# On the Origins 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

**JEL codes:** J21, J23, J24

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## On the Origins of STEM: High School Knowledge and Skills and Occupational Determination in an Era of Growing Inequality

### 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.[1] 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) fosters people's adaptability to the increased STEM skill requirements over the long run.

Before investigating how course work 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 three decades, with the share of employment for high skill and low skilled occupations increasing relative to that for middle skilled workers (Acemoglu and Autor 2011). Although STEM occupations are generally considered to be high skill jobs that demand specialized training (Xie, Killewald and Near 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

[1] STEM jobs are defined by U.S. Census Bureau (source: https://www.census.gov/people/io/methodology/). We consider both STEM jobs and STEM-related jobs as a broad category of STEM jobs. See Appendix Table A1 for a complete list of occupations.

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), 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, Levy, Murnane, 2003, and Spitz-Oener, 2006 and 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, Adelman 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 1,000 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 a 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 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.

## Related Literature

### *Workforce Polarization and STEM*

Many studies document the profound changes in occupational employment in the United States and other countries in recent decades (Autor, Levy and Murnane, 2003; Goos and Manning, 2007; Acemogly and Autor, 2011; Goos, Manning and Salomons, 2014, among others).[2] In addition, skill requirements have changed within occupations (Spitz-Oener, 2006; Deming and Kahn, 2018; Atalay et al., 2019).

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 (Bush 1945, National Academy of Sciences, National Academy of Engineering and Institute of Medicine 2007, National Academy of Sciences, National Academy of Engineering

[2] 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).

and Institute of Medicine 2010) and more generally on global economic development (Goldin and Katz 2008, Schofer, Ramirez and Meyer 2000).

Consequently, scholars have already investigated the importance of majoring in STEM and, more recently, how the returns to STEM degrees change over the working life.[3] Specifically, Deming and Noray (2019) 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. Against the background of these findings, the availability of data at different times over the career of the Class of 1982 of HS&B:SO is particularly interesting.

The occupations that are classified as STEM by the U.S. Census are heterogeneous with respect to the training and specializations of workers, the activities that are performed, and the goods and services that are produced (Carnevale, Smith and Melton 2011). For example, physicists, actuaries, medical scientists, and even social scientists are all classified as STEM occupations.

Furthermore, many occupations that are not considered STEM occupations have relatively high levels of occupational task demands that are STEM-related (Rothwell 2013). They, too, are a diverse group, but are mostly in the health professions ranging from physicians to optical goods workers. In contrast to most STEM occupations, many STEM-related occupations are occupied by workers who do not hold a bachelor's degree (or higher). The diversity of STEM and STEM-related fields is important for understanding the matching of individuals' training to occupation

[3] Field of study more generally is an important mediator when it comes to the determinants of the returns to education, see for example Lemieux (2014) and Kinsler and Pavan (2015). In this study, we do not investigate the contribution of field of study specifically. Note, however, that our results are robust to controlling for study degrees.

because many STEM fields require highly specialized training (Mann and DiPrete 2013, Shauman 2016, Xie and Killewald 2012) and for understanding persistence in specific occupations (Glass et al. 2013). Yet, a common feature of most of these fields is that they demand mathematics and analytic skills (Carnevale, Smith and Melton 2011). Appendix Table 1 includes a full list of all STEM and STEM-related occupations as defined by the U.S. Census.

*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 (Carraher and Schielmann 2007, Domina et al. 2015, Howe 2005 , Schmidt, Wang and McKnight 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 addition year of education on early adult wages. Their results are robust to controls for other academic coursework related to simply being on a more academically advanced track of study 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.

Using a natural experiment of high school course assignments in Danish schools, which provides additional evidence for causality, Joensen and Nielsen (2009) found a positive effect of high-level mathematics coursework (but not high-level liberal arts curriculum) on income in early adulthood. All of these studies have concluded that the most likely explanation for the observed effects of mathematics coursework on labor force outcomes is due to high school students' development of knowledge and skills in their coursework that were in demand in the labor force. 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.

As the studies described above have addressed, students take advanced mathematics courses for many reasons that may be endogenous to their subsequent labor force outcomes. Even prepared students may simply opt out of advanced mathematics in the later years of high school, preferring less demanding academic courses. Thus, who takes which high school mathematics courses involves both academic preparation from earlier years, which is partly a function of family background, and also students' individual choices and preferences as well as school attributes, such as course offerings and guidance and counseling practices. Consequently, 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 (Altonji, Blom and Meghir 2012, Bills 2003). 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 (Adelman 1999, Alexander and Pallas 1984, 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.

In summary, we take advantage of the new HSB:SO midlife survey and turn now to our analysis of the relationship between high school course taking and the longer run labor force outcomes for individuals at a later point in the life cycle. We begin by predicting early adult occupation in 1991 (STEM and wage percentile) with high school mathematics and science coursework and then predict midlife occupation, in 2013. We follow this with an analysis of whether high school coursework helped individuals to adapt as they progressed from early adulthood to midlife labor force participation.

## Data and Method

### *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 sample of nearly 30,000 sophomores and 28,000 seniors in over 1,000 high schools. Each school contained a representative sample of 36 sophomores and 36 seniors, making inferences about each school and its student body possible. For this study we use the sophomore longitudinal panel (N=14,830),[4] 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

[4] All unweighted sample sizes have been rounded to the nearest 10, as required by the NCES restricted use data license.

when most were about 50 years old. Our analyses use two panels: the 1980-1992 panel (N=11,850) and the 1980-2014 panel (N=8,790). From these we select respondents with a reported occupation in 1991 (N=10,730) or in 2013 (N=7,300).[5]

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, used in the current study, as well as information about family and health at midlife.

*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.[6] 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

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[5] 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.

[6] STEM jobs are defined by U.S. Census Bureau (source: https://www.census.gov/people/io/methodology/). We consider both STEM jobs and STEM-related jobs as a broad category of STEM jobs. See Appendix Table A1 for a complete list of occupations.

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.

*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. 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).

Finally, we also measure locus of control, a non-cognitive skill that is associated with academic achievement. In 1980, sample members responded to four items based on the Rotter scale of locus of control.[7] The indicator is a weighted average of the items standardized to a mean of zero, standard deviation of one, constructed by NCES.

*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:SO 1980-1992 and 1980-2014 panels. Table 1b shows summary statistics for the HS&B:SO 1980-1992 separately for respondents who work in STEM and those who do not. We clearly see that those working in STEM have higher fractions of Algebra2 and Advance math/calculus 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

[7] 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."

working in STEM clearly come from more favorable educational parental backgrounds. Hence it is important to control for these differences in the empirical analyses.

Table 1a and 1b about here

*Empirical Approach*

Our empirical strategy is to relate labor market outcomes—whether an individual is employed in 2013, whether she is working in a STEM occupation and the percentile of the occupation in the wage distribution—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):

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

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 $\delta_j$ represents high school fixed effects. Our coefficient of interest is $\beta_1$, 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 in 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 facilitated 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; 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.

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.

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 socio-economic 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. Although we do not include grade point average (GPA) as a control in our models, preferring to include controls of mathematics and science credits (which are an element of the computation of GPA), we did estimate an alternate set of models with GPA substituted as a control. 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. 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 weighted and we use multiple imputation (20 imputations) for missing values on all independent variables.

**Results**

We first show the nuanced versions of the standard polarization figures as discussed above. The analyses illustrate the connection between STEM and STEM-related fields and the changing structure of employment. For ease of presentation we refer to STEM and STEM-related simply as STEM fields. Figure 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 2008 broken down by occupation (excluding employment in agriculture).[8] The occupations are ranked on the horizontal axis according to the mean wage of workers in the occupation in 1980, which serves as a proxy for the average skill level of the occupation. The vertical axis shows the change in employment share from 1980 to 2008 at each occupational percentile. Below the 40th percentile, employment growth by occupation was declining nearly monotonically in occupational skills, with employment growth being positive below the 15$^{th}$ percentile and negative thereafter. Above the 40$^{th}$ percentile, growth in employment shares increases relatively monotonically in occupational skills, with occupations above the 60$^{th}$ 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-skill occupations being offset by the increase in employment in high and low-skill occupations. The red circles in Figure 1 depict the distribution of STEM occupations across skill 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

[8] A full list of occupations by STEM, STEM-related and non-STEM occupation along with the values to compute the figures change in employment share and average wages, are shown in Appendix Table A.

occupations are primarily higher-skill, there are also a non-trivial number of STEM occupations in the middle.

Figure 1 about here

Next, we examine the evolution of employment in STEM occupations along the occupational skill 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. Figure 2 Panel A shows the result for the first tercile, *i.e.* employment changes 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 Figure 1), it is apparent from Figure 2 Panel A, that employment in those occupations evolved very differently compared to employment in other low-skill, low-wage occupations. In particular, during the 1980s and 1990s, 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").[9]

Figure 2 about here

Figure 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, the tercile with the greatest employment share declines in Figure 1. When we focus on the second tercile, we are interested in to what extent the evolution of STEM employment counteracted the overall trend in employment

[9] 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).

declines in the middle of the U.S. wage distribution. The evolution of employment in STEM occupations over the three decades we focus on again points to an interesting pattern – while overall employment in those occupations was stagnating or declining (see "All occupations"), employment in STEM occupations was increasing ("STEM"). STEM occupations thus provided a countervailing force to the declining employment shares in the middle of the U.S. wage distribution.

The third tercile (Figure 2 Panel C) shows that if it weren't for STEM occupations, employment at the high-skill, high-wage end of the occupational distribution would have looked very different as well. During the 1980s and 2000s, employment would have declined even in those occupations, had the evolution of employment in STEM occupations not counteracted the decline. The fact that employment would have declined as a share in total employment even among high-wage occupations were it not for STEM occupations is striking.

This can be observed more clearly by considering the change in actual employment during the period, along the 1980 occupational skill distribution. Figure 3 shows the observed evolution of employment share (solid line) together with counterfactual employment share (dashed line), *i.e.* the evolution of employment share along the occupational skill distribution had employment in STEM occupations remained at its 1980 level. The figure demonstrates that employment in STEM occupations was not only an important component of employment growth at the high-skill, high-wage end of the occupational skill distribution; instead, STEM occupations played an important role for employment growth in the middle of the skill distribution as well in recent decades.

Figure 3 about here

Turning to wages, Figure 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 counterfactual changes (dashed line), *i.e.* holding wages in STEM occupations constant at their level in 1980. Again, it is striking how pervasive the influence of wage growth in STEM occupations was, encompassing every percentile of the occupational skill distribution above about the 20$^{th}$ percentile. Motivated by these findings, we look to the role of schools in preparing workers for the labor force.

Figure 4 about here

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 taking has a positive effect on long-term employment.

Table 2 about here

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 cognitive and non-cognitive skills (mathematics test scores and locus of control). With only this very limited 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.

Table 3 about here

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. As a further way to address endogeneity concerns, we take advantage of the school-level sampling design of the HS&B data. Because of this, 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 test scores. 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 mathematics test scores, locus of control, and science coursework. 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.

*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.

Table 4 about here

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, 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.

Table 5 about here

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 resuls 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 tranistions into more detail. Table 6 shows the results of regression specifications the 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.

Table 6 about here

*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, England 2010, Glass et al. 2013) 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; results for models of the 1991 outcomes are available from the authors upon request. 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.

Table 7 about here

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.[10] 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.

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

## 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 requirements over the long run. This 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 wide-spread. 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 skill 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 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. Bryk, Lee and Holland 1993, Coleman and Hoffer 1987, 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 (Bailey et al. 2016, Bryk, Lee and Holland 1993, Coleman, Hoffer and Kilgore 1982b, Coleman and Hoffer 1987). 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 job 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.

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). [11] Consistent with the theory of maximally maintained inequality (Raftery and Hout 1993), with the rising levels of course taking and curricular intensification have come the accumulation of more advanced mathematics credits and maintained inequality in the most advanced coursework (Domina and Saldana 2012).

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 and his colleagues (2015) recently found that when 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

[11] 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.

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.[12] 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. As discussed above, our modeling strategies attempt to mitigate this limitation, but we still recognize that unobservable factors could be biasing our results. As we also mentioned, our findings are robust to alternative model specifications. 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., Altonji, Blom and Meghir 2012, Coleman, Hoffer and Kilgore 1982a, Evans and Schwab 1995). 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,

[12] 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.

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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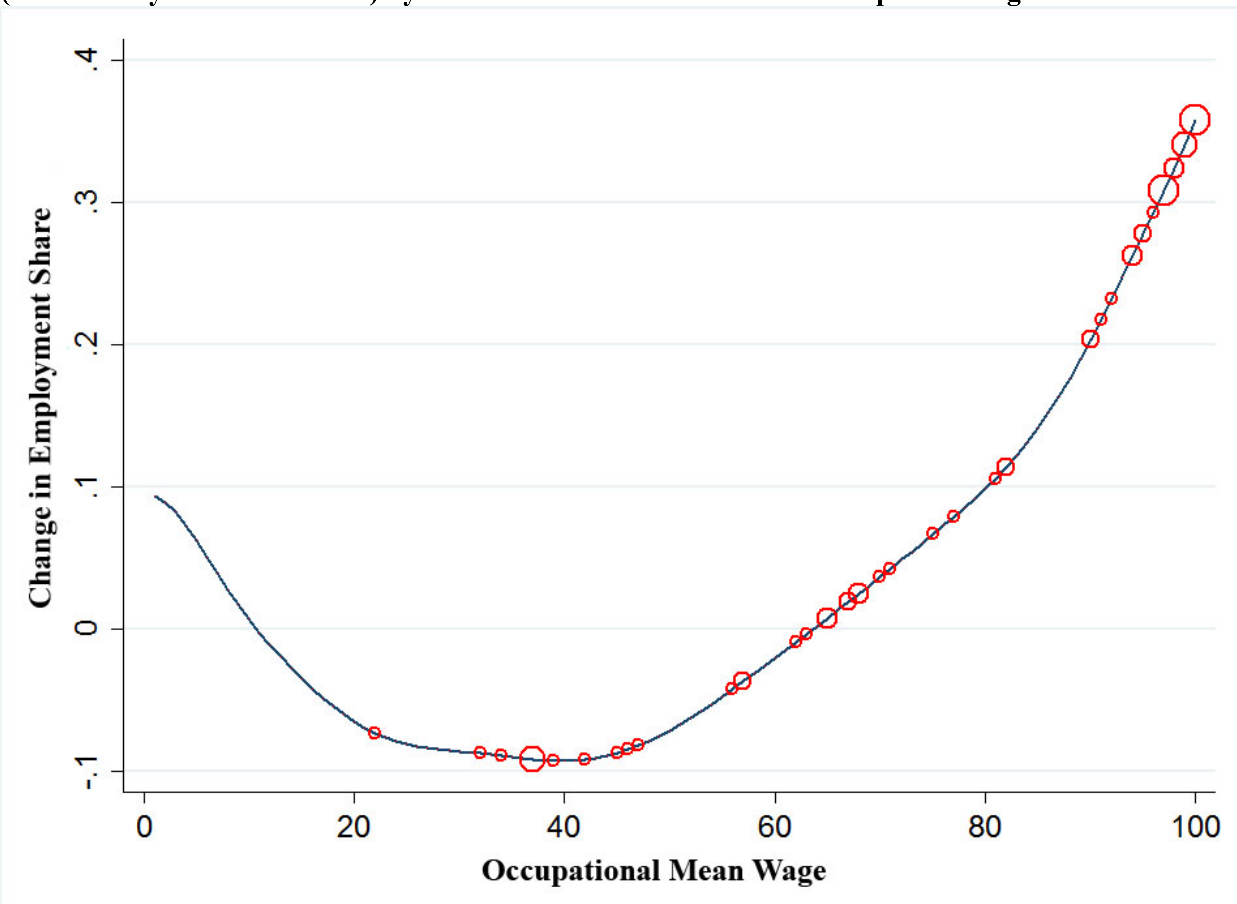
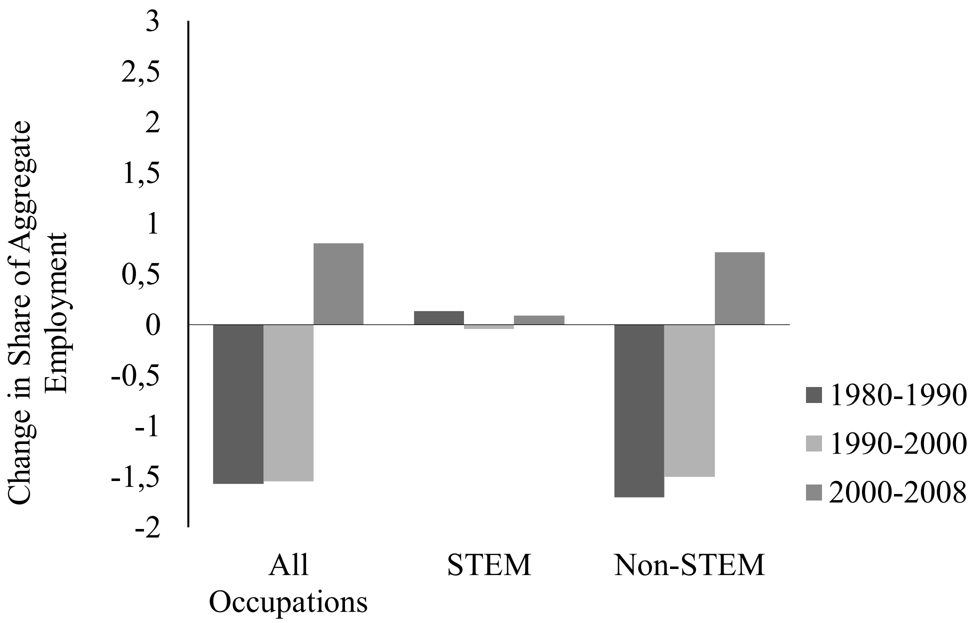
## Figures and Tables

**Figure 1: Smoothed Changes in Employment Share 1980-2008 and Number of STEM Occupations (indicated by radius of circles) by 1980 Percentile Rank of Mean Occupation Wage**

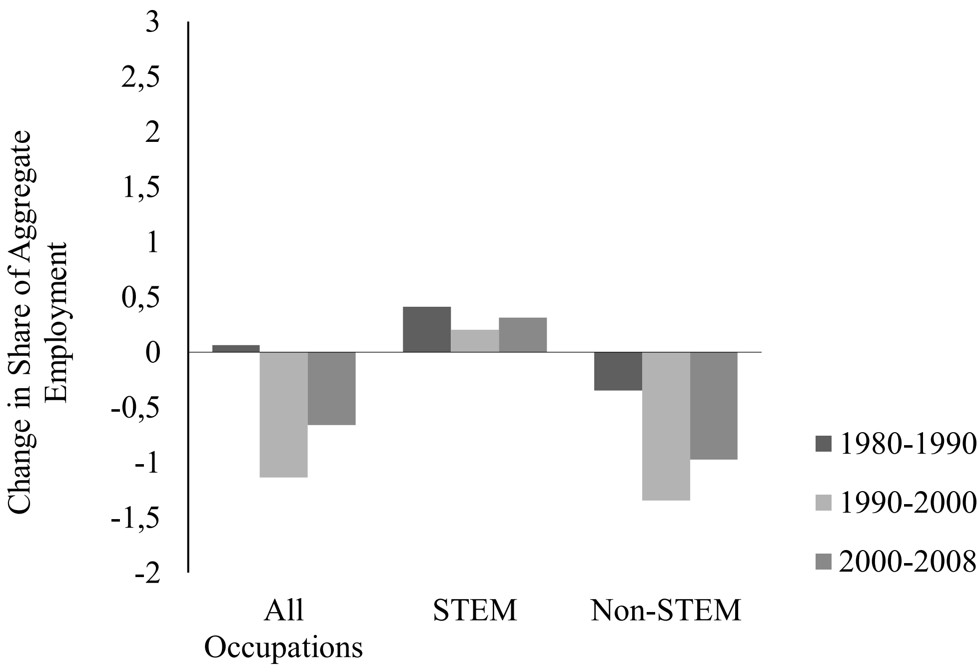



**Data Source:** Author calculations from U.S. Census PUMS and American Community Survey (ACS) data.

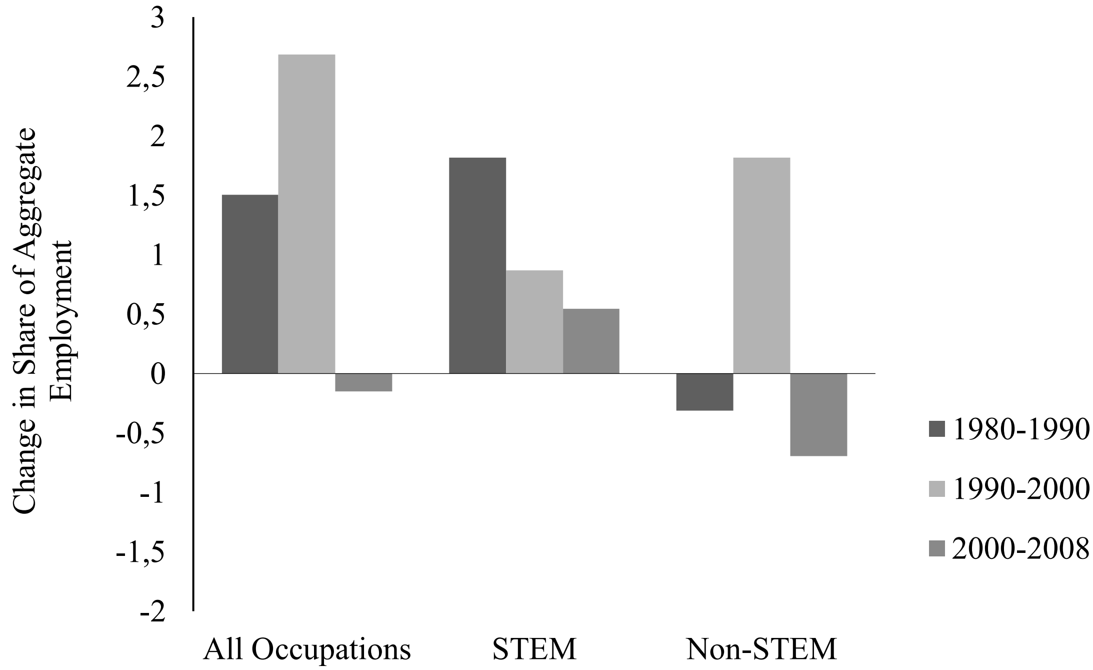
**Figure 2: Changes in Aggregate Employment Shares of Occupation, by Occupation Type (all, STEM, Non-STEM) and Decade (1980-2008), by Average Occupation Wage in 1980 Terciles**




Panel A. First Tercile



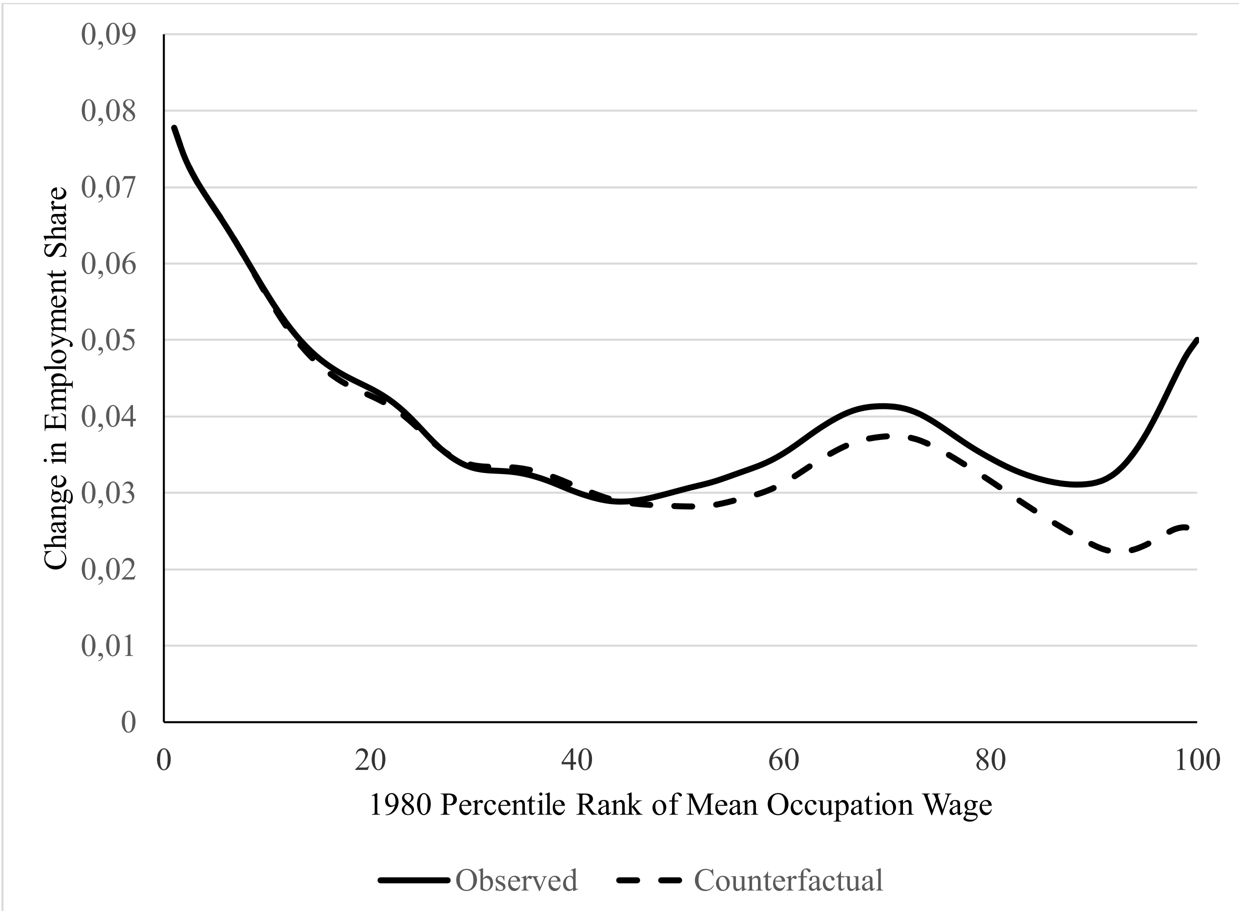

Panel B: Second Tercile




Panel C: Third Tercile

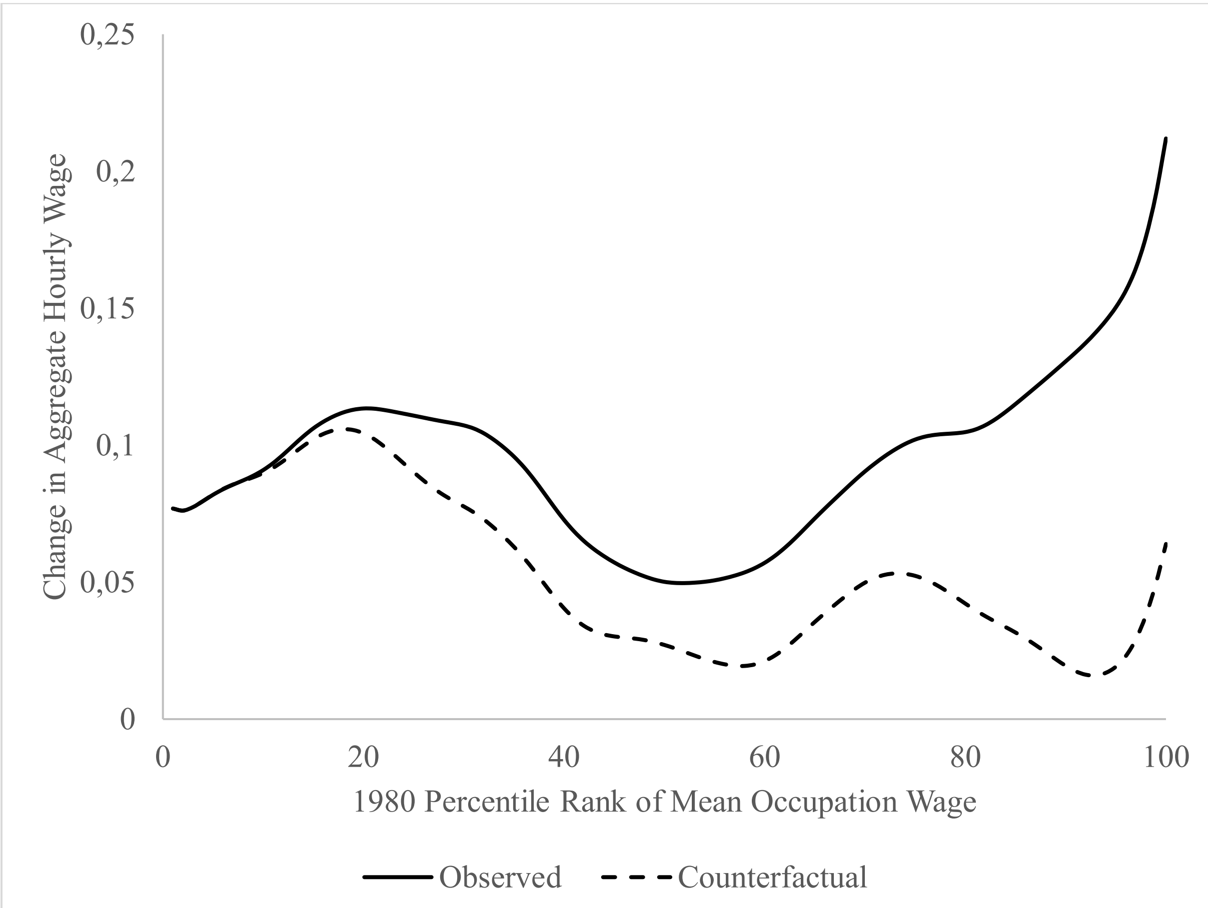
**Data Source:** Author calculations from U.S. Census PUMS and American Community Survey (ACS) data.

**Figure 3: Observed and Counterfactual Change in Employment Share, 1980-2008, by 1980 Percentile Rank of Mean Occupation Wage**




**Data Source:** Author calculations from U.S. Census PUMS and American Community Survey (ACS) data.
Note: The counterfactual condition is the change in employment share if STEM occupations had not grown (had stayed at 1980 levels).

**Figure 4: Observed and Counterfactual Change in Aggregate (log) Wage, 1980-2008, by 1980 Percentile Rank of Mean Occupation Wage**




**Data Source:** Author calculations from U.S. Census PUMS and American Community Survey (ACS) data.
Note: The counterfactual condition is the change in hourly wage if STEM occupations had not grown (had stayed at 1980 levels)

**Table 1a. Descriptive Statistics for HS&B:SO Analytic Samples**

| | 1991 | | 2013 | |
|---|---|---|---|---|
| Outcome | Working in STEM | Wage percentile | Working in STEM | 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) |
| 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 |

**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 | *** |
| 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 | |

*p<.05; **p<.01; ***p<.001 (two-tailed tests)

**Table 2: OLS Regression Estimates of Employment in 2013**

| | | |
|---|---|---|
| Highest math course | | |
| Algebra 1 | 0.077*** | 0.071** |
| | (0.022) | (0.022) |
| Geometry | 0.090*** | 0.078*** |
| | (0.023) | (0.023) |
| Algebra 2 | 0.086*** | 0.072** |
| | (0.023) | (0.023) |
| Adv math/Calculus | 0.096*** | 0.077** |
| | (0.025) | (0.025) |
| Highest science course | | |
| Biology | 0.010 | 0.005 |
| | (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 | 0.060 |
| N | 7,810 | 7,810 |

*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 |
| N | 10,730 | 10,730 | 10,730 | 10,730 | 10,560 | 10,560 | 10,560 | 10,560 |

*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 |
| N | 7,300 | 7,300 | 7,300 | 7,300 | 7,240 | 7,240 | 7,240 | 7,240 |

*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 |
| 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 | 5,640 |

*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 | 0.029 | 0.100 |
| N | 6,520 | 6,520 | 6,520 |

*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 |
| 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 |

*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.

**Appendix**

**Appendix Table A—Occupations Classified as STEM, STEM-Related, and Non-STEM with Values on 1980 and 2008 Occupation Mean Wage Percentile, Mean Wage, Mean Employment Share, and Difference Between 2008 and 1980 Mean Wage and Mean Employment Share. Corresponds to Figures 1-4.**

| Occupations | 1980 Percent Rank | 2008 Percent Rank | 1980 Mean Wage | 1980 Mean Employ Share | 2008 Mean Wage | 2008 Mean Employ Share | 2008-1980 Diff in Mean Wage | 2008-1980 Diff in Mean Empl Share |
|---|---|---|---|---|---|---|---|---|
| **STEM jobs** | | | | | | | | |
| Aerospace engineers | 99 | 97 | 3.438 | 7.672 | 3.646 | 7.717 | 0.208 | 0.045 |
| Metallurgical and materials engineers | 99 | 92 | 3.357 | 7.675 | 3.384 | 7.756 | 0.027 | 0.081 |
| Petroleum, mining, and geological engineers | 99 | 97 | 3.308 | 7.815 | 3.571 | 7.882 | 0.262 | 0.066 |
| Chemical engineers | 99 | 97 | 3.418 | 7.677 | 3.577 | 7.722 | 0.158 | 0.045 |
| Civil engineers | 97 | 95 | 3.266 | 7.682 | 3.487 | 7.721 | 0.221 | 0.039 |
| Electrical engineers | 99 | 96 | 3.325 | 7.672 | 3.561 | 7.726 | 0.236 | 0.054 |
| Industrial engineers | 96 | 91 | 3.182 | 7.683 | 3.367 | 7.744 | 0.185 | 0.062 |
| Mechanical engineers | 99 | 94 | 3.332 | 7.688 | 3.431 | 7.742 | 0.099 | 0.054 |
| Engineers and other professionals, n.e.c. | 98 | 96 | 3.304 | 7.692 | 3.524 | 7.726 | 0.220 | 0.034 |
| Computer systems analysts and computer scientists | 97 | 87 | 3.229 | 7.674 | 3.288 | 7.691 | 0.058 | 0.017 |
| Operations and systems researchers and analysts | 96 | 91 | 3.207 | 7.654 | 3.318 | 7.694 | 0.111 | 0.040 |
| Actuaries | 99 | 98 | 3.365 | 7.650 | 3.826 | 7.671 | 0.461 | 0.021 |
| Mathematicians and statisticians | 94 | 91 | 3.096 | 7.613 | 3.369 | 7.698 | 0.273 | 0.086 |
| Physicists and astronomists | 99 | 97 | 3.333 | 7.717 | 3.576 | 7.760 | 0.244 | 0.042 |
| Chemists | 94 | 91 | 3.151 | 7.655 | 3.351 | 7.693 | 0.200 | 0.038 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Atmospheric and space scientists | 94 | 94 | 3.153 | 7.653 | 3.432 | 7.730 | 0.279 | 0.078 |
| Geologists | 97 | 92 | 3.262 | 7.686 | 3.384 | 7.708 | 0.122 | 0.022 |
| Physical scientists, n.e.c. | 92 | 91 | 3.080 | 7.660 | 3.350 | 7.720 | 0.270 | 0.060 |
| Agricultural and food scientists | 67 | 67 | 2.881 | 7.682 | 3.032 | 7.730 | 0.151 | 0.048 |
| Biological scientists | 77 | 71 | 2.964 | 7.655 | 3.115 | 7.701 | 0.151 | 0.047 |
| Foresters and conservation scientists | 67 | 71 | 2.887 | 7.657 | 3.114 | 7.689 | 0.227 | 0.031 |
| Medical scientists | 97 | 85 | 3.217 | 7.724 | 3.268 | 7.745 | 0.051 | 0.021 |
| Economists, market and survey researchers | 97 | 93 | 3.257 | 7.690 | 3.429 | 7.722 | 0.172 | 0.032 |
| Psychologists | 81 | 85 | 2.998 | 7.623 | 3.241 | 7.659 | 0.243 | 0.036 |
| Social scientists and sociologists, n.e.c. | 70 | 70 | 2.912 | 7.608 | 3.089 | 7.652 | 0.177 | 0.045 |
| Urban and regional planners | 93 | 86 | 3.094 | 7.643 | 3.280 | 7.678 | 0.186 | 0.035 |
| Engineering technicians | 71 | 70 | 2.916 | 7.651 | 3.082 | 7.683 | 0.167 | 0.032 |
| Drafters | 64 | 61 | 2.843 | 7.623 | 2.989 | 7.656 | 0.145 | 0.033 |
| Surveryors, cartographers, mapping scientists/techs | 56 | 53 | 2.744 | 7.640 | 2.880 | 7.685 | 0.136 | 0.046 |
| Biological technicians | 45 | 52 | 2.684 | 7.617 | 2.859 | 7.665 | 0.174 | 0.048 |
| Chemical technicians | 74 | 65 | 2.947 | 7.638 | 3.008 | 7.683 | 0.061 | 0.045 |
| Other science technicians | 56 | 66 | 2.756 | 7.623 | 3.020 | 7.802 | 0.264 | 0.179 |
| Computer software developers | 82 | 96 | 3.010 | 7.625 | 3.524 | 7.696 | 0.513 | 0.071 |
| Technicians, n.e.c. | 68 | 47 | 2.905 | 7.632 | 2.769 | 7.581 | -0.135 | -0.051 |
| Sales engineers | 99 | 96 | 3.316 | 7.746 | 3.546 | 7.796 | 0.230 | 0.050 |
| **STEM-related jobs** | | | | | | | | |
| Managers of medicine and health occupations | 90 | 90 | 3.027 | 7.717 | 3.303 | 7.759 | 0.276 | 0.042 |
| Physicians | 96 | 98 | 3.190 | 8.009 | 3.764 | 7.956 | 0.574 | -0.052 |
| Dentists | 97 | 99 | 3.256 | 7.684 | 3.857 | 7.634 | 0.601 | -0.051 |
| Veterinarians | 80 | 91 | 2.986 | 7.893 | 3.334 | 7.833 | 0.348 | -0.060 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Optometrists | 97 | 96 | 3.256 | 7.703 | 3.539 | 7.659 | 0.282 | -0.044 |
| Podiatrists | 64 | 96 | 2.850 | 7.767 | 3.541 | 7.782 | 0.691 | 0.016 |
| Other health and therapy occupations | 64 | 83 | 2.849 | 7.682 | 3.210 | 7.666 | 0.361 | -0.016 |
| Registered nurses | 63 | 90 | 2.818 | 7.554 | 3.294 | 7.617 | 0.476 | 0.063 |
| Pharmacists | 90 | 97 | 3.047 | 7.748 | 3.748 | 7.645 | 0.702 | -0.103 |
| Dieticians and nutritionists | 36 | 58 | 2.595 | 7.570 | 2.920 | 7.593 | 0.325 | 0.024 |
| Respiratory therapists | 38 | 73 | 2.623 | 7.613 | 3.152 | 7.626 | 0.529 | 0.013 |
| Occupational therapists | 56 | 91 | 2.748 | 7.539 | 3.346 | 7.570 | 0.597 | 0.031 |
| Physical therapists | 61 | 91 | 2.815 | 7.590 | 3.336 | 7.623 | 0.520 | 0.033 |
| Speech therapists | 67 | 86 | 2.903 | 7.461 | 3.270 | 7.566 | 0.367 | 0.105 |
| Therapists, n.e.c. | 37 | 61 | 2.607 | 7.576 | 2.975 | 7.606 | 0.369 | 0.030 |
| Physicians' assistants | 33 | 92 | 2.556 | 7.830 | 3.384 | 7.707 | 0.828 | -0.123 |
| Clinical laboratory technologies and technicians | 46 | 61 | 2.695 | 7.597 | 2.959 | 7.625 | 0.263 | 0.028 |
| Dental hygienists | 66 | 86 | 2.855 | 7.406 | 3.280 | 7.421 | 0.425 | 0.015 |
| Health record technologists and technicians | 41 | 30 | 2.628 | 7.604 | 2.621 | 7.595 | -0.007 | -0.009 |
| Radiologic technologists and technicians | 45 | 73 | 2.687 | 7.612 | 3.148 | 7.621 | 0.461 | 0.009 |
| Licensed practical nurses | 22 | 51 | 2.473 | 7.553 | 2.844 | 7.625 | 0.371 | 0.073 |
| Health technologists and technicians, n.e.c. | 31 | 48 | 2.530 | 7.635 | 2.783 | 7.778 | 0.253 | 0.142 |
| Optical goods workers | 36 | 46 | 2.590 | 7.636 | 2.746 | 7.621 | 0.156 | -0.015 |
| Dental laboratory and medical appliance technicians | 37 | 30 | 2.596 | 7.657 | 2.607 | 7.581 | 0.011 | -0.076 |
| **Non-STEM related jobs** | | | | | | | | |
| Chief executives, public administrators, and legislators | 75 | 100 | 2.959 | 7.696 | 3.873 | 7.867 | 0.914 | 0.171 |
| Managers and administrators, n.e.c. | 89 | 82 | 3.025 | 7.777 | 3.195 | 7.778 | 0.170 | 0.002 |
| Financial managers | 94 | 92 | 3.137 | 7.710 | 3.375 | 7.761 | 0.238 | 0.052 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Human resources and labor relations managers | 91 | 88 | 3.060 | 7.727 | 3.293 | 7.755 | 0.233 | 0.027 |
| Managers and specialists in marketing, advertising | 95 | 93 | 3.154 | 7.774 | 3.412 | 7.781 | 0.258 | 0.007 |
| Managers in education and related fields | 92 | 82 | 3.079 | 7.700 | 3.198 | 7.758 | 0.118 | 0.058 |
| Managers of properties and real estate | 39 | 66 | 2.623 | 7.703 | 3.024 | 7.721 | 0.400 | 0.019 |
| Funeral directors | 44 | 64 | 2.676 | 7.894 | 2.995 | 7.794 | 0.319 | -0.099 |
| Accountants and auditors | 74 | 85 | 2.944 | 7.656 | 3.232 | 7.696 | 0.287 | 0.040 |
| Insurance underwriters | 66 | 85 | 2.856 | 7.608 | 3.242 | 7.661 | 0.387 | 0.053 |
| Other financial specialists | 80 | 88 | 2.986 | 7.660 | 3.293 | 7.722 | 0.307 | 0.061 |
| Management analysts | 97 | 94 | 3.215 | 7.714 | 3.464 | 7.738 | 0.249 | 0.023 |
| Personnel, HR, training, and labor rel. specialists | 72 | 71 | 2.935 | 7.664 | 3.115 | 7.689 | 0.180 | 0.025 |
| Purchasing agents and buyers of farm products | 61 | 59 | 2.804 | 7.815 | 2.951 | 7.730 | 0.147 | -0.084 |
| Buyers, wholesale and retail trade | 62 | 57 | 2.818 | 7.705 | 2.893 | 7.680 | 0.076 | -0.026 |
| Purchasing managers, agents, and buyers, n.e.c. | 83 | 83 | 3.020 | 7.684 | 3.211 | 7.719 | 0.191 | 0.035 |
| Business and promotion agents | 74 | 65 | 2.945 | 7.701 | 3.014 | 7.770 | 0.069 | 0.069 |
| Construction inspectors | 73 | 69 | 2.937 | 7.640 | 3.077 | 7.683 | 0.140 | 0.043 |
| Inspectors and compliance officers, outside | 80 | 85 | 2.983 | 7.667 | 3.264 | 7.709 | 0.281 | 0.042 |
| Management support occupations | 81 | 68 | 3.002 | 7.651 | 3.060 | 7.671 | 0.057 | 0.020 |
| Subject instructors, college | 91 | 71 | 3.055 | 7.652 | 3.097 | 7.678 | 0.042 | 0.026 |
| Kindergarten and earlier school teachers | 11 | 20 | 2.319 | 7.366 | 2.439 | 7.542 | 0.120 | 0.176 |
| Primary school teachers | 70 | 64 | 2.906 | 7.482 | 2.989 | 7.645 | 0.083 | 0.164 |
| Secondary school teachers | 73 | 67 | 2.937 | 7.537 | 3.028 | 7.696 | 0.091 | 0.159 |
| Special education teachers | 55 | 61 | 2.734 | 7.555 | 2.959 | 7.620 | 0.225 | 0.065 |
| Teachers, n.e.c. | 45 | 47 | 2.680 | 7.547 | 2.777 | 7.570 | 0.097 | 0.023 |
| Vocational and educational counselors | 67 | 52 | 2.879 | 7.553 | 2.852 | 7.622 | -0.027 | 0.069 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Librarians | 56 | 59 | 2.746 | 7.484 | 2.949 | 7.563 | 0.203 | 0.078 |
| Archivists and curators | 58 | 61 | 2.781 | 7.610 | 2.980 | 7.616 | 0.199 | 0.005 |
| Social workers | 54 | 53 | 2.728 | 7.593 | 2.872 | 7.643 | 0.144 | 0.049 |
| Clergy and religious workers | 10 | 43 | 2.298 | 7.910 | 2.702 | 7.793 | 0.404 | -0.117 |
| Welfare service workers | 5 | 48 | 2.185 | 7.514 | 2.789 | 7.640 | 0.603 | 0.126 |
| Lawyers and judges | 98 | 98 | 3.282 | 7.773 | 3.793 | 7.823 | 0.512 | 0.049 |
| Writers and authors | 74 | 73 | 2.946 | 7.640 | 3.183 | 7.663 | 0.237 | 0.023 |
| Technical writers | 82 | 90 | 3.019 | 7.635 | 3.310 | 7.639 | 0.291 | 0.003 |
| Designers | 58 | 60 | 2.766 | 7.634 | 2.954 | 7.662 | 0.188 | 0.027 |
| Musicians and composers | 43 | 50 | 2.671 | 7.448 | 2.836 | 7.576 | 0.165 | 0.128 |
| Actors, directors, and producers | 72 | 48 | 2.936 | 7.658 | 2.781 | 7.471 | -0.154 | -0.188 |
| Painters, sculptors, craft-artists, and print-makers | 44 | 67 | 2.675 | 7.613 | 3.060 | 7.681 | 0.385 | 0.068 |
| Photographers | 45 | 44 | 2.688 | 7.666 | 2.721 | 7.675 | 0.034 | 0.010 |
| Dancers | 14 | 25 | 2.384 | 7.427 | 2.581 | 7.566 | 0.197 | 0.139 |
| Art/entertainment performers and related occs | 35 | 46 | 2.574 | 7.661 | 2.768 | 7.547 | 0.193 | -0.114 |
| Editors and reporters | 65 | 69 | 2.853 | 7.635 | 3.074 | 7.680 | 0.221 | 0.045 |
| Announcers | 35 | 58 | 2.578 | 7.606 | 2.928 | 7.614 | 0.349 | 0.008 |
| Athletes, sports instructors, and officials | 36 | 44 | 2.585 | 7.683 | 2.711 | 7.620 | 0.125 | -0.063 |
| Airplane pilots and navigators | 100 | 96 | 3.576 | 7.695 | 3.531 | 7.785 | -0.045 | 0.089 |
| Broadcast equipment operators | 37 | 61 | 2.612 | 7.660 | 2.968 | 7.690 | 0.357 | 0.029 |
| Programmers of numerically controlled machine tools | 89 | 47 | 3.026 | 7.672 | 2.775 | 7.723 | -0.251 | 0.052 |
| Legal assistants and paralegals | 42 | 64 | 2.655 | 7.586 | 3.001 | 7.627 | 0.345 | 0.041 |
| Sales supervisors and proprietors | 50 | 56 | 2.713 | 7.833 | 2.882 | 7.781 | 0.168 | -0.052 |
| Insurance sales occupations | 71 | 68 | 2.926 | 7.720 | 3.067 | 7.701 | 0.140 | -0.019 |
| Real estate sales occupations | 58 | 60 | 2.761 | 7.721 | 2.952 | 7.728 | 0.191 | 0.007 |
| Financial service sales occupations | 98 | 94 | 3.295 | 7.720 | 3.448 | 7.780 | 0.153 | 0.060 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Advertising and related sales jobs | 67 | 73 | 2.879 | 7.657 | 3.131 | 7.712 | 0.252 | 0.055 |
| Salespersons, n.e.c. | 77 | 73 | 2.959 | 7.727 | 3.123 | 7.736 | 0.164 | 0.009 |
| Retail salespersons and sales clerks | 17 | 33 | 2.384 | 7.563 | 2.629 | 7.613 | 0.245 | 0.050 |
| Cashiers | 7 | 3 | 2.222 | 7.398 | 2.111 | 7.411 | -0.111 | 0.013 |
| Door-to-door sales, street sales, and news vendors | 11 | 17 | 2.310 | 7.424 | 2.401 | 7.562 | 0.091 | 0.138 |
| Sales demonstrators, promoters, and models | 17 | 17 | 2.413 | 7.351 | 2.417 | 7.353 | 0.004 | 0.002 |
| Computer and peripheral equipment operators | 46 | 50 | 2.688 | 7.614 | 2.834 | 7.642 | 0.146 | 0.028 |
| Secretaries and stenographers | 26 | 42 | 2.478 | 7.542 | 2.683 | 7.577 | 0.205 | 0.035 |
| Typists | 13 | 29 | 2.367 | 7.488 | 2.598 | 7.557 | 0.231 | 0.070 |
| Interviewers, enumerators, and surveyors | 17 | 37 | 2.392 | 7.459 | 2.643 | 7.584 | 0.251 | 0.125 |
| Hotel clerks | 5 | 7 | 2.168 | 7.489 | 2.253 | 7.516 | 0.085 | 0.027 |
| Transportation ticket and reservation agents | 67 | 45 | 2.885 | 7.613 | 2.729 | 7.634 | -0.157 | 0.021 |
| Receptionists and other information clerks | 10 | 18 | 2.302 | 7.469 | 2.417 | 7.510 | 0.116 | 0.041 |
| Correspondence and order clerks | 36 | 24 | 2.592 | 7.577 | 2.564 | 7.599 | -0.028 | 0.022 |
| Human resources clerks, excel payroll and timekeeping | 31 | 42 | 2.529 | 7.571 | 2.700 | 7.613 | 0.171 | 0.041 |
| Library assistants | 9 | 17 | 2.247 | 7.321 | 2.393 | 7.369 | 0.146 | 0.049 |
| File clerks | 14 | 21 | 2.378 | 7.474 | 2.508 | 7.517 | 0.130 | 0.044 |
| Records clerks | 22 | 43 | 2.474 | 7.555 | 2.705 | 7.617 | 0.231 | 0.062 |
| Bookkeepers and accounting and auditing clerks | 28 | 46 | 2.486 | 7.554 | 2.732 | 7.596 | 0.246 | 0.042 |
| Payroll and timekeeping clerks | 36 | 49 | 2.588 | 7.589 | 2.802 | 7.620 | 0.215 | 0.032 |
| Billing clerks and related financial records processing | 28 | 34 | 2.508 | 7.561 | 2.636 | 7.598 | 0.128 | 0.038 |
| Mail and paper handlers | 21 | 64 | 2.462 | 7.556 | 2.994 | 7.643 | 0.532 | 0.087 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Office machine operators, n.e.c. | 17 | 24 | 2.404 | 7.523 | 2.546 | 7.542 | 0.143 | 0.020 |
| Telephone operators | 42 | 21 | 2.650 | 7.578 | 2.515 | 7.566 | -0.135 | -0.012 |
| Postal clerks, excluding mail carriers | 90 | 67 | 3.033 | 7.636 | 3.031 | 7.653 | -0.002 | 0.016 |
| Mail carriers for postal service | 82 | 67 | 3.019 | 7.661 | 3.049 | 7.679 | 0.030 | 0.018 |
| Mail clerks, outside of post office | 19 | 19 | 2.414 | 7.519 | 2.437 | 7.567 | 0.023 | 0.048 |
| Messengers | 12 | 44 | 2.332 | 7.492 | 2.721 | 7.701 | 0.389 | 0.209 |
| Dispatchers | 58 | 43 | 2.771 | 7.710 | 2.704 | 7.695 | -0.067 | -0.014 |
| Shipping and receiving clerks | 45 | 22 | 2.677 | 7.631 | 2.531 | 7.633 | -0.146 | 0.002 |
| Stock and inventory clerks | 35 | 15 | 2.579 | 7.584 | 2.380 | 7.546 | -0.199 | -0.038 |
| Meter readers | 45 | 44 | 2.678 | 7.638 | 2.720 | 7.638 | 0.042 | 0.000 |
| Weighers, measurers, and checkers | 42 | 25 | 2.662 | 7.598 | 2.582 | 7.649 | -0.080 | 0.051 |
| Material recording, sched., prod., plan., expediting cl. | 55 | 58 | 2.738 | 7.629 | 2.922 | 7.680 | 0.184 | 0.051 |
| Insurance adjusters, examiners, and investigators | 50 | 57 | 2.714 | 7.620 | 2.900 | 7.645 | 0.186 | 0.025 |
| Customer service reps, invest., adjusters, excl. insur. | 55 | 29 | 2.733 | 7.616 | 2.592 | 7.591 | -0.140 | -0.025 |
| Eligibility clerks for government prog., social welfare | 37 | 57 | 2.595 | 7.588 | 2.887 | 7.629 | 0.292 | 0.041 |
| Bill and account collectors | 31 | 33 | 2.523 | 7.601 | 2.632 | 7.616 | 0.109 | 0.015 |
| General office clerks | 21 | 30 | 2.446 | 7.526 | 2.600 | 7.559 | 0.154 | 0.033 |
| Bank tellers | 11 | 11 | 2.307 | 7.508 | 2.354 | 7.527 | 0.046 | 0.019 |
| Proofreaders | 26 | 48 | 2.486 | 7.509 | 2.795 | 7.589 | 0.310 | 0.080 |
| Data entry keyers | 21 | 24 | 2.469 | 7.552 | 2.553 | 7.559 | 0.084 | 0.008 |
| Statistical clerks | 41 | 58 | 2.631 | 7.574 | 2.920 | 7.656 | 0.289 | 0.082 |
| Teacher's aides | 5 | 9 | 2.174 | 7.232 | 2.301 | 7.435 | 0.127 | 0.203 |
| Administrative support jobs, n.e.c. | 61 | 49 | 2.804 | 7.633 | 2.802 | 7.628 | -0.002 | -0.005 |
| Housekeepers, maids, butlers, and cleaners | 2 | 5 | 2.004 | 7.475 | 2.161 | 7.512 | 0.157 | 0.037 |
| Laundry and dry cleaning workers | 4 | 7 | 2.158 | 7.571 | 2.218 | 7.617 | 0.061 | 0.046 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Fire fighting, fire prevention, and fire inspection occs | 57 | 66 | 2.760 | 7.939 | 3.016 | 7.929 | 0.255 | -0.010 |
| Police and detectives, public service | 77 | 83 | 2.966 | 7.728 | 3.204 | 7.749 | 0.238 | 0.021 |
| Sheriffs, bailiffs, correctional institution officers | 55 | 58 | 2.740 | 7.700 | 2.903 | 7.701 | 0.163 | 0.001 |
| Crossing guards | 10 | 17 | 2.304 | 7.097 | 2.403 | 7.343 | 0.100 | 0.247 |
| Guards and police, except public service | 31 | 27 | 2.521 | 7.618 | 2.591 | 7.634 | 0.071 | 0.017 |
| Protective service, n.e.c. | 3 | 3 | 2.095 | 7.138 | 2.118 | 7.220 | 0.023 | 0.082 |
| Supervisors of food preparation and service | 13 | 10 | 2.368 | 7.646 | 2.353 | 7.686 | -0.014 | 0.039 |
| Bartenders | 6 | 14 | 2.216 | 7.614 | 2.369 | 7.500 | 0.153 | -0.113 |
| Waiters and waitresses | 1 | 4 | 1.998 | 7.338 | 2.122 | 7.415 | 0.124 | 0.078 |
| Cooks | 3 | 7 | 2.093 | 7.486 | 2.170 | 7.594 | 0.077 | 0.108 |
| Food preparation workers | 4 | 1 | 2.102 | 7.398 | 2.030 | 7.436 | -0.072 | 0.038 |
| Miscellaneous food preparation and service workers | 2 | 0 | 2.008 | 7.283 | 2.025 | 7.394 | 0.017 | 0.111 |
| Dental Assistants | 9 | 25 | 2.288 | 7.467 | 2.585 | 7.524 | 0.297 | 0.056 |
| Health and nursing aides | 8 | 14 | 2.228 | 7.527 | 2.365 | 7.599 | 0.137 | 0.071 |
| Supervisors of cleaning and building service | 42 | 38 | 2.632 | 7.665 | 2.650 | 7.706 | 0.018 | 0.041 |
| Superv. of landscaping, lawn service, groundskeeping | 56 | 42 | 2.744 | 7.673 | 2.691 | 7.751 | -0.053 | 0.078 |
| Gardeners and groundskeepers | 12 | 9 | 2.325 | 7.519 | 2.274 | 7.592 | -0.051 | 0.073 |
| Janitors | 19 | 16 | 2.413 | 7.565 | 2.393 | 7.579 | -0.021 | 0.014 |
| Pest control occupations | 26 | 30 | 2.486 | 7.673 | 2.617 | 7.729 | 0.131 | 0.056 |
| Barbers | 12 | 10 | 2.364 | 7.736 | 2.317 | 7.682 | -0.046 | -0.054 |
| Hairdressers and cosmetologists | 9 | 10 | 2.236 | 7.532 | 2.308 | 7.599 | 0.072 | 0.067 |
| Recreation facility attendants | 11 | 23 | 2.316 | 7.422 | 2.539 | 7.542 | 0.223 | 0.120 |
| Guides | 12 | 7 | 2.339 | 7.470 | 2.224 | 7.522 | -0.115 | 0.052 |
| Ushers | 5 | 1 | 2.171 | 7.173 | 2.050 | 7.181 | -0.120 | 0.008 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Baggage porters, bellhops and concierges | 17 | 21 | 2.395 | 7.550 | 2.517 | 7.587 | 0.122 | 0.037 |
| Recreation and fitness workers | 9 | 15 | 2.245 | 7.408 | 2.386 | 7.488 | 0.140 | 0.080 |
| Motion picture projectionists | 38 | 8 | 2.622 | 7.577 | 2.259 | 7.469 | -0.363 | -0.108 |
| Child care workers | 0 | 1 | 1.899 | 7.429 | 2.058 | 7.581 | 0.159 | 0.152 |
| Personal service occupations, n.e.c | 5 | 9 | 2.213 | 7.518 | 2.279 | 7.604 | 0.067 | 0.086 |
| Supervisors of personal service jobs, n.e.c | 35 | 37 | 2.585 | 7.714 | 2.648 | 7.750 | 0.062 | 0.036 |
| Public transportation attendants and inspectors | 77 | 48 | 2.972 | 7.544 | 2.795 | 7.642 | -0.178 | 0.098 |
| Animal caretakers, except farm | 5 | 7 | 2.163 | 7.568 | 2.198 | 7.631 | 0.036 | 0.064 |
| Automobile mechanics and repairers | 38 | 39 | 2.621 | 7.726 | 2.679 | 7.716 | 0.058 | -0.009 |
| Bus, truck, and stationary engine mechanics | 61 | 49 | 2.808 | 7.714 | 2.815 | 7.732 | 0.008 | 0.018 |
| Aircraft mechanics | 90 | 69 | 3.052 | 7.664 | 3.073 | 7.705 | 0.021 | 0.041 |
| Small engine repairers | 28 | 37 | 2.491 | 7.662 | 2.647 | 7.713 | 0.156 | 0.052 |
| Auto body repairers | 42 | 44 | 2.649 | 7.689 | 2.723 | 7.706 | 0.074 | 0.017 |
| Heavy equipement and farm equipment mechanics | 65 | 46 | 2.852 | 7.698 | 2.769 | 7.741 | -0.083 | 0.043 |
| Industrial machinery repairers | 65 | 59 | 2.853 | 7.700 | 2.946 | 7.729 | 0.093 | 0.030 |
| Machinery maintenance occupations | 67 | 52 | 2.903 | 7.661 | 2.865 | 7.754 | -0.038 | 0.092 |
| Repairers of industrial electrical equipment | 59 | 47 | 2.793 | 7.683 | 2.779 | 7.738 | -0.014 | 0.055 |
| Repairers of data processing equipment | 90 | 53 | 3.043 | 7.684 | 2.881 | 7.640 | -0.161 | -0.044 |
| Repairers of household appliances and power tools | 56 | 46 | 2.749 | 7.688 | 2.759 | 7.715 | 0.011 | 0.027 |
| Telecom and line installers and repairers | 92 | 64 | 3.082 | 7.690 | 2.993 | 7.693 | -0.089 | 0.003 |
| Repairers of electrical equipment, n.e.c. | 63 | 67 | 2.829 | 7.658 | 3.042 | 7.681 | 0.212 | 0.023 |
| Heating, air conditioning, and refrigeration mechanics | 62 | 50 | 2.816 | 7.671 | 2.825 | 7.676 | 0.009 | 0.004 |
| Precision makers, repairers, and smiths | 39 | 58 | 2.623 | 7.656 | 2.906 | 7.677 | 0.283 | 0.022 |
| Locksmiths and safe repairers | 37 | 46 | 2.611 | 7.707 | 2.767 | 7.724 | 0.156 | 0.017 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Repairers of mechanical controls and valves | 64 | 61 | 2.845 | 7.653 | 2.988 | 7.672 | 0.143 | 0.019 |
| Elevator installers and repairers | 95 | 86 | 3.169 | 7.653 | 3.281 | 7.694 | 0.112 | 0.040 |
| Millwrights | 94 | 66 | 3.100 | 7.690 | 3.023 | 7.764 | -0.077 | 0.074 |
| Mechanics and repairers, n.e.c. | 66 | 48 | 2.854 | 7.698 | 2.781 | 7.688 | -0.073 | -0.010 |
| Supervisors of construction work | 93 | 69 | 3.083 | 7.718 | 3.070 | 7.768 | -0.014 | 0.050 |
| Masons, tilers, and carpet installers | 57 | 26 | 2.758 | 7.539 | 2.589 | 7.617 | -0.170 | 0.079 |
| Carpenters | 48 | 39 | 2.705 | 7.562 | 2.657 | 7.622 | -0.048 | 0.060 |
| Drywall installers | 55 | 24 | 2.736 | 7.543 | 2.554 | 7.597 | -0.182 | 0.054 |
| Electricians | 81 | 59 | 2.996 | 7.656 | 2.934 | 7.680 | -0.062 | 0.024 |
| Electric power installers and repairers | 91 | 69 | 3.055 | 7.673 | 3.074 | 7.732 | 0.019 | 0.059 |
| Painters, construction and maintenance | 37 | 20 | 2.608 | 7.538 | 2.508 | 7.589 | -0.101 | 0.051 |
| Paperhangers | 58 | 42 | 2.773 | 7.576 | 2.694 | 7.493 | -0.079 | -0.083 |
| Plasterers | 58 | 26 | 2.776 | 7.545 | 2.590 | 7.590 | -0.187 | 0.046 |
| Plumbers, pipe fitters, and steamfitters | 73 | 51 | 2.944 | 7.639 | 2.840 | 7.680 | -0.103 | 0.042 |
| Concrete and cement workers | 58 | 31 | 2.776 | 7.510 | 2.627 | 7.598 | -0.149 | 0.087 |
| Glaziers | 54 | 49 | 2.730 | 7.645 | 2.803 | 7.629 | 0.073 | -0.016 |
| Insulation workers | 60 | 46 | 2.803 | 7.567 | 2.735 | 7.642 | -0.068 | 0.075 |
| Paving, surfacing, and tamping equipment operators | 54 | 25 | 2.729 | 7.668 | 2.582 | 7.660 | -0.148 | -0.007 |
| Roofers and slaters | 34 | 18 | 2.564 | 7.499 | 2.428 | 7.605 | -0.137 | 0.107 |
| Structural metal workers | 81 | 50 | 3.001 | 7.570 | 2.835 | 7.682 | -0.166 | 0.112 |
| Drillers of earth | 42 | 49 | 2.634 | 7.708 | 2.818 | 7.838 | 0.184 | 0.130 |
| Misc. construction and related occupations | 42 | 24 | 2.660 | 7.596 | 2.567 | 7.661 | -0.092 | 0.065 |
| Drillers of oil wells | 46 | 46 | 2.693 | 7.811 | 2.749 | 8.043 | 0.056 | 0.232 |
| Explosives workers | 63 | 59 | 2.822 | 7.688 | 2.935 | 7.732 | 0.113 | 0.044 |
| Miners | 75 | 51 | 2.951 | 7.682 | 2.851 | 7.916 | -0.100 | 0.233 |
| Other mining occupations | 66 | 38 | 2.861 | 7.732 | 2.654 | 7.948 | -0.207 | 0.216 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Production supervisors or foremen | 80 | 65 | 2.981 | 7.736 | 3.004 | 7.766 | 0.023 | 0.029 |
| Tool and die makers and die setters | 82 | 69 | 3.017 | 7.727 | 3.071 | 7.722 | 0.054 | -0.006 |
| Machinists | 64 | 52 | 2.831 | 7.685 | 2.851 | 7.729 | 0.020 | 0.044 |
| Boilermakers | 92 | 58 | 3.083 | 7.624 | 2.904 | 7.807 | -0.179 | 0.183 |
| Precision grinders and fitters | 71 | 39 | 2.924 | 7.706 | 2.680 | 7.709 | -0.245 | 0.004 |
| Patternmakers and model makers | 82 | 67 | 3.019 | 7.659 | 3.032 | 7.649 | 0.013 | -0.011 |
| Engravers | 34 | 25 | 2.572 | 7.571 | 2.581 | 7.595 | 0.008 | 0.024 |
| Other metal and plastic workers | 67 | 50 | 2.901 | 7.627 | 2.832 | 7.641 | -0.069 | 0.014 |
| Cabinetmakers and bench carpenters | 31 | 26 | 2.530 | 7.669 | 2.589 | 7.689 | 0.058 | 0.020 |
| Furniture/wood finishers, other prec. wood workers | 12 | 20 | 2.365 | 7.621 | 2.496 | 7.712 | 0.131 | 0.092 |
| Dressmakers, seamstresses, and tailors | 10 | 18 | 2.299 | 7.549 | 2.427 | 7.626 | 0.128 | 0.076 |
| Upholsterers | 21 | 24 | 2.451 | 7.652 | 2.571 | 7.671 | 0.119 | 0.019 |
| Shoemakers, other prec. apparel and fabric workers | 9 | 8 | 2.269 | 7.644 | 2.270 | 7.694 | 0.000 | 0.050 |
| Hand molders and shapers, except jewelers | 33 | 24 | 2.550 | 7.591 | 2.571 | 7.635 | 0.021 | 0.044 |
| Bookbinders | 34 | 24 | 2.571 | 7.563 | 2.564 | 7.604 | -0.007 | 0.041 |
| Other precision and craft workers | 38 | 31 | 2.622 | 7.653 | 2.624 | 7.668 | 0.002 | 0.016 |
| Butchers and meat cutters | 48 | 19 | 2.711 | 7.679 | 2.438 | 7.661 | -0.272 | -0.018 |
| Bakers | 19 | 10 | 2.433 | 7.658 | 2.324 | 7.596 | -0.109 | -0.062 |
| Batch food makers | 17 | 17 | 2.410 | 7.593 | 2.397 | 7.625 | -0.013 | 0.032 |
| Water and sewage treatment plant operators | 59 | 59 | 2.782 | 7.653 | 2.944 | 7.678 | 0.162 | 0.026 |
| Power plant operators | 94 | 92 | 3.099 | 7.679 | 3.379 | 7.735 | 0.281 | 0.057 |
| Plant and system operators, stationary engineers | 90 | 67 | 3.040 | 7.696 | 3.054 | 7.717 | 0.015 | 0.021 |
| Other plant and system operators | 75 | 73 | 2.957 | 7.707 | 3.151 | 7.774 | 0.194 | 0.067 |
| Lathe, milling, and turning machine operatives | 64 | 47 | 2.837 | 7.678 | 2.776 | 7.716 | -0.061 | 0.038 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Punching and stamping press operatives | 46 | 24 | 2.698 | 7.591 | 2.542 | 7.654 | -0.156 | 0.063 |
| Rollers, roll hands, and finishers of metal | 91 | 47 | 3.077 | 7.634 | 2.774 | 7.688 | -0.303 | 0.054 |
| Drilling and boring machine operators | 56 | 39 | 2.747 | 7.637 | 2.660 | 7.726 | -0.087 | 0.090 |
| Grinding, abrading, buffing, and polishing workers | 47 | 25 | 2.698 | 7.629 | 2.586 | 7.663 | -0.112 | 0.034 |
| Forge and hammer operators | 66 | 48 | 2.876 | 7.661 | 2.794 | 7.674 | -0.082 | 0.013 |
| Molders and casting machine operators | 37 | 25 | 2.606 | 7.607 | 2.575 | 7.675 | -0.030 | 0.068 |
| Metal platers | 43 | 30 | 2.666 | 7.638 | 2.621 | 7.700 | -0.045 | 0.062 |
| Heat treating equipment operators | 75 | 61 | 2.956 | 7.665 | 2.960 | 7.817 | 0.004 | 0.152 |
| Sawing machine operators and sawyers | 21 | 17 | 2.466 | 7.591 | 2.410 | 7.620 | -0.056 | 0.029 |
| Nail, tacking, shaping and joining mach ops (wood) | 17 | 20 | 2.394 | 7.572 | 2.459 | 7.619 | 0.065 | 0.047 |
| Other woodworking machine operators | 30 | 21 | 2.512 | 7.617 | 2.513 | 7.684 | 0.001 | 0.067 |
| Printing machine operators, n.e.c. | 56 | 39 | 2.743 | 7.624 | 2.665 | 7.653 | -0.078 | 0.029 |
| Typesetters and compositors | 45 | 43 | 2.682 | 7.579 | 2.703 | 7.631 | 0.021 | 0.052 |
| Winding and twisting textile and apparel operatives | 11 | 17 | 2.317 | 7.621 | 2.404 | 7.661 | 0.087 | 0.040 |
| Knitters, loopers, and toppers textile operatives | 14 | 17 | 2.380 | 7.627 | 2.400 | 7.607 | 0.020 | -0.020 |
| Textile cutting and dyeing machine operators | 12 | 11 | 2.353 | 7.612 | 2.365 | 7.645 | 0.012 | 0.034 |
| Textile sewing machine operators | 5 | 7 | 2.161 | 7.501 | 2.179 | 7.595 | 0.018 | 0.094 |
| Shoemaking machine operators | 5 | 7 | 2.206 | 7.525 | 2.172 | 7.604 | -0.034 | 0.079 |
| Clothing pressing machine operators | 5 | 7 | 2.173 | 7.511 | 2.195 | 7.545 | 0.022 | 0.034 |
| Miscellaneous textile machine operators | 12 | 24 | 2.363 | 7.614 | 2.571 | 7.600 | 0.207 | -0.014 |
| Cementing and gluing machne operators | 28 | 30 | 2.494 | 7.574 | 2.603 | 7.696 | 0.109 | 0.123 |
| Packers, fillers, and wrappers | 32 | 11 | 2.545 | 7.549 | 2.363 | 7.619 | -0.182 | 0.069 |
| Extruding and forming machine operators | 41 | 37 | 2.629 | 7.623 | 2.650 | 7.653 | 0.020 | 0.030 |
| Mixing and blending machine operators | 46 | 34 | 2.692 | 7.648 | 2.634 | 7.701 | -0.058 | 0.053 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Separating, filtering, and clarifying machine operators | 75 | 65 | 2.954 | 7.673 | 3.007 | 7.730 | 0.052 | 0.057 |
| Food roasting and baking machine operators | 58 | 24 | 2.772 | 7.633 | 2.551 | 7.657 | -0.220 | 0.025 |
| Washing, cleaning, and pickling machine operators | 42 | 17 | 2.645 | 7.611 | 2.401 | 7.644 | -0.244 | 0.033 |
| Paper folding machine operators | 12 | 42 | 2.347 | 7.556 | 2.690 | 7.648 | 0.343 | 0.092 |
| Furnance, kiln, and oven operators, apart from food | 67 | 48 | 2.903 | 7.669 | 2.797 | 7.723 | -0.106 | 0.054 |
| Slicing, cutting, crushing and grinding machine | 35 | 20 | 2.579 | 7.609 | 2.440 | 7.642 | -0.139 | 0.033 |
| Photographic process workers | 26 | 10 | 2.479 | 7.558 | 2.353 | 7.556 | -0.126 | -0.003 |
| Machine operators, n.e.c. | 41 | 26 | 2.628 | 7.615 | 2.588 | 7.647 | -0.040 | 0.032 |
| Welders, solderers, and metal cutters | 60 | 43 | 2.795 | 7.640 | 2.708 | 7.716 | -0.087 | 0.076 |
| Assemblers of electrical equipment | 33 | 24 | 2.549 | 7.569 | 2.541 | 7.622 | -0.008 | 0.052 |
| Painting and decoration occupations | 35 | 30 | 2.579 | 7.607 | 2.612 | 7.683 | 0.032 | 0.076 |
| Production checkers, graders, and sorters in manufacturing | 44 | 45 | 2.671 | 7.614 | 2.725 | 7.687 | 0.054 | 0.074 |
| Truck, delivery, and tractor drivers | 54 | 37 | 2.716 | 7.733 | 2.639 | 7.794 | -0.077 | 0.061 |
| Bus drivers | 36 | 25 | 2.588 | 7.540 | 2.574 | 7.584 | -0.014 | 0.044 |
| Taxi cab drivers and chauffeurs | 13 | 11 | 2.376 | 7.720 | 2.362 | 7.751 | -0.015 | 0.031 |
| Parking lot attendants | 9 | 8 | 2.293 | 7.521 | 2.260 | 7.572 | -0.032 | 0.051 |
| Railroad conductors and yardmasters | 95 | 64 | 3.167 | 7.866 | 3.002 | 7.909 | -0.166 | 0.043 |
| Locomotive operators: engineers and firemen | 96 | 73 | 3.172 | 7.795 | 3.130 | 7.918 | -0.042 | 0.123 |
| Railroad brake, coupler, and switch operators | 92 | 61 | 3.079 | 7.754 | 2.972 | 7.848 | -0.107 | 0.094 |
| Ship crews and marine engineers | 64 | 49 | 2.832 | 7.836 | 2.823 | 7.999 | -0.009 | 0.163 |
| Miscellaneous transportation occupations | 54 | 42 | 2.724 | 7.706 | 2.686 | 7.638 | -0.039 | -0.068 |
| Operating engineers of construction equipment | 67 | 50 | 2.880 | 7.647 | 2.835 | 7.722 | -0.045 | 0.075 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Crane, derrick, winch, hoist, longshore operators | 81 | 58 | 2.991 | 7.687 | 2.913 | 7.792 | -0.077 | 0.105 |
| Excavating and loading machine operators | 61 | 46 | 2.815 | 7.673 | 2.751 | 7.736 | -0.063 | 0.063 |
| Stevedores and misc. material moving occupations | 58 | 44 | 2.777 | 7.670 | 2.708 | 7.725 | -0.068 | 0.055 |
| Helpers, constructions | 17 | 18 | 2.402 | 7.465 | 2.428 | 7.548 | 0.026 | 0.083 |
| Helpers, surveyors | 21 | 9 | 2.471 | 7.486 | 2.286 | 7.582 | -0.185 | 0.096 |
| Construction laborers | 34 | 22 | 2.560 | 7.517 | 2.523 | 7.618 | -0.037 | 0.101 |
| Production helpers | 34 | 11 | 2.563 | 7.563 | 2.356 | 7.636 | -0.207 | 0.074 |
| Garbage and recyclable material collectors | 22 | 20 | 2.475 | 7.603 | 2.487 | 7.616 | 0.012 | 0.013 |
| Machine feeders and offbearers | 30 | 20 | 2.513 | 7.599 | 2.450 | 7.581 | -0.063 | -0.019 |
| Garage and service station related occupations | 5 | 7 | 2.175 | 7.579 | 2.233 | 7.544 | 0.058 | -0.036 |
| Vehicle washers and equipment cleaners | 13 | 8 | 2.372 | 7.525 | 2.256 | 7.600 | -0.115 | 0.074 |
| Packers and packagers by hand | 14 | 7 | 2.383 | 7.521 | 2.245 | 7.545 | -0.137 | 0.025 |
| Laborers, freight, stock, and material handlers, n.e.c. | 30 | 19 | 2.509 | 7.539 | 2.432 | 7.579 | -0.077 | 0.040 |

**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 | 2,470 |
| | 2013 | 34.00 | 54.48 | 4.30 | 2.57 | 4.65 | 1,440 |
| Algebra 1 | 1991 | 21.59 | 62.31 | 7.75 | 2.14 | 6.21 | 1,820 |
| | 2013 | 20.59 | 61.17 | 9.04 | 2.26 | 6.95 | 1,200 |
| Geometry | 1991 | 10.52 | 54.99 | 21.41 | 5.35 | 7.73 | 1,640 |
| | 2013 | 10.66 | 54.03 | 21.77 | 5.38 | 8.15 | 1,120 |
| Algebra 2 | 1991 | 5.37 | 32.48 | 32.48 | 15.63 | 14.03 | 2,870 |
| | 2013 | 4.88 | 30.77 | 33.43 | 16.62 | 14.30 | 2,030 |
| Adv Math/Calculus | 1991 | 2.95 | 14.95 | 24.57 | 41.59 | 15.93 | 1,930 |
| | 2013 | 2.63 | 14.35 | 24.23 | 41.67 | 17.12 | 1,520 |
| 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 | 7,300 |

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