e. changes in aggregate employment shares in the set of occupations included in the lowest tercile of the 1980 average wage distribution. Although there are few STEM occupations in the first tercile (as seen in Fig. 1), it is apparent from Fig. 2 Panel A, that employment in those occupations evolved very differently compared to employment in other low-wage occupations. In particular, during the 1980s, 1990s and after 2010, decades in which employment contracted in low-wage occupations generally (see “All occupations”), employment in low-wage STEM occupations was immune to those developments (“STEM”).[4]

Fig. 2 Panel B shows the evolution of the employment share of occupations included in the second tercile of the U.S. occupational average wage distribution. When we focus on the

the context of the “global talent flow”. Peri et al. (2015) investigate the consequences of foreign STEM workers on wages of natives. Arcidiacono et al. (2016) investigate differences across universities to graduate students in STEM fields. There are, of course, other technology-complementary skills. Deming (2017), for example, highlights the growing importance of social skills, as does Deming and Kahn (2018).

[3]For ease of presentation we refer to STEM and STEM-related simply as STEM fields. A full list of all 315 occupations considered by STEM (35 occupations), STEM-related (24 occupations) and non-STEM occupation are shown in AppendiX Table A1.

[4]Focusing on the first quintile, Autor and Dorn (2013) document how employment in service occupations at the low end of the wage distribution evolved very differently to the overall trends, and played a crucial role when it comes to employment growth at the low end of the wage distribution. In our Figure 2, employment in service occupations is included in the “Non-STEM” category. When we exclude service occupations from the “Non-STEM” category, we also find that the evolution of employment in that part of the wage distribution would have looked much grimmer than Figure 2, Panel A, suggests. In particular, the increase in total low-skill employment during the 2000s is the result of a large decline in employment in “Non-STEM and Non-Service” occupations, but an even larger increase in employment in service occupations (the detailed graphs can be obtained from the authors upon request).

second tercile, we are interested in to what extent the evolution of STEM employment counteracted the overall trend in employment in the middle of the U.S. occupational wage distribution. During the 1990s and 2000s, decades in which employment shares declined in this part of the occupational wage distribution (see "All occupations"), employment in STEM occupations ("STEM") clearly counteracted overall developments, providing a countervailing force to the declining employment shares in the middle of the U.S. wage distribution.

The third tercile (Fig. 2 Panel C) shows that if it weren't for STEM occupations, employment at the high-wage end of the occupational distribution would have looked very different as well. During the 1980s and after 2000, employment would have increased much less even in those occupations. The fact that employment as a share of total employment would have evolved very differently even among high-wage occupations were it not for STEM occupations is striking.

This pattern can be observed more clearly by considering the change in employment shares during the period, along the 1980 occupational wage distribution. Fig. 3 shows the observed evolution of employment share (solid line) together with the evolution of employment shares along the occupational wage distribution had employment in STEM occupations remained at its 1980 level (dashed line). The figure demonstrates that employment in STEM occupations was not only an important component of employment growth at the high-wage end of the occupational wage distribution, but also important for employment growth in the middle of the distribution in recent decades.

Turning to wages, Fig. 4 highlights the contribution of wage changes in STEM occupations to aggregate (log) wage changes along the occupational wage distribution, again by contrasting the observed changes (solid line) with changes that arise when wages in STEM occupations are held constant at their level in 1980 (dashed line). Again, it is striking how pervasive the influence of wage growth in STEM occupations was, encompassing every percentile of the occupational distribution above about the 20th percentile.

Motivated by these findings, we look to the role of schools in preparing workers for the labor force in this manuscript. Scholars have already investigated the importance of majoring in STEM and, more recently, how the returns to STEM degrees change over the working life.[5] Recent work by Deming and Noray(2020) find that for "applied" STEM majors such as engineering and computer science, the earnings premium is high at labor market entry, but then declines by more than 50 percent in the first decade of working life. The change in task content is particularly rapid for those STEM jobs, making the skills learned in college depreciate particularly fast. This pattern does not hold for "pure" STEM majors such as biology, chemistry, physics and mathematics.

[5]Field of study more generally is an important mediator when it comes to the determinants of the returns to education, and studies show that the returns to STEM degrees are particularly large, see for example Altonji et al. (2016), Lemieux (2014),Kinsler and Pavan(2015) and Grave and Goerlitz(2012). Altonji et al. (2012) and Lemieux (2014), among others, show the clustering of graduates from different fields of study in specific occupations. De Philippis (2017) investigates the role of high school science curriculum on STEM field enrollment and completion in college. We do not investigate the contribution of field of study specifically. Note, however, that our results are robust to controlling for study degrees.

Against the background of these findings, the availability of data of course taking in "pure" STEM classes in schools as well as data at different times over the career of the Class of 1982 of HS&B:SO is particularly interesting.

2.2. Schools, STEM preparation, and labor market outcomes

The substantive content of high school mathematics curriculum effectively sorts and stratifies students, and results in structuring unequal opportunities to learn and develop skills in high school. Typically, students advance through levels of mathematics courses in a lock-step pattern across years of high school because the knowledge and skills accumulate, with material in one year serving as a prerequisite for the next year (Adelman, 1999). Nearly all high school students take mathematics, at least in the first few years, but the level of their courses can vary considerably in content depth and level of abstraction. Algebra 1 provides a critical foundation by introducing abstract reasoning and analysis. It also serves as a gateway to advanced courses in both mathematics and science that require those abstract and analytic skills (Domina et al., 2015; Carraher and Schielmann, 2007; Howe, 2005; Schmidt et al., 2005).

Evidence suggests that the knowledge and skills developed in high school mathematics courses influences short-run labor force outcomes. Using HS&B:SO high school transcript data, Rose and Betts (2001, 2004) found that students who completed more advanced levels of mathematics coursework earned higher wages in 1991 compared to those who took less advanced mathematics courses. An important threshold in determining higher wages was whether or not students completed Algebra 1 and geometry by the end of high school, although students who took more advanced courses earned even higher wages. Furthermore, they found that mathematics coursework helped to explain the gap in early adult wages between people raised in lower and higher SES families, and it accounted for a substantial portion of the effect of an additional year of education on early adult wages. Their results are robust to controls for other academic coursework and to adjustments for selection into the courses (instrumental variable, propensity matching, high school fixed effects). Using HS&B:SO and the National Longitudinal Study of Youth 1997 (NLSY97) data, including high school transcripts, Levine and Zimmerman (1995) found a positive effect of taking more mathematics courses on entering technology occupations and on wages for early adult workers in those fields. Evidence from international studies also supports a link between knowledge and skills developed in advanced high school mathematics coursework and labor force outcomes. Two different British cohort studies, one using the 1958 birth cohort (Dolton and Vignoles, 2002) and the other using the 1970 birth cohort (Adkins and Noyes, 2016), found positive effects of advanced mathematics coursework on earnings at around age 33. These studies did not find similar effects of advanced coursework in science, English, or foreign language.

I Identification in this area of empirical research is complicated by issues of unobserved heterogeneity and potential heterogeneous preferences across students for different subjects in schools as, for example, highlighted by Altonji et al. (2012). The authors state "Even with excellent data, identifying the causal effects of high school courses on educational attainment, choice of college major and occupation, and wage rates is a difficult task (p.

197)".[6] Observed effects of coursework on labor force outcomes may be due to students' development of knowledge and skills, or may instead be a function of unmeasured factors that are unrelated to the individual's mathematics-related skills (Bills, 2003; Altonji et al., 2012).

Joensen and Nielsen (2009) is, to the best of our knowledge, the only study using a natural experiment of high school course assignments in Danish schools. The authors found a positive effect of high-level mathematics coursework (but not high-level liberal arts curriculum) on income in early adulthood. Their OLS results with many detailed controls are very similar to the IV result, suggesting that selection may not be a big issue.

Although it is impossible to be certain that the knowledge and skills that individuals develop in mathematics courses are causally related to labor force outcomes with a database like HS&B, the robustness of findings across datasets and analytic approaches described above is reassuring. A key limitation of these studies, however, is that they all examine the relationship between high school and earnings while respondents are still young. In addition, the HS&B:SO data provide rich opportunities to control on a range of factors related to course selection.

A related issue is whether the observed effect of mathematics coursework on labor force outcomes is due to the development of mathematics knowledge and skills, or if it reflects a more general pattern of stratification within the school, with implications beyond mathematics to level of advanced curriculum across subjects. Indeed, tracking is a concept that has been used to describe within school categories of learning opportunities, like academic/college preparatory, general, and vocational streams of study (Gamoran and Mare, 1989; Hallinan, 1996). Students in more advanced tracks have access to higher quality instruction and more advanced learning opportunities that result in better skills in reading and writing skills (Carbonaro and Gamoran, 2002), and they are more likely to take foreign language and other college preparatory courses (Alexander and Pallas, 1984; Adelman, 1999; Nord et al., 2011). Although tracks have been used as a general indicator of level of academic curriculum, Lucas (1999) showed with the HS&B:SO that many schools did not actually track students in the early 1980s, and students often took a mix of courses at different levels. Our analyses control for foreign language coursework to account for more generalized advanced programs of study.

3. Data and method

3.1. Sample

High School and Beyond (HS&B) began in 1980 as part of the National Center for Education Statistics (NCES) Secondary Longitudinal Studies Program. The base year and first follow-ups contained a representative two-stage stratified probability sample of nearly 30,000 sophomores in over 1000 high schools. The first stage sampled high schools with a tenth grade, and the second stage involved sampling students from tenth grade rosters

[6]For a thorough discussion of the dynamic decision process as well as the different approaches taken in the literature for estimation seeAltonji et al. (2016). Webber (2014) investigates differences in lifecycle earnings across majors, including STEM majors, and particularly focuses on taking self-selection effects into account.

provided by the school. NCES constructed sample weights (based on the inverse of the probability of selection) that took into account the complex sample design, including oversamples (e.g., Catholic, high performing private, and public schools with a large share of Cuban students) and other elements of the stratified design (based on factors like region of the country, urbanicity). Further adjustments were made for school and student non-response (Jones et al., 1983). Subsequent follow-ups weights were further adjusted for non-response (Sebring et al., 1987; Muller et al., 2019). Each school contained a representative sample of 36 sophomores, making inferences about each school and its student body possible. For this study we use the sophomore longitudinal panel (N=14,830),[7] which was re-surveyed in 1982 (when most were high school seniors), 1984, 1986, and 1992; in 2014, the HS&B sophomores were re-interviewed when most were about 50 years old. Our analyses use two panels: the 1980–1992 panel (individuals who participated in the two waves, N = 11,850) and the 1980–2014 panel (N = 8790) and the weights constructed for those panels. From these we select respondents with a reported occupation in 1991 (N = 10,730) or in 2013 (N = 7300).[8]

Base year and first follow up student questionnaires gathered rich information about educational experiences and the development of cognitive (reading, math, science and social studies test scores) and non-cognitive skills (e.g., locus of control, self-concept, extracurricular activities, course taking, academic effort), as well as detailed information about family background (e.g., parental education, family composition, siblings, parenting practices and parents' educational and occupational expectations for their children). High school transcripts were gathered for the sophomore cohort and provide detailed course taking information for each year of high school. All follow-ups gathered information about cohort members' educational, employment, and family activities and transitions. The 2014 survey gathered occupation and labor market information, as well as information about family and health at midlife (Muller et al., 2019).

3.2. Measures

Labor Force Outcomes.—Our dependent variables are whether the respondent is working in a STEM or STEM-related occupation in 1991 and in 2013 and the average wage percentile of the respondents' occupations in those two years. We define STEM or STEM-related occupation using the U.S. Census definition.[9] Unfortunately, HS&B:SO does not include information on wages, so that we have to impute that information from other sources. Our measure is the respondent's occupation average wage percentile. It is computed by rank ordering occupations according to average wage in all non-agricultural occupations in the public-use microdata sample (PUMS) of the U.S. Census 1990 and the American Community Survey (ACS) respectively for 1991 and 2013. Based on the national distributions in each year, the percentile score for the average wage is assigned to the HS&B:SO respondent's 1991 and 2013 occupations.

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[7]All unweighted sample sizes have been rounded to the nearest 10, as required by the NCES restricted use data license.
[8]These sample sizes are for the models predicting a STEM or STEM related occupation. Because the wage percentile of the occupation was unavailable for a handful of cases, the sample sizes for the wage percentile models are slightly smaller (10,560 for 1991 and 7,240 for 2013). Descriptive statistics for these samples are available upon request.
[9]For a detailed description seehttps://www.census.gov/people/io/methodology/ and Appendix Table A1.

STEM Training, Knowledge and Skills.—Our main analytic interest is in the effects of the STEM training that students obtained in high school. Using students' high school transcripts that show all courses taken, we characterize the highest level of mathematics and science taken by the end of high school. In mathematics, our levels distinguish between lower than Algebra 1 (omitted category), Algebra 1, geometry, Algebra 2, and advanced mathematics (e.g., precalculus, trigonometry) and/or calculus. Although the substantive curriculum covered in science courses generally requires less prerequisite knowledge from the previous year, science courses are typically also sequenced; we distinguish levels by less than biology (the omitted category, such as general science), biology, chemistry, physics, and advanced science as the highest level.[10] During the period that HS&B:SO students attended high school, completing Algebra 2 or more was a clear indicator of preparation for college (Adelman, 1999). We also control for the total number of credits taken so that any estimated effect of the levels of advanced mathematics and science reflects the curriculum and not simply more hours of classroom exposure.

To measure mathematics cognitive skills, we include the students' 1982 mathematics test score, standardized to a mean of zero and standard deviation of one. Although related to one another, mathematics test scores and coursework represent distinct dimensions of cognitive skills development and academic preparation. The HS&B:SO base year mathematics test score measures a combination of knowledge of mathematics concepts, mathematics ability, and also reflects what has been learned from high school coursework (Coleman and Hoffer, 1987; Rose and Betts, 2001; Rose and Betts, 2004).[11]

Finally, we also measure locus of control, one dimension of non-cognitive skills that is associated with academic achievement. In 1980, sample members responded to four items based on the Rotter scale of locus of control.[12] The indicator, constructed by NCES, is a weighted average of the items standardized to a mean of zero and a standard deviation of one.

Controls.—In addition to the numbers of mathematics and science credits mentioned above, we also control for the number of foreign language credits to account for the student simply taking more advanced high school courses in general. Our background controls include student's sociodemographic (gender, race and ethnicity, age) and family characteristics (highest parental educational attainment [less than high school, high school graduate, some college, college graduate] and the number of siblings) and student's education attainment by 1992. Table 1a shows summary statistics for the HS&B:SO1980–1992 and 1980–2014 panels. Table 1b shows summary statistics for the HS&B: SO1980–1992 separately for respondents who work in STEM and those who do not. We clearly see that those working in STEM have higher fractions of Algebra 2 and Advance math/calculus

[10]See Appendix Table A2 for the distribution of math and science course taken by sample members.

[11]Note that the mathematics test used in our models was administered in 1982, after some of the coursework was completed. This provides a conservative estimate of the effects of coursework on the outcomes. Students were given a similar test in 1980; substituting the early test score in the models our estimated effects of mathematics and science are larger.

[12]The four items are "How strongly do you feel about each of the following statements?" a) Good luck is more important than hard work for success; b) Every time I try to get ahead, something or somebody stops me; c) Planning only makes a person unhappy, since plans hardly ever work out anyway; and d) People who accept their condition in life are happier than those who try to change things." Response categories include: "Agree strongly," "Agree," "Disagree," "Disagree strongly," and "No opinion."

course completion, as well as physics and advanced science. They also learned more foreign languages in school and did better in terms of math test scores. In terms of background characteristics, Whites are overrepresented in STEM whereas Hispanics are underrepresented, with no notable differences for the other race categories. In terms of family background, those working in STEM clearly come from more favorable educational parental backgrounds. Hence it is important to control for these differences in the empirical analyses.

3.3. Empirical approach

Our empirical strategy is to relate labor market outcomes to the training and knowledge and skills that the worker developed during high school. To do so, we estimate the following baseline equation using Ordinary Least Squares (OLS):

$$Y_{ij} = \beta_0 + \beta_1 X_i + \beta_2 Z_i + \delta_j + \varepsilon_{ij} \quad (1)$$

where Y_{ij} denotes the labor market outcome of interest for individual i from high school j, X_i is a vector of STEM training, knowledge, and skills variables, Z_i is a vector of controls (presenting nested models, first only numbers of mathematics, science and foreign language credits, second student and family sociodemographic characteristics, and third degree attainment), and finally δ_j represents high school fixed effects. Our coefficient of interest is β_1, which represents the relationship between STEM training, knowledge skills and labor market outcomes.

In our main analysis, we consider labor market outcomes at two points in time. We first consider how high school training is related to long-term employment outcomes generally; that is, we investigate how employment in 2013 is related to high-school course-taking. At this point, the individuals are around age 50 and have witnessed two decades of large changes in the labor market. We examine whether their training in school is related to employment (as opposed to unemployment) in the long-run. In a next step, we focus on employment in STEM occupations, and distinguish between medium- and long-term outcomes; that is, we first investigate whether an individual is employed in a STEM occupation in 1991. At this point, the individuals are approximately 28 years old and most have completed their academic degrees by this point. As we have shown in the previous section, STEM occupations better weathered the labor market changes that workers in this cohort were forced to endure. By looking at 1991 first, we try to capture the labor market succees at mid-career.

We then again take a longer-term stance and consider whether the worker was employed in a STEM occupation in 2013. Importantly, we can examine this relationship both with and without controlling for an indicator of whether the individual was in a STEM occupation in 1991 to see if, conditional on this, training and skills affected later labor market outcomes. We also present a saturated model predicting the 2013 outcomes for individuals who did not hold a STEM job in 1991 (about 89% of the 1991 analytic sample) as a step to estimate the effects of STEM training, knowledge, and skills on switching into STEM in the later period, at midlife.

Finally, we use the same strategy of model nesting to examine two other outcomes, the percentile of the average wage of the worker's occupation in 1991 and 2013. This is another metric of labor market success and, again, it is important to understand the role of training and knowledge in the ultimate financial success of the individual.

As discussed earlier, a key limitation of our work, along with much of the work in this area, is the endogenous nature of training. Students are not randomly assigned to courses in high school, nor are students randomly assigned to high schools. In fact, it may be that some schools do not offer the training that is offered in other, often more affluent schools. Different types of parents, with different family background characteristics, are likely sending their children to different types of schools and encourage them to take different types of classes. Although we are unable to completely address this issue, we can include a large number of controls in an effort to mitigate omitted variable bias.[13] In addition, we can control for fixed high school characteristics, thereby comparing individuals who attended the same high school with the same cognitive and non-cognitive skills, and the some observable parental background characteristics, who took different courses. Moreover, be reminded that we are looking at one cohort of sophomores at high schools in 1980, so unobserved socioeconomic macro effects were relevant for all of them, as was the state of technology at that time, as well as the predictions of how technology would evolve in the future. While all of this is imperfect, it does alleviate some concerns about comparisons across students who were attending high schools of differing quality.

Our results are quite robust to a variety of different specification choices. As part of the analysis process, we conducted many sensitivity analyses and robustness checks. We estimated all models with a reduced sample that only included cases for which both 1991 and both 2013 outcome variables were non-missing.[14] Although we do not include grade point average (GPA) as a control in our models, preferring to include controls of mathematics and science credits separately (which are an element of the computation of GPA), we did estimate an alternate set of models with GPA substituted as a control. GPA is a weak or insignificant predictor of working in a STEM occupation in all models. Although GPA did predict workers' occupation percentile of the wage distribution, the coefficient is attenuated to insignificance when 1992 level of educational attainment was included in the models, both in predicting the early adult and midlife outcomes. As we present, the math course level is a strong predictor.[15]

Results of all of these sensitivity tests are consistent with the findings that we present. We also estimated several heterogeneous effects models, by 1992 educational attainment, low and high mathematics test scores, and low and high non-cognitive skills. Although a full analysis of heterogeneous effects is beyond the scope of this study, we do present selected results by gender. Models based on alternative specifications are available upon request.

[13]Of course, just adding more controls is not always better, and we need to be aware of "bad control" issues (see, for example, Angrist and Pischke, 2015, p. 525ff.). The first set of controls we use such as math test scores and locus of control were generally measured early on, at the beginning of students' school course choices that are relevant for our analyses. Degree attainment in 1992 might be viewed more critically as it is correlated with our explanatory variables of main interest and the outcome variables. A similar logic applies when we control for "STEM occupation in 1991". We carefully adjust our discussion of results accordingly.

[14]See Appendix Table A3 for analyses based on reduced sample.

[15]Results can be obtained from the authors upon request.

Only the selected coefficients for estimated effects of coursework, test scores, and non-cognitive skills are shown; full models are available from the authors upon request. Analyses are performed with weights for fourth follow-up (1991 outcome) and fifth follow-up questionnaire data (2013 outcome), and we use multiple imputation (20 imputations) for missing values on all independent variables (Muller et al., 2019).

4. Results

Table 2 shows the results of the models estimating whether high school course taking is at all related to longer-term labor market employment prospects. The first column shows the results for a specification that controls for parental background, number of credits in various fields, the results of the second column are for specifications that additionally include information about the respondents' educational attainment by 1992. The overall pattern is very similar for both sets of results: high school math course-taking at the level of Algebra 1 or higher has a positive effect on long-term employment. This suggests that Algebra 1, when more abstract concepts are introduced into the curriculum, is important for long run access to jobs.

Table 3 presents the results of models estimating the effects of high school students' STEM course taking and skills on an indicator for whether the individual is employed in a STEM occupation in 1991. Column 1 shows the results for the most parsimonious model, controlling only for the number of mathematics and science credits. The first four coefficients in the column are indicators for the highest level of mathematics taken compared to the omitted category of less than Algebra 1. We also include indicators for whether the individual has taken biology, chemistry, physics, and/or advanced science. Finally, we include measures of cognitive and non-cognitive skills (mathematics test scores and locus of control). With this set of controls, we find that individuals with more advanced mathematics and sciences courses are significantly more likely to be employed in a STEM occupation in 1991. To get a sense of the magnitude, an individual who took advanced mathematics or calculus is predicted to be 9.0 percentage points more likely on average to be working in a STEM occupation compared to someone who took less than Algebra 1, net of controls. People who took Algebra 2 have an advantage of 2.8 percentage points on average compared to those who took less than Algebra 1. From the first model we see that individuals who took physics and advanced science coursework are on average 8.5 and 4.5 percentage points, respectively, more likely to be in a STEM occupation in 1991 compared to people who took low level science (less than biology), independent of their mathematics course level and net of controls. The second model, in column 2, also includes controls for family and sociodemographic background, including indicators for race and gender, and produces very similar estimates. All coefficients are robust to these extensions of the specification.

The model shown in column 3 adds controls for 1992 educational attainment which renders part of the coefficients insignificant such as the importance of math test scores in determining the outome. We next take advantage of the school-level sampling design of the HS&B data. Because of this school-level sampling, we observe multiple students within the same high school and can include high school fixed effects in our specification. Column 4 presents the results when we include background, educational attainment, and high school fixed effects. With this last model we estimate that a student who took advanced mathematics or calculus in high school is on average 7.4 percentage points more likely to be in a STEM or STEM-related occupation in 1991 compared to someone in his or her high school who only completed less than Algebra 1 mathematics, net of family background, math test scores, locus of control and their other college preparatory coursework (foreign language).

As shown earlier, employment in STEM occupations evolved more favorably in recent decades than in other (non-STEM) occupations, and we consider employment in a STEM occupation therefore to be a useful proxy for labor market success. We consider the relative average wage of the occupation as another. In Table 3, columns 5 – 8, we present the results where our outcome is the percentile ranking of the occupation in terms of average wage. When we do this, we find again that advanced level mathematics and science courses are positively associated with wages, as are cognitive and non-cognitive skills. Individuals who completed advanced mathematics or calculus by the end of high school have an occupation that is more than a decile higher in relative average wages compared to a person who only completed less than Algebra 1, net of controls. Even in the model that includes 1992 educational attainment and in which individuals are compared only to others in their same high school (school fixed effects), those who took advanced mathematics or calculus have an occupation with average wages that are around 8.1 percentile points higher than an otherwise similar schoolmate who only took less than Algebra 1 (note that wage ranks generally increase in math course taking). The mathematics coursework, mathematics test scores and non-cognitive skills effects are robust to changes in the specifications, but the estimates of science coursework effects are not statistically significant once degree attainment is included in the model, shown in column 7.

4.1. Midlife labor market outcomes

Beyond the relationship between STEM training and short-run labor market outcomes, what is even more interesting is how early training and skills affect long-run success. This is particularly important in the context of the HS&B cohort. While personal computers were only first appearing when this cohort was in school, the labor market they entered changed tremendously in the years that followed. How have members of this cohort fared, and did their early training and skills help?

In Table 4, columns 1 – 4, we examine the role of these earlier experiences on an indicator of whether the individual is working in a STEM occupation in 2013, and columns 5 – 8 present the results when we look at the occupation's percentile of the wage distribution in 2013. The results estimating effects of coursework on STEM occupations in 1991 and 2013 are remarkably consistent. Advanced mathematics, Algebra 2, geometry, physics, and advanced science all predict whether an individual ends up in a STEM occupation in 2013, even controlling for the academic degree earned by 1992. The model in column 4 indicates that the results for advanced mathematics or calculus and physics are robust to high school fixed effects estimates. Interestingly, in none of the specifications mathematics test scores and non-cognitive skills as proxied by locus of control are significant.

When we examine the percentile distribution of the average wage of the occupation for individuals' 2013 occupations, we again see a strong relationship between mathematics coursework and the percentile of the wage distribution, again even when we control for high school fixed effects (column 8). Individuals who took advanced mathematics or calculus in high school hold occupations with nearly a decile higher average wages, even when their degree attainment is held constant. Mathematics test scores and non-cognitive skills predict the percentile of the individual's occupation in the wage distribution, as well.

However, it may be the case that, in this long-run analysis, we are simply picking up the fact that there is persistence over time in occupational choice. To address this concern, we estimate similar regressions but now add controls for whether the individual was employed in a STEM occupation in the earlier period, shown in Table 5, columns 1 – 4 and 6 – 9. By including this control, our coefficients of interest now provide information about one's ability to change into or persist in a STEM occupation. If, for example, early skills and training led to early STEM jobs, which in turn led to later STEM jobs, the inclusion of this new variable would entirely absorb the effects of STEM training. As an extra step, we estimate an additional (fully saturated) model selecting only those who were not in a STEM occupation in 1991 and were therefore in a position to transition into a STEM occupation; they comprise about 89 percent of the 1992 sample. These results are presented in Table 5, columns 5 and 10.

Individuals who held a STEM occupation in 1991 are 47 percentage points more likely to be in a STEM occupation in 2013 compared to those who did not hold a STEM occupation in 1991. It is interesting to note that, although the coefficient on this indicator is large, positive and statistically significant, there is still a significant role for STEM training on the likelihood that an individual is observed in a STEM occupation in 2013. People who took advanced mathematics or calculus in high school are 8.0 percentage points more likely on average to be in a STEM occupation in 2013 compared to those who took lower than Algebra 1 (Column 4, including school fixed effects). When we examine the wage percentile of an individual's occupation, we see again that holding a STEM job in 1991 is associated with being in an occupation with a higher average wage in midlife, but there remain substantial roles for early coursework and cognitive and non-cognitive skills. Models 5 and 10 show that there is also a role for early math coursework among individuals that did not occupy a STEM occupation in 1991. Those who took advanced math or calculus were 8.4 times more likely to be in a STEM occupation in 2013 and the percentile rank of their occupation was over eight points higher compared with individuals who took lower than Algebra 1.

The previous results indicate that employment in a STEM occupation in the long-run is not merely a reflection of those who entered STEM occupations early in their career. For this reason we look into occupational transitions into more detail. Table 6 shows the results of regression specifications that are similar to the previous ones; this time, however, the dependent variables are indicator variables for the transition from a non-STEM to a STEM occupation between 1991 and 2013 (Column 1), from STEM to a non-STEM occupation (Column 2), or for staying in a STEM occupation (Column 3). Here we observe that advanced math or calculus coursework predicts moving from a non-STEM occupation to a

STEM occupation and persisting in a STEM occupation between 1991 and 2013, during the period when STEM occupations were expanding. Physics coursework predicts persistence in STEM, as well.

4.2. Heterogeneous effects by gender

Overall, these results suggest that STEM training in school predicts later labor market adaptability and success. So far, we have assumed that the estimated effects of coursework and skill are constant across our sample. Although it is beyond the scope of the present analysis to examine all dimensions of heterogeneous effects, the gender gap in STEM education and occupations (Buchmann and DiPrete, 2006; Glass et al., 2013; England, 2010) makes gender an especially important consideration. To examine the possibility that the relationships between STEM training and midlife occupation are different for men and women, we split our sample to estimate selected models by gender. As our main interest is in long-run effects, we only present models predicting the 2013 occupation.[16] We present the results from the fully saturated models, before and after including whether the respondent held a STEM occupation in 1991, shown in Table 7.

We observe positive estimated effects of having taken advanced mathematics/calculus coursework on holding a STEM occupation in 2013 and the wage percentile of the occupation for both men and women. When 1991 STEM occupation is held constant, the advanced mathematics or calculus coursework effect on holding a STEM occupation remains statistically significant for men and women. For women, taking Algebra 1 or Algebra 2 significantly increases their likelihood of working in STEM occupation in 2013. The effect of taking Algebra 1, geometry, Algebra 2 or advanced mathematics or calculus compared to taking lower than Algebra 1 mathematics on 2013 occupational wage percentile are positive and statistically significant for women. Women who took advanced mathematics or calculus hold occupations that are around a decile higher in average wage percentile. Although we observe nuanced differences in the estimated effects of coursework on labor force outcomes, the differences between men and women are not statistically significant. It is striking to observe that the high school mathematics coursework positively predicts holding a STEM occupation and the occupational average wage percentile of both men and women at midlife.

In Table 7 we also observe that women but not men who scored higher on their high school math achievement test occupy higher wage occupations, and this difference is statistically significant.[17] Based on fully saturated models, among women a one standard deviation increase in high school math test score is associated with an occupational wage that is over three percentiles higher on the wage distribution.

5. Discussion and conclusion

This study examines whether high school coursework in mathematics and science (which we refer to as STEM training) fosters people's adaptability to the increased STEM skill

[16] Results for models of the 1991 outcomes are available from the authors upon request

[17] An ancillary analysis indicates that the interaction term in a pooled model is also statistically significant.

requirements over the long run. This topic is an important, highly policy relevant research question, as policy makers around the world try to entice pupils to enroll more in high school courses that prepare them for the increasing STEM skill requirements of work, and more and more schools establish STEM programs. However, to date, we know little about how the formal educational processes in schools – the curriculum to which students are exposed – prepares individuals for the later STEM skill requirements of the labor market.

For students of the Class of 1982, who we analyze in this study, the nature of work changed rapidly and much more unexpectedly than for later cohorts. They were in school at a time period in which computers and information technology more generally just started to become widespread. The internet would not be available for civilian users for another decade. Our findings shed light on how the formal educational processes in schools—the curriculum to which students were exposed—contribute to how individuals navigate the challenges of a rapidely changing labor market. Reports and policy initiatives have long emphasized the importance of STEM education for economic growth, and the need for students to develop skills and prepare for STEM jobs. Although scholars have linked STEM training to STEM and STEM related-occupations in the short run, to our knowledge this study is the first national study in the U.S. linking STEM training during adolescence to occupations at midlife. The results highlight how school curriculum provides individuals with resources to adapt to changing workforce demands.

We first described the role of STEM and STEM-related occupations when it comes to labor market polarization in recent decades and document that STEM occupations in the middle of the occupational wage distribution had important countervailing effects on the evolution of employment—with the net employment effect in those "middle" occupations still being negative, but to a considerably smaller extent due to the positive evolution of employment in STEM occupations. This pattern is important against the backdrop of recent technological changes that profoundly changed job content and skill requirements in the labor market, with detrimental effects particularly for workers with jobs in the middle of the occupational skill distribution.

It has been over half a century since the release of the *Coleman Report* (Coleman et al., 1966) that showed that family background plays an important role in determining who gets advanced learning opportunities, higher quality schools provide advanced academic preparation for children from less advantaged backgrounds. This observation was elaborated two and a half decades later with the HS&B (c.f. Coleman and Hoffer, 1987, Bryk et al., 1993, Rose and Betts, 2001), which pinpointed the role of high school mathematics coursework in distinguishing higher quality learning opportunities. The findings of the current study contribute to this body of knowledge by suggesting the enduring effects of exposure to more advanced mathematics curriculum.

Succeeding in advanced coursework requires a combination of advanced academic curricular offerings at school and individual cognitive and non-cognitive skills to meet the coursework demands and learn. Quality schools may provide the advanced curriculum and a social environment of peers and supporting adults in which students are encouraged to excel and develop cognitive skills (Coleman et al., 1982b; Coleman and Hoffer, 1987; Bryk et al., 1993; Bailey et al., 2017). Our results suggest independent effects of mathematics coursework on labor force outcomes net of these school and environmental factors, first with controls at the individual level to estimate the effect of coursework independent of background and skills, and then with school fixed effects models to estimate the outcomes for a student relative to his or her high school peers.

We examined two different outcomes—having a STEM or STEM-related occupation and the occupation's percentile rank from the distribution of mean wages—early in adulthood and at midlife. These two outcomes capture two important dimensions related to workforce inequality. The capacity to obtain a STEM job is certainly an important element of workforce success because of the employment growth in these occupations. Yet, most members of the HS&B:SO cohort, 89 percent in 1991 and 86 percent in 2013, did not hold STEM or STEM-related jobs. The average wage percentile of the occupation captures an alternate dimension of inequality. Given the growth of STEM jobs and as technology becomes a broader component of our everyday lives, it is likely that STEM skills are in demand and hold a wage premium even in non-STEM occupations (Rothwell, 2013). Indeed, we estimated substantial and robust effects of mathematics coursework on occupation wage percentile. Among those who did not hold a STEM or STEM-related occupation in 1991, we found effects of mathematics coursework on 2013 workforce outcomes. We observed a connection between STEM training during high school and STEM occupation, and between STEM training and higher wage and skill occupations, across all types of occupations. It is worth noting that we also observed an effect of physics coursework on many of the STEM workforce outcomes, net of the math coursework. This finding is worthy of future study.

The HS&B:SO cohort finished high school the year before the publication of *A Nation at Risk* (Gardner et al., 1983), a report that recommended intensification of advanced curriculum in high schools, particularly in STEM fields. At the heart of the report was the recommendation that *all* students, not just the more select college-bound students, should be required to take more advanced foundational mathematics coursework. Indeed, subsequent cohorts of students have graduated with increasingly higher levels of rigorous coursework (Nord et al., 2011). Whereas less than 37 percent of the HS&B:SO cohort graduated having completed Algebra 2 or higher (Green et al., 1995), 71 percent of the Class of 2013 had taken Algebra 2 or higher level mathematics (Kena et al., 2016).[18]

There is also a question of whether we can expect that the long run returns to advanced coursework for younger cohorts who are recent and future high school graduates will be the same as what we have observed for the High School Class of 1982. This is, of course, impossible to observe until the younger cohorts reach midlife. However, evidence on short run returns to more advanced mathematics coursework is affirmative, with qualification. In younger cohorts, more advanced coursework predicts postsecondary degree completion and higher wages in early adulthood net of postsecondary degree completion (Gaertner et al., 2014; Rose and Betts, 2004). By contrast, Domina et al. (2015) recently found that when

[18]This percentage refers to all high school graduates. Forty-two percent of individuals in our sample took Algebra 2. The difference is due primarily to our exclusion from the analysis of persons who were not in the labor force.

California mandated that students take Algebra 1 prior to entering high school, there was substantial inequality in the benefits of the course in terms of higher test scores. Higher achieving students appeared to benefit from the courses, but lower achieving students' test scores appeared to have been hurt. A recent national study of curriculum content in Algebra 1 courses showed that there is considerable variability in the rigor of the courses, with students of color taking courses with less rigorous curricular material (Brown et al., 2013). Clearly, the actual curricular content rather than the course title is an important consideration in evaluating the effects of future coursework, especially as more students take advanced coursework. We cannot be certain of what skills will be needed in the future, yet our findings from this study suggest that advanced mathematics curriculum provides foundational training to adapt.

Although this study provides important new evidence about the possible role of schools in individuals' capacity to adapt and succeed at work through midlife, and therefore about the role of schools in the production of inequality, it also has limitations that are worth mentioning. The panel was not interviewed between 1992 and 2014, a period of 22 years during which the economy was changing at a rapid pace. Moreover, the 2014 interview was short, and we lack detail about respondents' current wages and their workforce participation during most of their adult working years. For example, we do not know what other jobs they held in the intervening years, about their unemployment spells, or even wages.[19] Data on these topics could provide extremely rich information about mechanisms and processes through which the high school experiences lead to the outcomes that we observed. It should be a priority to fill in some of this information, if possible, from either administrative records or future interviews. Additionally, observational data do not allow us to determine whether the mathematics coursework that students took in high school *caused* them to have better or worse labor force outcomes. These problems about making causal inferences are inherent in research designs like HS&B, and have been a source of debate using HS&B (c.f., Evans and Schwab, 1995, Coleman et al., 1982a, Altonji et al., 2012). We attempt to acknowledge this limitation both in our modeling strategy and in the interpretation of results. Finally, although it is important to consider the possibilities of heterogeneous effects, such as for individuals from different racial and ethnic or social classes, or people who have higher and lower cognitive or non-cognitive skills, such analyses are both beyond the scope of the present study and in some cases may require different data. Data limitations are especially acute for estimating the binary STEM outcome and for fixed effects models. Nonetheless, full consideration of heterogeneous effects should be a future priority.

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[19]Information about wages was collected for a subset of the midlife follow-up respondents, but the sample size is not sufficient to use in the analyses of this study.

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Appendix

Tables A1, A2, A3

Table A1

Occupations Classified as STEM, STEM-Related, and Non-STEM, and values of their position in the 1980 occupational wage percentile.

Occupations	1980 Percent Rank
STEM jobs	
Aerospace engineers	99
Metallurgical and materials engineers	99
Petroleum, mining, and geological engineers	99
Chemical engineers	99
Civil engineers	97
Electrical engineers	99
Industrial engineers	96
Mechanical engineers	99
Engineers and other professionals, n.e.c.	98
Computer systems analysts and computer scientists	97
Operations and systems researchers and analysts	96
Actuaries	99
Mathematicians and statisticians	94
Physicists and astronomists	99
Chemists	94
Atmospheric and space scientists	94
Geologists	97
Physical scientists, n.e.c.	92
Agricultural and food scientists	67
Biological scientists	77
Foresters and conservation scientists	67
Medical scientists	97
Economists, market and survey researchers	97

Occupations	1980 Percent Rank
Psychologists	81
Social scientists and sociologists, n.e.c.	70
Urban and regional planners	93
Engineering technicians	71
Drafters	64
Surveryors, cartographers, mapping scientists/techs	56
Biological technicians	45
Chemical technicians	74
Other science technicians	56
Computer software developers	82
Technicians, n.e.c.	68
Sales engineers	99
STEM-related jobs	
Managers of medicine and health occupations	90
Physicians	96
Dentists	97
Veterinarians	80
Optometrists	97
Podiatrists	64
Other health and therapy occupations	64
Registered nurses	63
Pharmacists	90
Dieticians and nutritionists	36
Respiratory therapists	38
Occupational therapists	56
Physical therapists	61
Speech therapists	67
Therapists, n.e.c.	37
Physicians' assistants	33
Clinical laboratory technologies and technicians	46
Dental hygienists	66
Health record technologists and technicians	41
Radiologic technologists and technicians	45
Licensed practical nurses	22
Health technologists and technicians, n.e.c.	31
Optical goods workers	36
Dental laboratory and medical appliance technicians	37
Non-STEM related jobs	
Chief executives, public administrators, and legislators	75
Managers and administrators, n.e.c.	89
Financial managers	94
Human resources and labor relations managers	91

Occupations	1980 Percent Rank
Managers and specialists in marketing, advertising	95
Managers in education and related fields	92
Managers of properties and real estate	39
Funeral directors	44
Accountants and auditors	74
Insurance underwriters	66
Other financial specialists	80
Management analysts	97
Personnel, HR, training, and labor rel. specialists	72
Purchasing agents and buyers of farm products	61
Buyers, wholesale and retail trade	62
Purchasing managers, agents, and buyers, n.e.c.	83
Business and promotion agents	74
Construction inspectors	73
Inspectors and compliance officers, outside	80
Management support occupations	81
Subject instructors, college	91
Kindergarten and earlier school teachers	11
Primary school teachers	70
Secondary school teachers	73
Special education teachers	55
Teachers, n.e.c.	45
Vocational and educational counselors	67
Librarians	56
Archivists and curators	58
Social workers	54
Clergy and religious workers	10
Welfare service workers	5
Lawyers and judges	98
Writers and authors	74
Technical writers	82
Designers	58
Musicians and composers	43
Actors, directors, and producers	72
Painters, sculptors, craft-artists, and print-makers	44
Photographers	45
Dancers	14
Art/entertainment performers and related occs	35
Editors and reporters	65
Announcers	35
Athletes, sports instructors, and officials	36
Airplane pilots and navigators	100

Occupations	1980 Percent Rank
Broadcast equipment operators	37
Programmers of numerically controlled machine tools	89
Legal assistants and paralegals	42
Sales supervisors and proprietors	50
Insurance sales occupations	71
Real estate sales occupations	58
Financial service sales occupations	98
Advertising and related sales jobs	67
Salespersons, n.e.c.	77
Retail salespersons and sales clerks	17
Cashiers	7
Door-to-door sales, street sales, and news vendors	11
Sales demonstrators, promoters, and models	17
Computer and peripheral equipment operators	46
Secretaries and stenographers	26
Typists	13
Interviewers, enumerators, and surveyors	17
Hotel clerks	5
Transportation ticket and reservation agents	67
Receptionists and other information clerks	10
Correspondence and order clerks	36
Human resources clerks, excel payroll and timekeeping	31
Library assistants	9
File clerks	14
Records clerks	22
Bookkeepers and accounting and auditing clerks	28
Payroll and timekeeping clerks	36
Billing clerks and related financial records processing	28
Mail and paper handlers	21
Office machine operators, n.e.c.	17
Telephone operators	42
Postal clerks, excluding mail carriers	90
Mail carriers for postal service	82
Mail clerks, outside of post office	19
Messengers	12
Dispatchers	58
Shipping and receiving clerks	45
Stock and inventory clerks	35
Meter readers	45
Weighers, measurers, and checkers	42
Material recording, sched., prod., plan., expediting cl.	55

Occupations	1980 Percent Rank
Insurance adjusters, examiners, and investigators	50
Customer service reps, invest., adjusters, excl. insur.	55
Eligibility clerks for government prog., social welfare	37
Bill and account collectors	31
General office clerks	21
Bank tellers	11
Proofreaders	26
Data entry keyers	21
Statistical clerks	41
Teacher’s aides	5
Administrative support jobs, n.e.c.	61
Housekeepers, maids, butlers, and cleaners	2
Laundry and dry cleaning workers	4
Fire fighting, fire prevention, and fire inspection occs	57
Police and detectives, public service	77
Sheriffs, bailiffs, correctional institution officers	55
Crossing guards	10
Guards and police, except public service	31
Protective service, n.e.c.	3
Supervisors of food preparation and service	13
Bartenders	6
Waiters and waitresses	1
Cooks	3
Food preparation workers	4
Miscellaneous food preparation and service workers	2
Dental Assistants	9
Health and nursing aides	8
Supervisors of cleaning and building service	42
Superv. of landscaping, lawn service, groundskeeping	56
Gardeners and groundskeepers	12
Janitors	19
Pest control occupations	26
Barbers	12
Hairdressers and cosmetologists	9
Recreation facility attendants	11
Guides	12
Ushers	5
Baggage porters, bellhops and concierges	17
Recreation and fitness workers	9
Motion picture projectionists	38
Child care workers	0
Personal service occupations, n.e.c	5

Occupations	1980 Percent Rank
Supervisors of personal service jobs, n.e.c	35
Public transportation attendants and inspectors	77
Animal caretakers, except farm	5
Automobile mechanics and repairers	38
Bus, truck, and stationary engine mechanics	61
Aircraft mechanics	90
Small engine repairers	28
Auto body repairers	42
Heavy equipement and farm equipment mechanics	65
Industrial machinery repairers	65
Machinery maintenance occupations	67
Repairers of industrial electrical equipment	59
Repairers of data processing equipment	90
Repairers of household appliances and power tools	56
Telecom and line installers and repairers	92
Repairers of electrical equipment, n.e.c.	63
Heating, air conditioning, and refrigeration mechanics	62
Precision makers, repairers, and smiths	39
Locksmiths and safe repairers	37
Repairers of mechanical controls and valves	64
Elevator installers and repairers	95
Millwrights	94
Mechanics and repairers, n.e.c.	66
Supervisors of construction work	93
Masons, tilers, and carpet installers	57
Carpenters	48
Drywall installers	55
Occupations	
Electricians	81
Electric power installers and repairers	91
Painters, construction and maintenance	37
Paperhangers	58
Plasterers	58
Plumbers, pipe fitters, and steamfitters	73
Concrete and cement workers	58
Glaziers	54
Insulation workers	60
Paving, surfacing, and tamping equipment operators	54
Roofers and slaters	34
Structural metal workers	81
Drillers of earth	42
Misc. construction and related occupations	42

Occupations	1980 Percent Rank
Drillers of oil wells	46
Explosives workers	63
Miners	75
Other mining occupations	66
Production supervisors or foremen	80
Tool and die makers and die setters	82
Machinists	64
Boilermakers	92
Precision grinders and fitters	71
Patternmakers and model makers	82
Engravers	34
Other metal and plastic workers	67
Cabinetmakers and bench carpenters	31
Furniture/wood finishers, other prec. wood workers	12
Dressmakers, seamstresses, and tailors	10
Upholsterers	21
Shoemakers, other prec. apparel and fabric workers	9
Hand molders and shapers, except jewelers	33
Bookbinders	34
Other precision and craft workers	38
Butchers and meat cutters	48
Bakers	19
Batch food makers	17
Water and sewage treatment plant operators	59
Power plant operators	94
Plant and system operators, stationary engineers	90
Other plant and system operators	75
Lathe, milling, and turning machine operatives	64
Punching and stamping press operatives	46
Rollers, roll hands, and finishers of metal	91
Drilling and boring machine operators	56
Grinding, abrading, buffing, and polishing workers	47
Forge and hammer operators	66
Molders and casting machine operators	37
Metal platers	43
Heat treating equipment operators	75
Sawing machine operators and sawyers	21
Nail, tacking, shaping and joining mach ops (wood)	17
Other woodworking machine operators	30
Printing machine operators, n.e.c.	56
Typesetters and compositors	45
Winding and twisting textile and apparel operatives	11

Occupations	1980 Percent Rank
Knitters, loopers, and toppers textile operatives	14
Textile cutting and dyeing machine operators	12
Textile sewing machine operators	5
Shoemaking machine operators	5
Clothing pressing machine operators	5
Miscellaneous textile machine operators	12
Cementing and gluing machne operators	28
Packers, fillers, and wrappers	32
Extruding and forming machine operators	41
Mixing and blending machine operators	46
Separating, filtering, and clarifying machine operators	75
Food roasting and baking machine operators	58
Washing, cleaning, and pickling machine operators	42
Paper folding machine operators	12
Furnance, kiln, and oven operators, apart from food	67
Slicing, cutting, crushing and grinding machine	35
Photographic process workers	26
Machine operators, n.e.c.	41
Welders, solderers, and metal cutters	60
Assemblers of electrical equipment	33
Painting and decoration occupations	35
Production checkers, graders, and sorters in manufacturing	44
Truck, delivery, and tractor drivers	54
Bus drivers	36
Taxi cab drivers and chauffeurs	13
Parking lot attendants	9
Railroad conductors and yardmasters	95
Locomotive operators: engineers and firemen	96
Railroad brake, coupler, and switch operators	92
Ship crews and marine engineers	64
Miscellaneous transportation occupations	54
Operating engineers of construction equipment	67
Crane, derrick, winch, hoist, longshore operators	81
Excavating and loading machine operators	61
Stevedores and misc. material moving occupations	58
Helpers, constructions	17
Helpers, surveyors	21
Construction laborers	34
Production helpers	34
Garbage and recyclable material collectors	22
Machine feeders and offbearers	30

Occupations	1980 Percent Rank
Garage and service station related occupations	5
Vehicle washers and equipment cleaners	13
Packers and packagers by hand	14
Laborers, freight, stock, and material handlers, n.e.c.	30

Data Source: Author calculations from U.S. Census PUMS and American Community Survey (ACS) data.

Table A2

Cross-tabulation of Math and Science Courses Taken in 1991 and 2013 Samples.

		General science	Biology	Chemistry	Physics	Advanced science	N
Below Algebra 1	1991	34.56	55.74	3.77	2.23	3.69	2470
	2013	34.00	54.48	4.30	2.57	4.65	1440
Algebra 1	1991	21.59	62.31	7.75	2.14	6.21	1820
	2013	20.59	61.17	9.04	2.26	6.95	1200
Geometry	1991	10.52	54.99	21.41	5.35	7.73	1640
	2013	10.66	54.03	21.77	5.38	8.15	1120
Algebra 2	1991	5.37	32.48	32.48	15.63	14.03	2870
	2013	4.88	30.77	33.43	16.62	14.30	2030
Adv Math/Calculus	1991	2.95	14.95	24.57	41.59	15.93	1930
	2013	2.63	14.35	24.23	41.67	17.12	1520
Total	1991	15.18	43.18	18.57	13.37	9.70	10,730
	2013	13.62	40.57	19.99	14.99	10.84	7300

Data Source: Author calculations from U.S. Department of Education, National Center for Education Statistics, The High School &Beyond Midlife Follow-Up Study, Sophomore Cohort.

Row Percentage within each math course is shown for each science course.

Table A3

OLS Regression Estimates of 1991 and 2013 Labor Market Outcomes, Restricted to Reduced Sample (N = 6520).

	STEM 1991				STEM 2013			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Highest math course								
Algebra 1	0.011	0.014	0.011	0.025	0.032 *	0.031 *	0.029	0.040 *
	(0.014)	(0.013)	(0.013)	(0.014)	(0.015)	(0.015)	(0.015)	(0.016)
Geometry	0.036	0.038 *	0.029	0.046 *	0.029	0.028	0.022	0.008
	(0.019)	(0.018)	(0.017)	(0.019)	(0.016)	(0.017)	(0.017)	(0.020)
Algebra 2	0.048 *	0.052 **	0.038 *	0.065 **	0.048 **	0.049 **	0.044 *	0.033
	(0.020)	(0.019)	(0.018)	(0.021)	(0.017)	(0.018)	(0.018)	(0.022)
Adv math/ Calculus	0.123 ***	0.127 ***	0.103 ***	0.129 ***	0.088 ***	0.090 ***	0.085 ***	0.075 **
	(0.024)	(0.024)	(0.023)	(0.026)	(0.023)	(0.023)	(0.024)	(0.029)
Highest science course								

	STEM 1991				STEM 2013			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Biology	− 0.011	− 0.010	− 0.012	− 0.040 *	0.000	0.000	− 0.001	0.000
	(0.013)	(0.012)	(0.013)	(0.016)	(0.014)	(0.014)	(0.014)	(0.017)
Chemistry	0.010	0.013	0.002	− 0.027	0.001	− 0.001	− 0.004	− 0.005
	(0.019)	(0.018)	(0.019)	(0.022)	(0.021)	(0.021)	(0.021)	(0.024)
Physics	0.080 **	0.087 ***	0.075 **	0.041	0.071 **	0.074 **	0.070 **	0.067 *
	(0.025)	(0.025)	(0.025)	(0.030)	(0.027)	(0.026)	(0.026)	(0.030)
Advanced science	0.066 **	0.070 **	0.058 *	0.020	0.045	0.044	0.042	0.042
	(0.022)	(0.023)	(0.023)	(0.031)	(0.026)	(0.026)	(0.026)	(0.032)
Math test score	0.007	0.010	0.006	0.004	− 0.006	− 0.006	− 0.007	− 0.002
	(0.007)	(0.007)	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)	(0.008)
Locus of control	0.014 **	0.014 **	0.011 *	0.004	0.003	0.003	0.002	0.006
	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)
STEM 1991					0.475 ***	0.474 ***	0.469 ***	0.466 ***
					(0.026)	(0.026)	(0.026)	(0.024)
Background	No	Yes	Yes	Yes	No	Yes	Yes	Yes
1992 education	No	No	Yes	Yes	No	No	Yes	Yes
School fixed effects	No	No	No	Yes	No	No	No	Yes
R^2	0.227	0.229	0.231	0.371	0.186	0.224	0.240	0.396

Data Source: Author calculations from U.S. Department of Education, National Center for Education Statistics, The High School &Beyond Midlife Follow-Up Study, Sophomore Cohort.

* $p<.05$

** $p<.01$

*** $p<.001$ (two-tailed tests)

Note: Reduced model includes the numbers of mathematics credits, science credits, and foreign language credits. Background characteristics include race/ethnicity, gender, age, parental education, and number of siblings. 1992 education is the respondents' educational attainment (less than high school degree, high school graduate, postsecondary certificate, associate's degree, bachelor's degree, master's degree, advanced or professional degree) by 1992.

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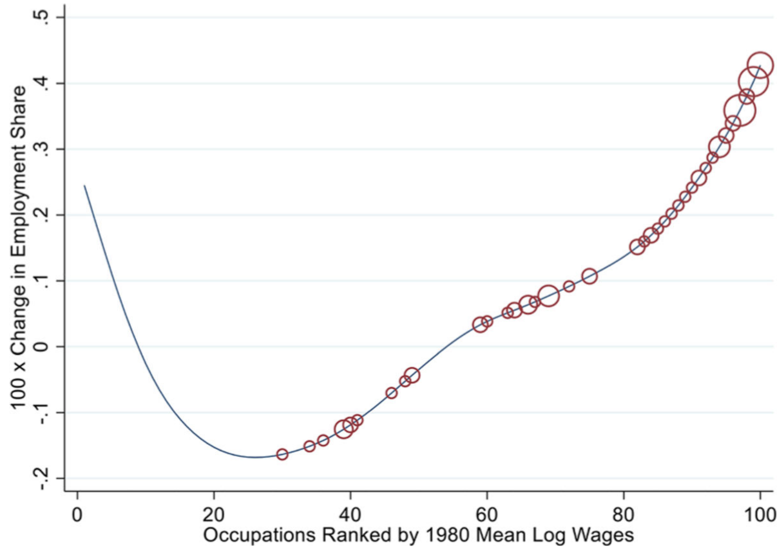

Fig. 1.

Smoothed Changes in Employment Shares 1980–2019 and Number of STEM Occupations (indicated by radius of circles) by 1980 Percentile Rank of Mean Occupations' Wages

Notes: The figure plots changes in employment shares by 1980 occupational wage percentile rank using a locally weighted smoothing regression (bandwidth 0.8 with 100 observations), where wage percentiles are measured as the employment-weighted percentile rank of an occupation's mean log wage in the Census IPUMS 1980 5 percent extract. Employment in each occupation is calculated using workers' hours of annual labor supply times the Census sampling weights. Consistent occupation codes are from Autor and Dorn (2013). The circles superimposed on the plot at different occupational percentiles indicate the location of STEM occupations along the occupational wage structure, where the size of the circle indicates the number of STEM occupations. **Data Source:** Authors calculations from U.S.Census PUMS and American Community Survey (ACS) data.

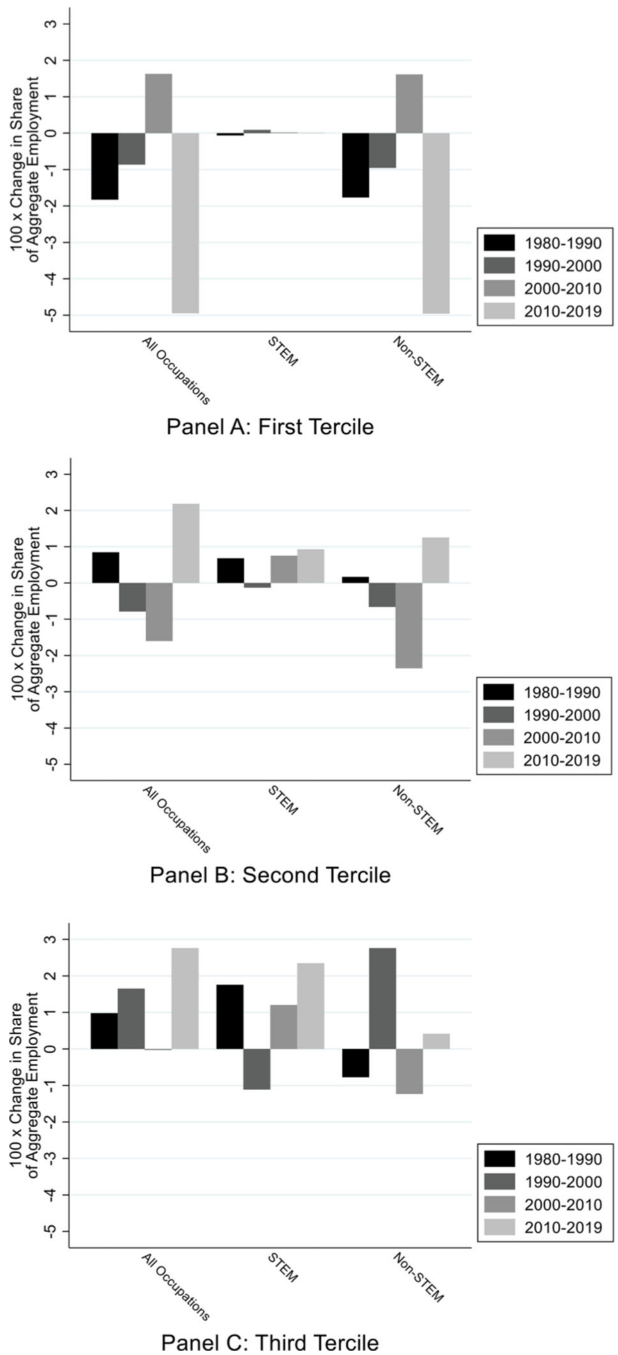

Fig. 2.

Changes in Share of Aggregate Employment, by Occupation Type (all, STEM, Non-STEM) and Decade (1980–2019), by Average Occupation Wage in 1980 Terciles

Notes: The figure plots decadal changes in shares of aggregate employment for all occupations, STEM occupations and non-STEM occupations, separately by terciles of the 1980 occupational wage rank. The occupational wage ranks are measured as the employment-weighted percentile rank of an occupation's mean log wage in the Census IPUMS 1980 5 percent extract. Employment in each occupation is calculated using workers' hours of annual labor supply times the Census sampling weights. Consistent occupation codes are from Autor and Dorn (2013). **Data Source:** Authors calculations from U.S.Census PUMS and American Community Survey (ACS) data 1980, 1990, 2000, 2010 and 2019.

Fig. 3.

Change in Employment Share, 1980–2019, by 1980 Percentile Rank of Mean Occupation Wage

Notes: The figure plots changes in employment shares by 1980 occupational wage percentile rank using a locally weighted smoothing regression (bandwidth 0.8 with 100 observations), where wage percentiles are measured as the employment-weighted percentile rank of an occupation's mean log wage in the Census IPUMS 1980 5 percent extract. Employment in each occupation is calculated using workers' hours of annual labor supply times the Census sampling weights. Consistent occupation codes are from Autor and Dorn (2013). The "observed" line depicts the actually observed changes in employment shares, the dashed "comparison" line shows the changes when STEM employment is held constant at the 1980 STEM employment level. **Data Source:** Authors calculations from U.S.Census PUMS and American Community Survey (ACS) data.

Fig. 4.

Changes in Mean Wages by Occupational Wage Percentile among Full-Time, Full-Year (FTFY) Workers, 1980–2019

Notes: The figure plots changes in mean log real weekly wages between 1980 and 2019, by 1980 occupational wage percentile rank using a locally weighted smoothing regression (bandwidth 0.8 with 100 observations), where wage percentiles are measured as the employment-weighted percentile rank of an occupation's mean log wage in the Census IPUMS 1980 5 percent extract. Weekly wages are calculated as annual earnings divided by weeks worked. The dashed "comparison" line shows the change in log real wages had STEM occupations' wages not grown between 1980 and 2019. **Data Source:** Authors calculations from U.S. Census PUMS and American Community Survey (ACS) data.

Table 1a

Descriptive Statistics for HS&B:SO Analytic Samples.

Outcome	1991 Working in STEM	1991 Wage percentile	2013 Working in STEM	2013 Wage percentile
STEM occupations 2013			0.14	0.14
STEM occupations 1991	0.10	0.10	0.10	0.10
Wage percentile		47.83		54.35
		(30.00)		(29.22)
Highest math course				
Below algebra 1	0.27	0.27	0.26	0.26
Algebra 1	0.20	0.20	0.20	0.20
Geometry	0.14	0.14	0.14	0.14
Algebra 2	0.24	0.24	0.23	0.23
Advanced math/Calculus	0.15	0.15	0.16	0.16
Highest science course				
Less than biology	0.18	0.18	0.18	0.18
Biology	0.45	0.45	0.45	0.45
Chemistry	0.16	0.16	0.16	0.16
Physics	0.11	0.11	0.11	0.11
Advanced science	0.09	0.09	0.10	0.10
Foreign language course				
0	0.51	0.51	0.51	0.51
1	0.17	0.17	0.17	0.17
2	0.18	0.18	0.18	0.18
3 or more	0.14	0.14	0.15	0.15
Math test score	0.05	0.05	0.05	0.05
	(0.90)	(0.90)	(0.90)	(0.90)
Locus of control	0.02	0.02	0.04	0.04
	(0.93)	(0.93)	(0.93)	(0.93)
Math credits	3.03	3.03	3.06	3.06
	(1.22)	(1.22)	(1.23)	(1.23)

Outcome	1991 Working in STEM	1991 Wage percentile	2013 Working in STEM	2013 Wage percentile
Science credits	2.16	2.16	2.18	2.18
	(1.11)	(1.11)	(1.12)	(1.12)
Male	0.50	0.49	0.48	0.48
Age	27.33	27.33	27.33	27.33
	(0.59)	(0.59)	(0.59)	(0.60)
Number of siblings	2.90	2.90	2.90	2.90
	(1.75)	(1.75)	(1.76)	(1.76)
Race				
White	0.74	0.74	0.73	0.74
Hispanic	0.12	0.12	0.12	0.12
Native American	0.01	0.01	0.01	0.01
Asian	0.01	0.01	0.01	0.01
Black	0.11	0.11	0.12	0.11
Other race	0.01	0.01	0.01	0.01
Parental education				
Below high school	0.12	0.12	0.12	0.12
High school graduate	0.33	0.33	0.33	0.33
Some college	0.27	0.27	0.27	0.27
College graduate or above	0.23	0.23	0.24	0.24
Missing	0.05	0.05	0.04	0.04
Education attainment in 1992				
Below high school	0.05	0.05	0.04	0.04
High school graduate	0.49	0.49	0.49	0.49
Certificate	0.12	0.12	0.10	0.10
Associates	0.09	0.09	0.09	0.09
Bachelor	0.21	0.21	0.22	0.22
Master	0.03	0.03	0.03	0.03
PhD/Professional	0.01	0.01	0.01	0.01
Missing	0.00	0.00	0.01	0.01
N	10,730	10,560	7,300	7,240

Data Source: Author calculations from U.S. Department of Education, National Center for Education Statistics, The High School &Beyond Midlife Follow-Up Study, Sophomore Cohort.

Table 1b.

Descriptive Statistics by Working in STEM Occupations in 1991.

	Not working in STEM	Working in STEM	Sig.
Highest math course			
Below algebra 1	0.29	0.10	***
Algebra 1	0.21	0.11	***
Geometry	0.15	0.12	*
Algebra 2	0.23	0.31	***
Advanced math/Calculus	0.13	0.36	***
Highest science course			
Less than biology	0.19	0.06	***
Biology	0.48	0.26	***
Chemistry	0.16	0.21	***
Physics	0.09	0.29	***
Advanced science	0.09	0.18	***
Foreign language course			
0	0.54	0.31	***
1	0.17	0.16	N.S.
2	0.16	0.29	***
3 or more	0.13	0.23	***
Math test score	− 0.00	0.54	***
	(0.88)	(0.93)	
Locus of control	− 0.02	0.34	***
	(0.94)	(0.78)	
Math credits	2.97	3.57	***
	(1.21)	(1.20)	
Science credits	2.08	2.91	***
	(1.07)	(1.22)	
Male	0.50	0.47	N.S.
Age	27.34	27.22	***
	(0.59)	(0.52)	***
Number of siblings	2.93	2.68	***
	(1.76)	(1.67)	
Race			
White	0.73	0.80	***
Hispanic	0.13	0.07	***
Native American	0.01	0.00	***
Asian	0.01	0.02	***
Black	0.11	0.10	N.S.
Other race	0.01	0.01	N.S.
Parental education			
Below high school	0.12	0.08	***

	Not working in STEM	Working in STEM	Sig.
High school graduate	0.34	0.27	***
Some college	0.27	0.28	N.S.
College graduate or above	0.22	0.34	***
Missing	0.05	0.03	N.S.
Education attainment in 1992			
Below high school	0.05	0.01	***
High school graduate	0.52	0.20	***
Certificate	0.12	0.09	*
Associates	0.08	0.16	***
Bachelor	0.19	0.42	***
Master	0.03	0.08	***
PhD/Professional	0.01	0.04	***
Missing	0.00	0.00	*
N	9,530	1,190	

Data Source: Author calculations from U.S. Department of Education, National Center for Education Statistics, The High School &Beyond Midlife Follow-Up Study, Sophomore Cohort.

* p<.05

** p<.01

*** p<.001 (two-tailed tests).

Table 2

OLS Regression Estimates of Employment in 2013.

Highest math course		
	(1)	(2)
Highest math course		
Algebra 1	0.078***	0.072**
	(0.022)	(0.022)
Geometry	0.090***	0.079***
	(0.023)	(0.023)
Algebra 2	0.087***	0.072**
	(0.023)	(0.023)
Adv math/Calculus	0.096***	0.077**
	(0.025)	(0.025)
Highest science course		
Biology	0.010	0.004
	(0.021)	(0.021)
Chemistry	0.036	0.024
	(0.026)	(0.026)
Physics	0.051	0.038
	(0.029)	(0.029)
Advanced science	0.051	0.038
	(0.030)	(0.030)
Math test score	0.005	0.001
	(0.008)	(0.008)
Locus of control	0.014	0.011
	(0.007)	(0.007)
Background	Yes	Yes
1992 education	No	Yes
R2	0.050	0.059
N	7,810	7,810

Data Source: Author calculations from U.S. Department of Education, National Center for Education Statistics, The High School &Beyond Midlife Follow-Up Study, Sophomore Cohort.

* $p<.05$

** $p<.01$

*** $p<.001$ (two-tailed tests).

Note: Reduced model includes the numbers of mathematics credits, science credits, and foreign language credits. Background characteristics include race/ethnicity, gender, age, parental education, and number of siblings. 1992 education is the respondents' educational attainment (less than high school degree, high school graduate, postsecondary certificate, associate's degree, bachelor's degree, master's degree, advanced or professional degree) by 1992.

Table 3

OLS Regression Estimates of 1991 Labor Market Outcomes.

	STEM 1991				Wage Percentile 1991			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Highest math course								
Algebra 1	0.007	0.007	0.004	0.001	3.466**	3.327**	3.313**	3.958***
	(0.010)	(0.010)	(0.009)	(0.010)	(1.194)	(1.144)	(1.132)	(1.170)
Geometry	0.010	0.009	0.003	0.001	5.414***	5.221***	4.747***	4.390**
	(0.013)	(0.013)	(0.012)	(0.013)	(1.374)	(1.360)	(1.343)	(1.352)
Algebra 2	0.028*	0.028*	0.013	0.018	8.828***	8.091***	6.039***	5.566***
	(0.013)	(0.013)	(0.013)	(0.015)	(1.358)	(1.329)	(1.313)	(1.380)
Adv math/Calculus	0.090***	0.090***	0.066***	0.074***	12.823***	11.807***	8.128***	8.069***
	(0.018)	(0.018)	(0.017)	(0.020)	(1.661)	(1.609)	(1.566)	(1.704)
Highest science course								
Biology	− 0.012	− 0.012	− 0.014	− 0.022*	− 0.325	− 0.448	− 0.670	− 0.640
	(0.009)	(0.009)	(0.009)	(0.011)	(1.146)	(1.106)	(1.099)	(1.207)
Chemistry	0.000	0.000	− 0.013	− 0.019	2.758	2.246	0.342	1.200
	(0.014)	(0.014)	(0.014)	(0.016)	(1.601)	(1.560)	(1.549)	(1.645)
Physics	0.085***	0.088***	0.072***	0.057**	7.736***	4.927**	2.321	2.304
	(0.020)	(0.020)	(0.020)	(0.022)	(1.875)	(1.845)	(1.795)	(1.910)
Advanced science	0.045**	0.045**	0.030	0.017	4.258*	3.702*	1.445	2.403
	(0.017)	(0.016)	(0.017)	(0.020)	(1.773)	(1.710)	(1.683)	(1.976)
Math test score	0.014**	0.016**	0.010	0.009	3.675***	2.495***	1.505**	1.630**
	(0.005)	(0.005)	(0.005)	(0.006)	(0.512)	(0.513)	(0.511)	(0.532)
Locus of control	0.013***	0.013***	0.010**	0.006	1.347**	1.496***	0.954*	0.929*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.417)	(0.410)	(0.407)	(0.409)
Background	No	Yes	Yes	Yes	No	Yes	Yes	Yes
1992 education	No	No	Yes	Yes	No	No	Yes	Yes
School fixed effects	No	No	No	Yes	No	No	No	Yes
R^2	0.084	0.086	0.107	0.234	0.120	0.177	0.215	0.327

	STEM 1991				Wage Percentile 1991			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
N	10,730	10,730	10,730	10,730	10,560	10,560	10,560	10,560

Data Source: Author calculations from U.S. Department of Education, National Center for Education Statistics, The High School &Beyond Midlife Follow-Up Study, Sophomore Cohort.

* p<.05

** p<.01

*** p<.001 (two-tailed tests).

Note: Reduced model includes the numbers of mathematics credits, science credits, and foreign language credits. Background characteristics include race/ethnicity, gender, age, parental education, and number of siblings. 1992 education is the respondents' educational attainment (less than high school degree, high school graduate, postsecondary certificate, associate's degree, bachelor's degree, master's degree, advanced or professional degree) by 1992.

Table 4

OLS Regression Estimates of 2013 Labor Market Outcomes.

	STEM 2013				Wage Percentile 2013			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Highest math course								
Algebra 1	0.027	0.026	0.023	0.037*	4.811***	3.851**	3.641**	3.048*
	(0.014)	(0.014)	(0.015)	(0.016)	(1.441)	(1.372)	(1.368)	(1.432)
Geometry	0.042**	0.041*	0.032	0.023	8.313***	7.239***	6.271***	5.672***
	(0.016)	(0.017)	(0.017)	(0.020)	(1.633)	(1.522)	(1.526)	(1.674)
Algebra 2	0.065***	0.065***	0.054**	0.057**	9.733***	8.056***	6.492***	5.993***
	(0.017)	(0.017)	(0.017)	(0.021)	(1.631)	(1.530)	(1.528)	(1.712)
Adv math/Calculus	0.139***	0.140***	0.123***	0.129***	14.610***	12.706***	9.967***	9.891***
	(0.023)	(0.024)	(0.024)	(0.027)	(1.972)	(1.861)	(1.878)	(2.087)
Highest science course								
Biology	− 0.016	− 0.017	− 0.019	− 0.027	3.384*	2.502	2.109	2.657
	(0.014)	(0.014)	(0.014)	(0.016)	(1.389)	(1.316)	(1.321)	(1.475)
Chemistry	− 0.003	− 0.005	− 0.012	− 0.020	4.397*	3.168	1.813	3.661
	(0.021)	(0.020)	(0.020)	(0.024)	(1.771)	(1.697)	(1.693)	(1.935)
Physics	0.100***	0.104***	0.094***	0.082**	9.484***	6.165**	4.338*	5.508*
	(0.028)	(0.028)	(0.027)	(0.030)	(1.994)	(1.928)	(1.961)	(2.287)
Advanced science	0.066*	0.067**	0.059*	0.048	6.393**	4.665*	2.922	2.122
	(0.026)	(0.026)	(0.025)	(0.031)	(2.211)	(2.142)	(2.137)	(2.475)
Math test score	0.003	0.003	− 0.000	0.003	3.587***	2.714***	2.086***	2.471***
	(0.007)	(0.008)	(0.008)	(0.008)	(0.595)	(0.589)	(0.587)	(0.620)
Locus of control	0.005	0.005	0.003	0.002	2.600***	2.473***	2.078***	1.670***
	(0.005)	(0.005)	(0.005)	(0.006)	(0.484)	(0.477)	(0.474)	(0.490)
Background	No	Yes	Yes	Yes	No	Yes	Yes	Yes
1992 education	No	No	Yes	Yes	No	No	Yes	Yes
School fixed effects	No	No	No	Yes	No	No	No	Yes
R^2	0.075	0.079	0.087	0.254	0.170	0.208	0.229	0.385

	STEM 2013				Wage Percentile 2013			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
N	7,300	7,300	7,300	7,300	7,240	7,240	7,240	7,240

Data Source: Author calculations from U.S. Department of Education, National Center for Education Statistics, The High School &Beyond Midlife Follow-Up Study, Sophomore Cohort.

* *p*<.05

** *p*<.01

*** *p*<.001 (two-tailed tests).

Note: Reduced model includes the numbers of mathematics credits, science credits, and foreign language credits. Background characteristics include race/ethnicity, gender, age, parental education, and number of siblings. 1992 education is the respondents' educational attainment (less than high school degree, high school graduate, postsecondary certificate, associate's degree, bachelor's degree, master's degree, advanced or professional degree) by 1992.

Table 5

OLS Regression Estimates of 2013 Labor Market Outcomes, Controlling for STEM 1991.

	STEM 2013					Wage percentile 2013				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Highest math course										
Algebra 1	0.023	0.021	0.019	0.031*	0.022	4.512**	3.621**	3.510*	2.848*	1.395
	(0.014)	(0.014)	(0.014)	(0.015)	(0.014)	(1.451)	(1.378)	(1.372)	(1.426)	(1.505)
Geometry	0.028	0.027	0.022	0.007	0.015	7.682***	6.692***	5.971***	5.262**	4.238**
	(0.016)	(0.016)	(0.016)	(0.019)	(0.016)	(1.619)	(1.509)	(1.517)	(1.661)	(1.622)
Algebra 2	0.044**	0.043**	0.039*	0.032	0.044*	8.947***	7.341***	6.102***	5.341**	5.077**
	(0.015)	(0.016)	(0.017)	(0.020)	(0.018)	(1.612)	(1.520)	(1.521)	(1.707)	(1.675)
Adv math/Calculus	0.086***	0.087***	0.082***	0.080**	0.084***	13.27***	11.33***	9.096***	8.718***	8.615***
	(0.022)	(0.022)	(0.022)	(0.026)	(0.024)	(1.957)	(1.845)	(1.866)	(2.069)	(2.021)
Highest science course										
Biology	− 0.013	− 0.014	− 0.015	− 0.014	0.008	3.207*	2.396	2.110	2.870	2.497
	(0.013)	(0.013)	(0.013)	(0.016)	(0.014)	(1.384)	(1.314)	(1.318)	(1.470)	(1.449)
Chemistry	− 0.010	− 0.012	− 0.014	− 0.013	0.002	3.848*	2.712	1.638	3.634	2.168
	(0.019)	(0.019)	(0.019)	(0.022)	(0.020)	(1.776)	(1.706)	(1.698)	(1.916)	(1.831)
Physics	0.061*	0.063*	0.060*	0.057*	0.051	8.065***	4.777*	3.375	4.642*	2.778
	(0.025)	(0.025)	(0.025)	(0.028)	(0.026)	(1.979)	(1.929)	(1.959)	(2.267)	(2.251)
Advanced science	0.035	0.035	0.033	0.034	0.050*	5.234*	3.546	2.176	1.479	3.454
	(0.024)	(0.024)	(0.024)	(0.029)	(0.025)	(2.186)	(2.126)	(2.117)	(2.457)	(2.296)
Math test score	− 0.002	− 0.002	− 0.003	0.001	− 0.000	3.373***	2.542***	2.011***	2.390***	2.295***
	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.589)	(0.579)	(0.578)	(0.613)	(0.655)
Locus of control	0.000	− 0.000	− 0.001	0.000	0.003	2.449***	2.327***	2.004***	1.642***	2.267***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.479)	(0.472)	(0.472)	(0.487)	(0.539)
STEM 1991	0.471***	0.470***	0.467***	0.463***		11.00***	11.85***	10.66***	11.66***	
	(0.026)	(0.026)	(0.026)	(0.023)		(1.409)	(1.337)	(1.322)	(1.337)	
Background	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
1992 education	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes

	STEM 2013					Wage percentile 2013				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
School fixed effects	No	No	No	Yes	No	No	No	No	Yes	No
STEM 1991 = 0	No	No	No	No	Yes	No	No	No	No	Yes
R^2	0.227	0.229	0.231	0.371	0.027	0.186	0.224	0.240	0.396	0.194
N	7,300	7,300	7,300	7,300	5,680	7,240	7,240	7,240	7,240	5640

Data Source: Author calculations from U.S. Department of Education, National Center for Education Statistics, The High School &Beyond Midlife Follow-Up Study, Sophomore Cohort.

* *p*<.05

** *p*<.01

*** *p*<.001 (two-tailed tests).

Note: Reduced model includes the numbers of mathematics credits, science credits, and foreign language credits. Background characteristics include race/ethnicity, gender, age, parental education, and number of siblings. 1992 education is the respondents' educational attainment (less than high school degree, high school graduate, postsecondary certificate, associate's degree, bachelor's degree, master's degree, advanced or professional degree) by 1992.

Table 6

OLS Regression Estimates of Occupational Transition between 1991 and 2013.

	Move from non-STEM to STEM	Move from STEM to non-STEM	Staying in STEM
Highest math course			
Algebra 1	0.020	− 0.002	0.014
	(0.014)	(0.009)	(0.008)
Geometry	0.014	0.005	0.021
	(0.015)	(0.013)	(0.011)
Algebra 2	0.040*	0.017	0.022
	(0.016)	(0.015)	(0.013)
Adv math/Calculus	0.061**	0.031	0.072***
	(0.021)	(0.017)	(0.017)
Highest science course			
Biology	0.011	0.006	− 0.017*
	(0.013)	(0.010)	(0.008)
Chemistry	0.007	0.012	− 0.010
	(0.018)	(0.013)	(0.014)
Physics	0.037	0.007	0.067**
	(0.022)	(0.015)	(0.021)
Advanced science	0.041	0.029	0.028
	(0.023)	(0.016)	(0.018)
Math test score	− 0.001	0.009	− 0.004
	(0.006)	(0.005)	(0.006)
Locus of control	0.002	0.005	0.005
	(0.005)	(0.003)	(0.004)
Background	Yes	Yes	Yes
1992 education	Yes	Yes	Yes
R2	0.015	0.025	0.100
N	6,520	6,520	6,520

Data Source: Author calculations from U.S. Department of Education, National Center for Education Statistics, The High School &Beyond Midlife Follow-Up Study, Sophomore Cohort.

* $p<.05$

** $p<.01$

*** $p<.001$ (two-tailed tests).

Note: Reduced model includes the numbers of mathematics credits, science credits, and foreign language credits. Background characteristics include race/ethnicity, gender, age, parental education, and number of siblings. 1992 education is the respondents' educational attainment (less than high school degree, high school graduate, postsecondary certificate, associate's degree, bachelor's degree, master's degree, advanced or professional degree) by 1992.

Table 7

OLS Regression Estimates of Labor Market Outcomes in 2013 by Gender.

	STEM 2013				Wage Percentile 2013			
	Men		Women		Men		Women	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Highest math course								
Algebra 1	− 0.001	− 0.001	0.050 *	0.040 *	2.076	2.106	4.580 *	4.209 *
	(0.018)	(0.017)	(0.020)	(0.020)	(1.962)	(1.961)	(1.929)	(1.944)
Geometry	0.014	0.018	0.044	0.024	4.559 *	4.635 *	7.471 ***	6.829 **
	(0.024)	(0.022)	(0.023)	(0.023)	(2.262)	(2.240)	(2.137)	(2.148)
Algebra 2	0.041	0.019	0.070 **	0.059 *	3.859	3.461	8.574 ***	8.198 ***
	(0.025)	(0.023)	(0.025)	(0.024)	(2.192)	(2.186)	(2.158)	(2.164)
Adv math/Calculus	0.132 ***	0.080 **	0.115 **	0.086 *	8.069 **	7.126 **	11.532 ***	10.807 ***
	(0.032)	(0.029)	(0.037)	(0.036)	(2.598)	(2.585)	(2.726)	(2.715)
Highest science course								
Biology	− 0.010	− 0.005	− 0.033	− 0.029	0.737	0.739	2.723	2.779
	(0.017)	(0.016)	(0.021)	(0.020)	(1.810)	(1.798)	(1.965)	(1.955)
Chemistry	− 0.034	− 0.025	− 0.003	− 0.015	0.939	1.000	2.216	1.816
	(0.026)	(0.025)	(0.031)	(0.028)	(2.442)	(2.463)	(2.397)	(2.392)
Physics	0.109 ***	0.090 **	0.054	0.005	3.253	2.767	5.832	4.345
	(0.033)	(0.030)	(0.045)	(0.041)	(2.597)	(2.589)	(3.046)	(3.042)
Advanced science	0.075 *	0.054	0.034	0.006	2.412	1.855	3.001	2.111
	(0.034)	(0.033)	(0.039)	(0.035)	(2.740)	(2.734)	(3.262)	(3.212)
Math test score	0.010	0.005	− 0.010	− 0.010	0.937	0.821	3.342 ***	3.333 ***
	(0.011)	(0.009)	(0.011)	(0.010)	(0.786)	(0.780)	(0.864)	(0.853)
Locus of control	0.002	− 0.001	0.005	0.001	2.077 **	2.025 **	2.082 **	1.994 **
	(0.007)	(0.006)	(0.008)	(0.007)	(0.648)	(0.646)	(0.721)	(0.721)
STEM 1991		0.444 ***		0.477 ***		8.449 ***		12.578 ***
		(0.036)		(0.034)		(1.893)		(1.854)
Background	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

	STEM 2013				Wage Percentile 2013			
	Men		Women		Men		Women	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1992 Education	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.123	0.249	0.076	0.227	0.210	0.217	0.223	0.239
N	3,390	3,390	3,910	3,910	3,350	3,350	3,890	3,890

Data Source: Author calculations from U.S. Department of Education, National Center for Education Statistics, The High School &Beyond Midlife Follow-Up Study, Sophomore Cohort.

* *p*<.05

** *p*<.01

*** *p*<.001 (two-tailed tests).

Note: Reduced model includes the numbers of mathematics credits, science credits, and foreign language credits. Background characteristics include race/ethnicity, gender, age, parental education, and number of siblings. 1992 education is the respondents' educational attainment (less than high school degree, high school graduate, postsecondary certificate, associate's degree, bachelor's degree, master's degree, advanced or professional degree) by 1992.