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ABSTRACT

Science, Technology, Engineering, and Math (STEM) jobs are a key contributor to economic growth and national competitiveness. Yet STEM workers are perceived to be in short supply. This paper shows that the "STEM shortage" phenomenon is explained by technological change, which introduces new job skills and makes old ones obsolete. We find that the initially high economic return to applied STEM degrees declines by more than 50 percent in the first decade of working life. This coincides with a rapid exit of college graduates from STEM occupations. Using detailed job vacancy data, we show that STEM jobs change especially quickly over time, leading to flatter age-earnings profiles as the skills of older cohorts became obsolete. Our findings highlight the importance of technology-specific skills in explaining life-cycle returns to education, and show that STEM jobs are the leading edge of technology diffusion in the labor market.

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Appendix is available at http://www.nber.org/data-appendix/w25065

1 Introduction

A vast body of work in economics finds that technological change increases the relative wages of educated workers by complementing their skills, leading to rising wage inequality (e.g. Katz and Murphy 1992, Berman et al. 1994, Autor et al. 2003, Acemoglu and Autor 2011). Empirical confirmation of this skill-biased technological change (SBTC) hypothesis comes from the increasing return to a college education, which is interpreted as a single-index measure of worker skill.[1] Yet despite large differences in the curricular content of college majors and in returns to field of study, there is little direct evidence linking changes in skill demands to the specific human capital learned in school.[2] Simply put, the process by which technology changes the returns to skills by altering job tasks remains mostly a "black box".[3]

In this paper, we study the impact of changes in the skill content of work on the labor market returns to a form of specific human capital—Science, Technology, Engineering, and Math (STEM) degrees.[4] STEM careers are ideal for studying the link between technology

[1]In the canonical skill-biased technological change (SBTC) framework, technological progress increases the productivity of high-skilled workers more than low-skilled workers, and so the skill premium increases when technological change "races ahead" of growth in the supply of skills (Tinbergen 1975, Goldin and Katz 2007). Acemoglu and Autor (2011) develop a task-based framework that allows for a more general type of technological bias, and they show the replacement of routine "middle-skill" tasks by machines could lead to polarization of the wage distribution. In both cases, however, there is a single index of skill, and technologies are not linked to specific job tasks.

[2]The SBTC literature cited above shows the impact of technological change on the returns to general skills (e.g. a college education). There is also a large literature studying heterogeneity in returns to field of study (e.g. Arcidiacono 2004, Pavan 2011, Altonji, Blom and Meghir 2012, Carnevale et al. 2012, Kinsler and Pavan 2015, Altonji, Arcidiacono and Maurel 2016, Kirkeboen et al. 2016 Few studies connect technological change to changes in the returns to specific skills. One exception is the literature studying general versus more vocational educational systems across countries, which generally finds that 1) youth in countries with a more vocational focus have higher employment and earnings initially, but lower wage growth (Golsteyn and Stenberg 2017, Hanushek et al. 2017); and 2) that individual differences in the returns to general vs. vocational education are near zero for the marginal student, with observable differences due mostly to selection (Malamud 2010, Malamud and Pop-Eleches 2010).

[3]"Insider econometrics" studies within firms show that technology adoption favors skilled workers, while also having specific, non-neutral impacts on jobs that vary in their task content and specific skill requirements (e.g. Autor et al. 2002, Bresnahan et al. 2002, Bartel et al. 2007, Ichniowski and Shaw 2009)

[4]Field of study is an important mediator for understanding the returns to education. Lemieux (2014) estimates that occupational choice and matching to field of study can explain about half of the total return to a college degree, and Kinsler and Pavan (2015) find that science majors who work in science-related jobs earn about 30% more than science majors working in unrelated jobs.

and changing skill demands, both because STEM degrees lead to well-defined career paths and because STEM jobs require specific, verifiable skills. Moreover, as a key contributor to innovation and productivity growth in most advanced economies, STEM education is important to study in its own right (e.g. Griliches 1992, Jones 1995, Carnevale et al. 2011, Peri et al. 2015).

Using a near-universe of online job vacancy data collected between 2007 and 2017 by the employment analytics firm Burning Glass Technologies (BG), we show that job skill requirements change significantly over the course of a decade. We use the BG data to calculate a systematic measure of job skill change, and show that skill demands in STEM occupations have changed especially quickly. The faster rate of change in STEM is driven both by more rapid obsolescence of old skills and by faster adoption of new skills. For example, we find that the share of STEM vacancies requiring skills related to machine learning and artificial intelligence increased by 460 percent between 2007 and 2017.

To understand the impact of changing skill demands, we develop a simple, stylized model of education and career choice. In our model, workers learn career-specific skills in school and are paid a competitive wage in the labor market according to the skills they have acquired. Workers also learn skills on-the-job. Over time, the productivity gains from on-the-job learning are lower in careers with higher rates of skill change, because more of the skills learned in past years become obsolete. Jobs with high rates of change have higher starting wages and flatter age-earnings profiles, and they disproportionately employ young workers.

We document several new facts about labor market returns for STEM majors, which match the predictions of our model. The earnings premium for STEM majors is highest at labor market entry, and declines by more than 50 percent in the first decade of working life. This pattern holds for "applied" STEM majors such as engineering and computer science, but not for "pure" STEM majors such as biology, chemistry, physics and mathematics. Flatter wage growth coincides with a relatively rapid exit of STEM majors from STEM occupations.

These patterns are present in multiple data sources—both cross-sectional and longitudinal—and are robust to controls for important determinants of earnings such as ability and family income, selection into graduate school, and other factors.

We also find that high-ability workers choose STEM careers initially, but exit them over time. Within the framework of the model, this is explained by differences across fields in the relative return to on-the-job learning. High ability workers are faster learners, in all jobs. However, the *relative* return to ability is higher in careers that change *less*, because learning gains accumulate. Consistent with this prediction, we find that workers with one standard deviation higher ability are 8 percentage points more likely to work in STEM at age 24, but no more likely to work in STEM at age 40. We also show that the wage return to ability decreases with age for STEM majors.

While the BG data only go back to 2007, we calculate a similar measure of job task change using a historical dataset of classified job ads assembled by Atalay et al. (2018). We show that the computer and IT revolution of the 1980s coincided with higher rates of technological change in STEM jobs, and that young STEM workers were also paid relatively high wages during this same period. This matches the pattern of evidence for the 2007–2017 period and confirms that the relationship between STEM careers, job change and age-earnings profiles is not specific to the most recent decade.

This paper makes three main contributions. First, we introduce new evidence on the economic payoff to STEM majors and STEM careers, and we argue that it is consistent with vintage human capital becoming less valuable as new skills are introduced to the workplace.[5] Importantly, while STEM jobs do indeed change faster than others, the pattern of declining relative returns for faster-changing fields is a more general phenomenon that is not unique

[5]Most existing work focuses on the determinants of college major choice when students have heterogeneous preferences and/or learn over time about their ability (e.g. Altonji, Blom and Meghir 2012, Webber 2014, Silos and Smith 2015, Altonji, Arcidiacono and Maurel 2016, Arcidiacono et al. 2016, Ransom 2016, Leighton and Speer 2017). An important exception is Kinsler and Pavan (2015), who develop a structural model with major-specific human capital and show that science majors earn much higher wages in science jobs even after controlling for SAT scores, high school GPA and worker fixed effects. Hastings et al. (2013) and Kirkeboen et al. (2016) find large impacts of major choice on earnings after accounting for self-selection, although neither study explores the career dynamics of earnings gains from majoring in STEM fields.

to STEM.

Second, the results enrich our understanding of the impact of technology on labor markets. Past work either assumes that technological change benefits skilled workers because they adapt more quickly, or links *a priori* theories about the impact of computerization to shifts in relative employment and wages across occupations with different task requirements (e.g. Galor and Tsiddon 1997, Caselli 1999, Autor et al. 2003, Firpo et al. 2011, Deming 2017). We measure changing job task requirements directly and within narrowly defined occupation categories, rather than inferring it indirectly from changes in relative wages and skill supplies (Card and DiNardo 2002). A large body of work in economics has shown how technological change at the macro level leads to fundamental changes in job tasks such as greater use of computers, more emphasis on lateral communication and decentralized decision-making with the firm (e.g. Autor et al. 2002, Bresnahan et al. 2002, Bartel et al. 2007). Our results broadly corroborate the findings of this literature, while also highlighting how STEM jobs are the leading edge of technology diffusion in the labor market.[6]

Third, our results provide an empirical foundation for a large body of work in economics on vintage capital and technology diffusion (e.g. Griliches 1957, Chari and Hopenhayn 1991, Parente 1994, Jovanovic and Nyarko 1996, Violante 2002, Kredler 2014). In vintage capital models, the rate of technological change governs the diffusion rate and the extent of economic growth (Chari and Hopenhayn 1991, Kredler 2014). We provide direct empirical evidence on this important parameter, and our results match some of the key predictions of these classic models.[7] Consistent with our findings, Krueger and Kumar (2004) show that an increase

[6] Our paper is also related to a large literature studying the economics of innovation at the technological frontier (e.g. Wuchty et al. 2007, Jones 2009). STEM jobs may have higher rates of change because they are heavily concentrated in the "innovation sector" of the economy (Moretti 2012). Stephan (1996)finds a relatively flat age-earnings profile for academic researchers in science, and notes that this is likely related to the need to compensate new scientists for risky investments in frontier knowledge production.

[7] In Chari and Hopenhayn (1991) and Kredler (2014), new technologies require vintage-specific skills, and an increase in the rate of technological change raises the returns for newer vintages and flattens the age-earnings profile. However, the equilibria in these models requires newer vintages to have lower starting wages but faster wage growth. A key difference in our model is that we allow for learning in school, which helps explain the initially high wage premium for STEM majors. In Gould et al. (2001), workers make precautionary investments in general education to insure against obsolescence of technology-specific skills.

in the rate of technological change increases the optimal subsidy for general vs. vocational education, because general education facilitates the learning of new technologies.

This paper builds on a line of work studying skill obsolescence, beginning with Rosen (1975).[8] Our results are also related to a small number of studies of the relationship between age and technology adoption. MacDonald and Weisbach (2004) develop a "has-been" model where skill obsolescence among older workers is increasing in the pace of technological change, and they use the inverted age-earnings profile of architects as a motivating example.[9] Friedberg (2003) and Weinberg (2004) study age patterns of computer adoption in the workplace, while Aubert et al. (2006) find that innovative firms are more likely to hire younger workers.

Our findings also help explain why there is a widespread perception that STEM workers are in short supply, despite the high labor market payoff to majoring in STEM fields (Arcidiacono 2004, Carnevale et al. 2012, Kinsler and Pavan 2015, Cappelli 2015, Arcidiacono et al. 2016). STEM graduates in applied subjects such as engineering and computer science earn higher wages initially, because they learn job-relevant skills in school. Yet over time, new technologies replace the skills and tasks originally learned by older graduates, causing them to experience flatter wage growth and eventually exit the STEM workforce. Faster technological progress creates a greater sense of shortage, but it is the new STEM *skills* that are scarce, not the workers themselves.

Advanced economies differ widely in the policies and institutions that support school-to-work transitions for young people (Ryan 2001). Hanushek et al. (2017) find that countries

[8] McDowell (1982) studies the decay rate of citations to academic work in different fields, finding higher decay rates for physics and chemistry compared to history and English. Neuman and Weiss (1995) infer skill obsolescence from the shape of wage profiles in "high-tech" fields, and Thompson (2003) studies changes in the age-earnings profile after the introduction of new technologies in the Canadian Merchant Marine in the late 19th century.

[9] MacDonald and Weisbach (2004) argue that "Advances in computing have revolutionized the field....Older architects have found it uneconomic to master the complex computer skills that enable the young to produce architectural services so easily and flexibly...Thus these advances have allowed younger architects to serve much of the market for architectural services, causing the older generation to lose much of its business." Similarly, Galenson and Weinberg (2000) show that changing demand for fine art in the 1950s caused a decline in the age at which successful artists typically produced their best work.

emphasizing apprenticeships and vocational training have lower youth unemployment rates at labor market entry but higher rates later in life, suggesting a tradeoff between general and specific skills. Our results show that this tradeoff also holds for field of study in U.S. four-year colleges. Applied STEM degrees provide high-skilled vocational education, which pays off in the short-run because it is at the technological frontier. However, since technological progress erodes the value of these skills over time, the long-run payoff to STEM majors is likely much smaller than short-run comparisons suggest. More generally, the labor market impact of rapid technological change depends critically on the extent to which schooling and "lifelong learning" can help build the skills of the next generation.

The remainder of the paper proceeds as follows. Section 2 describes the BG data and documents changes in the skill requirements of work. Section 3 presents the model and develops a set of empirical predictions. Section 4 presents the main results and connects them to the predictions of the model. Section 5 studies job task change in earlier periods. Section 6 concludes.

2 The Changing Skill Requirements of Work

2.1 Job Vacancy Data

We study changing job requirements using data from Burning Glass Technologies (BG), an employment analytics and labor market information firm that scrapes job vacancy data from more than 40,000 online job boards and company websites. BG applies an algorithm to the raw scraped data that removes duplicate postings and parses the data into a number of fields, including job title and six digit Standard Occupational Classification (SOC) code, industry, firm, location, and education and work experience. BG also codes key words and phrases into a large number of unique skill requirements. More than 93 percent of all job ads have at least one skill requirement, and the average number is 9. These range from vague and general (e.g. Detail-Oriented, Problem-Solving, Communication Skills) to detailed and job-specific (e.g. Phlebotomy, Javascript, Truck Driving). BG began collecting data in 2007, and our data span the 2007–2017 period. Hershbein and Kahn (2018) and Deming and Kahn (2018) discuss the coverage of BG data and comparisons to other sources such as the Job Openings and Labor Force Turnover (JOLTS) survey. BG data provide good coverage of professional occupations, especially those requiring a bachelor's degree, but are less comprehensive for occupations with lower educational requirements.

We restrict the BG sample to occupation groups in which most jobs require a bachelor's degree. Using the 2010 Standard Occupational Classification (SOC) codes, this includes two digit codes 11 through 29 and 41 through 43—management, business and financial operations, computer and mathematical, architecture and engineering, life/physical/social science, community and social service, legal, education and training, art/design/media, healthcare practitioners, sales, and office and administrative support.[10] We also exclude vacancies that require less than a bachelor's degree or with missing education requirements, although our main results are not sensitive to these restrictions. Finally, following Hershbein and Kahn (2018) we exclude vacancies with missing employers. This leaves us with a total sample of 968,457 vacancies in 2007 and 4,140,469 vacancies in 2017. The higher number of vacancies in 2017 is due to the increased coverage of BG data (more jobs posted online), as well as a higher share of vacancies with nonmissing employers and education requirements. There are 13,544 unique skills in our analysis dataset.

We group the large number of distinct skill requirements in the BG data into a smaller number of distinct and non-exhaustive categories. The Data Appendix provides a full list of skill categories and the words and phrases we used to construct them. We undertake this classification exercise partly to make the data easier to understand, but also to avoid confusing the changing popularity of certain phrases (e.g. "teamwork" vs. "collaboration") with true changes in job skills.

Table 1 shows baseline rates of job skill requirements in 2007 by broad occupation groups.

[10]For the complete list, see https://www.bls.gov/soc/soc_structure_2010.pdf

Each column is the share of job ads that list at least one skill requirement in the indicated category. 61 percent of vacancies for management occupations required social skills, compared to only 54 percent for STEM occupations. For cognitive skills, the pattern is reversed—54 percent for STEM, compared to only 42 percent for management.[11]

There are four main takeaways from Table 1. First, the pattern of job skill requirements broadly lines up with expectations as well as external data sources such as the Occupational Information Network (O*NET). Management occupations are much more likely to list key words and phrases associated with people management as job skill requirements. Financial knowledge is more commonly required in management and business occupations. Art, design and media occupations are much more likely to require skills like writing and creativity, while sales and administrative support occupations are more likely to require customer service. Second, three core skills—social, cognitive and character—are required relatively frequently in all jobs. Third, compared to other occupations, STEM jobs have a distinct profile. While STEM jobs have higher cognitive skill requirements and are much more likely to require technical skills such as technical support, data analysis and Machine Learning / Artificial Intelligence (ML/AI), they are less likely to require social skills, character skills or creativity. Fourth, both STEM and art/design/media are far more likely than other occupations to list specific software (e.g. Python, AutoCAD) as job requirements.

2.2 Descriptive Patterns of Job Change, 2007–2017

Vacancy data are ideal for measuring the changing skill requirements of jobs, for two reasons. First, vacancies directly measure employer demand for specific skills. Second, vacancy data allow for a detailed study of changing skill demands *within* occupations over time. Due to data limitations, most prior work in economics studies changes in demand *across* occupations. Autor et al. (2003) show how the falling price of computing power lowered the demand

[11]We follow Deming and Kahn (2018) in our classification of most skills, including social, cognitive, character, management, finance, customer service, office software and specific software skills. We also add a number of new categories, including creativity, business systems, technical support, data analysis, and Machine Learning / Artificial Intelligence (ML/AI). See the Data Appendix for details.

for routine tasks, causing the number of jobs that are routine-task intensive to decline. Deming (2017) conducts a similar analysis studying rising demand for social skill-intensive occupations since 1980. Both studies rely on certain occupations becoming more or less numerous over time.

Table 2 shows job skill requirements in 2017. Comparing Table 1 to Table 2 shows how job skill requirements have changed over a ten year period. There are three main lessons from Table 2. First, skill requirements have increased for nearly all categories and occupations. Second, we find particularly large increases—about 10 percentage points each—for social skills and character skills. Third, we find especially large increases in the share of vacancies requiring data analysis and ML/AI.[12] This increase is heavily concentrated in STEM occupations, where the share of vacancies requiring ML/AI skills increased from 3.9 percent in 2007 to 18 percent in 2017. The growth in ML/AI requirements is consistent with the rapid diffusion of automation technologies documented by Brynjolfsson et al. (2018).

One concern is that the sample of firms posting online job vacancies has changed over time. We address this by estimating regressions of the frequency of each skill category on an indicator for the 2017 year, the total number of skills listed in the vacancy (to control for any trend in the length and specificity of job ads), education and experience requirements, and occupation (6 digit SOC) by city (MSA) by employer fixed effects. This compares the same narrowly defined jobs posted in the same labor market by the same employer, a decade later. The results—in Appendix Table A1—are qualitatively unchanged when we adjust for differences in sample composition.

Comparing Table 1 to Table 2 shows that the skill content of jobs changed significantly over the 2007–2017 period. These changes would largely be missed by analyses that study across-occupation shifts using available labor market data such as the American Community Survey (ACS). For example, Deming (2017) shows large increases in employment shares for

[12]"Data Analysis" includes phrases such "Big Data", "Data Science", "Data Modeling", and "Predictive Analytics". ML/AI includes phrases such as "Artificial Intelligence", "Machine Learning", "Neural Networks", "Deep Learning" and "Automation Tools", as well as commonly used software such as Apache Hadoop and TensorFlow. See the Data Appendix for a complete list of key phrases for each skill category.

social-skill intensive occupations over the 1980–2012 period. However, most of the across-occupation change occurs between 1980 and 2000. Yet here we find relatively large increases in skill intensity *within* occupations.

2.3 Job Change and the Importance of New Skills

Measuring changes in the skill content of work helps us understand the direction of skill demand. However, the magnitude of change itself has important implications for workers' careers. When a job is changing rapidly, the skills learned in school or on the job may no longer be useful. We present an initial look at the turnover of job skill requirements in Figure 1. Figure 1 classifies a small number of the many job skills in BG data as either "old" or "new", and studies both the disappearance of old skills and the appearance of new skills between 2007 and 2017 by occupation category.

We define old skills as those with at least 1,000 appearances in 2007 and that either no longer exist or are 5 times less frequent in 2017. We define new skills as those with at least 1,000 appearances in 2017, and that either did not exist in 2007 or were 20 times more frequent in 2017.[13] The results are not sensitive to these somewhat arbitrary definitions of old and new skills.

Figure 1 shows the change in the share of job ads that requested old skills and new skills in 2017, by occupation category. To control for changes in sample composition, we present coefficients from a vacancy-level regression of the frequency of new and old skill requirements on an indicator for the 2017 year, the total number of skills listed in the vacancy, education and experience requirements, and occupation-city-employer fixed effects.

There are four main lessons from Figure 1. First, the overall rate of skill "turnover" is high. Among vacancies posted by the same firm for the same 6 digit occupation, about 20 (13) percent contained at least one new (old) skill requirement in 2017. Second, turnover is

[13] By these definitions, there are 311 old skills (2.3 percent of the total) and 786 new skills (5.8 percent of the total). Some of the most common old skills are "IBM Websphere", "Solaris", "Lotus Applications" and "Visual Basic", and some of the most common new skills are "Social Media", "Python", "Scrum" and "Software as a Service (SaaS)".

asymmetric–jobs appear to be adding skills faster than they are subtracting them. Because we have grouped similar skills into categories and constructed the variables to have a maximum of one (e.g. two mentions of social skills don't count more than one), this asymmetry is not due to job ads becoming longer or more repetitive. Rather, it suggests that jobs may be increasing in complexity, similar to the "upskilling" phenomenon documented by Hershbein and Kahn (2018).

Third, STEM occupations have the highest turnover. 35 percent of STEM job vacancies listed at least one new skill in 2017. The next highest occupation category is media and design, at 25 percent. Notably, STEM jobs also have the highest rate of decline for old skills. Social Service (including Education) and Health jobs have the lowest rate of skill turnover.

Finally, while not shown, we find that about half of new and old skill turnover is driven by specific software requirements, and close to two-thirds for STEM occupations. Software is a particularly important measure of occupational change.[14] Business innovation is increasingly driven by improvements in software, both in the information technology (IT) sector and in more traditional areas such as manufacturing (Arora et al. 2013, Branstetter et al. 2018). Moreover, software requirements are specific and verifiable, and thus likely to signal substantive changes in job skills. One concern is that some skill requirements (e.g. "Big Data", "Patient Care Monitoring") simply represent a relabeling of existing job functions. In contrast, firms will probably only require a specific software program in a job description if they expect a new hire to use it on the job.

[14] Specific software and business processes fall in and out of favor. For engineering and architecture occupations, rapidly growing skill requirements include computer-aided design programs such as AutoCAD and Revit, and process improvement schema such as Six Sigma and Root Cause Analysis. For computer occupations, the fastest growing skills are softwares such as Python and JavaScript as well as general terms related to data analysis (including ML/AI) and data management. Some examples of specific softwares that became much less frequently required between 2007 and 2017 are UNIX, SAP, Oracle Pro/Engineer and Adobe Flash.

2.4 Measuring Changes in the Skill Content of Work

We next construct a formal measure of changes in the skill content of work between 2007 and 2017. For each year, we collect all the skill requirements that ever appear in a job vacancy for a particular occupation. We then calculate the share of job ads in which each skill appears in each year. This includes zeroes—skills that are new in 2017 or because they disappear over the decade. We compute the absolute value of the difference in shares for each skill, and then sum them up by occupation to obtain an overall measure of change:[15]

$$SkillChange_o = \sum_{s=1}^{S} \left\{ Abs \left[\left(\frac{Skill_o^s}{JobAds_o} \right)_{2017} - \left(\frac{Skill_o^s}{JobAds_o} \right)_{2007} \right] \right\} \quad (1)$$

Conceptually, equation (1) measures the amount of net skill change in an occupation.[16] Table 3 presents the 3 and 6 digit (SOC) occupation codes with the highest and lowest measures of $SkillChange_o$. We restrict the sample to professional occupations with at least 25,000 total vacancies in the 3-digit case and 10,000 total vacancies in the six-digit case. This is for ease of presentation only, and we include all occupations codes in our analysis. The vacancy-weighted mean value for $SkillChange_o$ is 1.80, and the standard deviation for 6 (3) digit occupations is 1.14 (0.98).

Overall, STEM jobs have a rate of skill change that is more than one standard deviation higher than all other occupations (3.06 vs. 1.81 for 3 digit SOCs). Column 1 of Panel A shows the 3 digit SOC codes with the highest values of $SkillChange_o$. STEM jobs com-

[15]To account for differences over the decade in the frequency of job vacancies and skills per vacancy, we multiply equation (1) by the ratio of total skills in 2007 to total skills in 2017, for each occupation. This accounts for compositional changes in the BG data and prevents us from confusing changes in the frequency of job postings with changes in the average skill requirements of any given job posting.

[16]This approach assigns a greater value to the skill change measure in equation (1) if occupations start requiring more skills overall. We also consider an alternative measure that scales equation (1) by the average number of skill requirements per vacancy. This bounds equation (1) between 0 and 1, effectively computing a replacement rate of skills for each occupation. A value of zero indicates a job that requires exactly the same skills in 2007 and 2017, while a value of one indicates a job that requires a completely new set of skills. This downweights instances where $SkillChange_o$ is large because an occupation started requiring more skills overall. The occupation-level correlation between this measure and the unadjusted measure is 0.95, and our results are robust to using either version. See Appendix Table A2 for a list of occupations with the highest and lowest values of change according to this method.

prise 7 of the 10 professional occupations with the highest rate of skill change over the 2007–2017 period.[17] These include Engineers, Physical Scientists, Computer Occupations, Operations Specialties Managers, and Mathematical Scientists (including Statisticians). The 6 digit SOC codes with the highest values of $SkillChange_o$ shown in Panel B include Computer Programmers, Software Developers, Environmental Engineers, Network and Computer Systems Administrators, and Mechanical Drafters.

Panels C and D of Table 3 show the 3 and 6 digit professional occupations with the least skill change between 2007 and 2017.[18] The professional occupations with the least amount of skill change include teachers, health practitioner jobs (including nurses, physicians and dentists), entertainers and performers, health technologists and technicians, and counselors and social workers.

At the 6 digit level, the occupations with the lowest values of $SkillChange_o$ include mostly health and education jobs such as Dentists, Psychiatrists, Physicians, and Teachers. Many of these jobs require some form of occupational license or certification. In jobs with formal barriers to entry, skill change might manifest through changes in training rather than changes in skill requirements. For example, if medical schools change the way they train doctors over time, it might not be necessary to ask for new skills in job ads because employers know that younger workers have learned them in school. Thus our approach may understate job change in cases such as these. As a robustness check, we also recalculate the $SkillChange_o$ using only software, and find very similar results.[19]

[17] The 3 digit non-professional occupations with the highest values of $SkillChange_o$ include Sales Representatives, Secretaries and Administrative Assistants, Office and Administrative Support Workers, and Financial Clerks.

[18] 3 digit non-professional occupations with the lowest values of $SkillChange_o$ include Motor Vehicle Operators, Cooks and Food Preparation, Food Processing Workers, Personal Appearance Workers, and Materials Moving Workers.

[19] Most of the fastest growing skills between 2007 and 2017 are software-related. The occupation-level correlation between the baseline $SkillChange_o$ measure and one that only includes software is 0.72. All of the main results of the paper are robust to using only software to measure job change, or to excluding specific software entirely. Appendix Table A3 presents a version of Table 3 that ranks occupations by $SkillChange_o$ when the calculation is restricted only to software skills. The fastest-changing three digit occupations for software skills are Architects, Computer Occupations, Drafters and Engineering Technicians, Engineers and Mathematical Scientists. After that, a number of occupation groups appear that are not in Table 3, such as Art and Design Workers and Media and Communications Workers. Like Table 3, most of the slowest-changing

The results in Table 3 suggest that workers in STEM may have to acquire more new skills over the course of their career than workers in other occupations. To investigate this further, we study how job skills change with experience requirements. First we replicate the calculation of the skill change measure in equation (1), restricting the sample to jobs that require between 0 and 2 years of work experience. As above, we find that 7 of the 10 professional occupations with the highest rate of skill change are in STEM, and the occupation-level correlation between the two measures is 0.94.

Second, we directly study changes in job skill requirements by work experience. We estimate a vacancy-level regression of skills on years of experienced required, controlling for education requirements, the number of skills in each posting, and firm-by-MSA fixed effects. This approach shows how job skill requirements change with work experience, across vacancies listed by the same firm in the same labor market.

Figure 2 presents the years of experience coefficients from this regression for new skills (defined as in Section 2.3 above). As in Figure 1, STEM jobs are more likely than other professional jobs to require new skills. However, the pattern by experience requirements is also quite different. The share of STEM jobs requiring new skills holds steady and even increases slightly from entry level jobs up to 8-9 years of experience. This means that experienced STEM workers seeking employment in 2017 are often required to possess skills that were not required when they entered the labor market in 2007 or earlier. In contrast, the share of other professional jobs requiring new skills declines from 25 percent for entry level jobs to 20 percent for jobs that require 6 or more years of experience.

Summing up, there are three main lessons from the descriptive analyses in Section 2 above. First, the skill requirements of professional occupations vary substantially, and STEM jobs are more likely than others to require technical skills such as proficiency with specific software. Second, job skill requirements changed significantly between 2007 and 2017, and

occupations are in health care and education. In results not reported, we compare our list of fastest-growing software skills to trend data from Stack Overflow, a website where software developers ask and answer questions and share information. We find a very close correspondence between the fastest-growing software requirements in BG data and the software packages experiencing the highest growth in developer queries.

the rate of change was especially high for STEM occupations. Third, STEM jobs are much more likely than others to require experienced workers to learn new skills on the job that did not exist when they were in college.

3 Model

Do job skill requirements matter for wages and career dynamics? In this section we develop a simple, stylized model of educational and career choice. The model takes a standard approach to career choice and wage determination under perfect competition. The key innovation is that we allow for differences across careers in the replacement rate of job skills (which we will sometimes refer to as job "tasks") over time. Over time, the skills that workers learned in school and in early years on the job become obsolete, pushing down earnings relative to careers in which skill requirements change more slowly.

3.1 Model Setup

Consider a large number of perfectly competitive industries or industry-occupation pairs j in each year t, each of which produces a unique final good Y_{jt} according to a linear technology that aggregates output over a continuum of tasks spanning the unit interval:

$$Y_{jt} = \int_0^1 y_{jt}(i)di \tag{2}$$

The "service" or production level $y_{jt}(i)$ of task i in industry or occupation j at time t is defined as the marginal productivity in each task α_{jt} times the total amount of labor supplied for each task, l_{jt} (Acemoglu and Autor 2011). Following Neal (1999) and Pavan (2011), we refer to an occupation-industry pair as a "career" and refer to j as indexing "careers" throughout the paper.

Each career contains a large number of identical profit-maximizing firms. Labor is the only factor of production, so profits are just total revenue minus total wages. The zero profit condition ensures that workers are paid their marginal product over the tasks they perform in each career, with market wages that are equal to Y_{jt} times an exogenous output price P^*.

3.2 Schooling and Labor Supply

There are many individuals, each endowed with ability a and taste parameter u, who graduate from college and enter the job market at time $t = 0$.[20] Before entering the job market, individuals choose a field of study $s \in (0, 1)$. We conceptualize s as the share of time in school spent studying technical subjects. Fields of study or "majors" exist along the $s \in (0, 1)$ space, with low values of s representing non-technical fields such as English Literature and high values representing Engineering or Computer Science. The parameter u represents a taste for technical fields, and is a random variable that is joint uniformly distributed with a.

After choosing a field of study, individuals enter the job market and supply a single unit of labor to career j in each subsequent year $t \geq 0$.[21] As described earlier, workers earn wages according to their productivity schedule over tasks α_{jt}. Thus we can write the worker's problem as:

$$\underset{s,j_t}{Max}\left\{\left[\sum_{t=0}^{T} PDV\Big(W_{jt}(a, s, \alpha_{jt})\Big)\right] - C(a, u, s)\right\} \tag{3}$$

Each worker chooses an initial field of study and a career in each year to maximize the presented discounted value of her lifetime earnings W, minus her field-specific cost of schooling. Workers of the same (a, u) type make identical schooling and career choices, so we suppress individual subscripts for convenience. Individuals are perfectly informed about their own ability and have full knowledge of the profile of future returns, so the initial choice of s fully determines the profile j_t that workers enter over time. Following Spence (1978), we assume that the cost of schooling is decreasing in ability and that technical fields of study are

[20] We study a single cohort of job market entrants to simplify the presentation of the model. However, all of the results generalize to adding multiple cohorts of job market entrants.

[21] There is no labor supply decision on either the extensive or intensive margin. Workers allocate all of their labor to a single industry in any year, but can work in different industries over time.

relatively more costly to study for lower ability individuals, so $C > 0$, $\frac{\partial C}{\partial a} < 0$ and $\frac{\partial^2 C}{\partial a \partial s} < 0$.

3.3 Task Production Function

An individual's productivity in task i takes the following general form:

$$\alpha_{jt}(i) = f\left(a, s, F_j, \Delta_j\right) \tag{4}$$

Productivity depends on individual ability, the schooling choice, and a set of career-specific parameters F_j and Δ_j. F_j represents the amount of career-specific learning that happens in school. F_j will be higher in some careers than others if learning in those careers is more rewarded in the labor market. We assume that F_j is increasing in s, so that more career-specific learning happens in technical fields.

We define careers along the $s_j \in (0, 1)$ "field of study" space from less to more technical. Workers learn more career-specific tasks when their schooling choice is more closely aligned with the technical complexity of their chosen career s_j. Specifically, let the worker's productivity level after graduating from school be $F_j S^*$, where S^* is a loss function that penalizes learning in fields that are more distant in s space from the worker's chosen career.[22]

Workers also learn on the job. Each year that an individual works in career j, her productivity in the tasks existing at time t increases by a, the worker's ability.[23] The functional form of a is arbitrary, and we assume $a \geq 1$ for simplicity. It is only necessary that the tenure premium is increasing in ability, which amounts to assuming that higher ability workers learn job tasks more quickly (e.g. Nelson and Phelps 1966, Galor and Tsiddon 1997, Caselli 1999).

We define $\Delta_j \in [0, 1]$ as a career-specific rate of task change. At the start of each year, a fraction Δ_j of tasks that were in the production function for Y_{jt} are replaced by new

[22] For example, we could let $S^* = [1 - abs\left(s - s_j\right)]$ so that workers learn exactly F_j when the fit between field of study and industry is exact.

[23] A natural extension would be to allow for a career-specific rate of on-the-job learning (e.g. add an L_j to equation (4)). Since we do not have any data that would allow us to measure L_j, any career-specific differences in learning are collinear with our measure of job skill change, Δ_j. We discuss this further in Section 4.

tasks in Y_{jt+1}. We refer to the year that a task was introduced as the task's vintage v, with $t \geq v \geq 0$. Since tasks are replaced in constant proportions in each year, we can write a simple expression $g_{jt}(v)$ for the share of tasks coming from each vintage v at any time t:[24]

$$g_{jt}(0) = (1 - \Delta_j)^t; v = 0 \tag{5}$$

$$g_{jt}(v) = \Delta_j(1 - \Delta_j)^{(t-v)}; v > 0 \tag{6}$$

Equation (5) describes the share of tasks from some initial period $v = 0$ that are still in the production function in each future year $t > v$. Equation (6) gives the same expression for later vintages. Since tasks are replaced in constant proportions each year, old task vintages diminish in importance but never totally vanish (Chari and Hopenhayn 1991).

Putting this all together, the worker's productivity in each task, industry and year is:

$$\alpha_{jt}(i) = \begin{cases} (F_j S^*) + [a(t+1)] = \alpha_{jt}^{PRE} & \text{if } v = 0 \\ a(t - v + 1) = \alpha_{jt}^{POST(v)} & \text{if } v > 0. \end{cases} \tag{7}$$

The expression for α_{jt}^{PRE} represents tasks that are learned in school and on the job—these are from vintages equal to or earlier than the year an individual graduates. Later vintage tasks—represented by $\alpha_{jt}^{POST(v)}$—are learned only on the job.

[24] The proportion of tasks from each vintage at a given time t can be written as:

$$\begin{array}{llll} t = 0 & i_0 \in [0, 1] & & \\ t = 1 & i_0 \in [0, 1 - \Delta_j] & i_1 \in (1 - \Delta_j, 1] & \\ t = 2 & i_0 \in [0, (1 - \Delta_j)^2] & i_1 \in ((1 - \Delta_j)^2, (1 - \Delta_j)] & i_2 \in ((1 - \Delta_j), 1] \\ t = n & i_0 \in [0, (1 - \Delta_j)^t] & i_v \in ((1 - \Delta_j)^{(t-v+1)}, (1 - \Delta_j)^{(t-v)}] & i_t \in ((1 - \Delta_j), 1] \end{array}$$

with i_v just denoting the set of tasks in vintage v. With a constant share of tasks Δ_j replaced in each period, the share of tasks coming from each vintage v at any time t can be written as $g_{jt}(v) = (1 - \Delta_j)^{(t-v)} - (1 - \Delta_j)^{(t-v+1)} = \Delta_j(1 - \Delta_j)^{(t-v)}$.

3.4 Equilibrium Task Prices and Individual Wages

The linear task services production function in (3) combined with the zero profit conditions means that equilibrium task prices can be written as:

$$p_{ijt} = \alpha_{ijt}(a, s). \tag{8}$$

Equation (8) shows that workers of the same (a, s) type are paid the same price for each task. We obtain the equilibrium wages paid to each type by integrating over the prices for tasks performed in career j and time t, with the weights given by $g_{jt}(v)$:

$$\begin{aligned} W_{jt} &= \int_0^1 p_{ijt} di = \int_0^1 \alpha_{ijt}(a, s) di \\ &= \left\{(1 - \Delta_j)^t \alpha_{jt}^{PRE}\right\} + \left\{\sum_{v=1}^{t;t>0} \Delta_j (1 - \Delta_j)^{t-v} \alpha_{jt}^{POST(v)}\right\} \end{aligned} \tag{9}$$

The first term represents the worker's productivity in task vintages that existed in the year they graduated.

In the year of job market entry, $W_{j,t=0} = F_j S^* + a$. In $t = 1$, the worker becomes more productive in these initial task vintages through on-the-job learning. However, these learning gains are offset by the share Δ_j of initial tasks being replaced by newer tasks, which the worker has not had as much time to learn.

The full expression for wages in year one is $W_{j,t=1} = (1 - \Delta_j)(F_j S^* + 2a) + \Delta_j a$. The expression for W_{jt} expands thereafter, with increased productivity in older tasks weighing against declining task shares and increasing entry of new tasks.

3.5 Key Predictions

The model yields four key predictions:

1. *Wage growth is lower in careers with higher rates of skill change* Δ_j. We show this by defining wage growth since the beginning of working life as $(W_{jt} - W_{j0})$ and taking

the derivative of this expression with respect to Δ_j. The full proof is in the Model Appendix. If $\Delta_j = 0$, there is no obsolescence and equation (9) reduces to a simple expression where wages increase linearly with ability over time. As $\Delta_j \to 1$, both terms in equation (9) go to zero except in the entry year $t = 0$. As Δ_j increases, a larger share of skills learned in previous periods becomes obsolete. This diminishes the return to on-the-job learning, flattening the wage profile and making newer cohorts of workers (who have learned the new tasks in school) more attractive.

2. *Workers sort out of high Δ_j careers over time*—This is a corollary to the result above. As $t \to \infty$, the importance of the initial schooling choice diminishes and individuals may earn more by switching into a lower Δ_j career. Empirically, we should observe workers sorting into careers with lower values of the skill change parameter Δ_j as they age.

3. *Technical careers have higher starting wages, and high ability workers are more likely to begin in technical careers* —This follows directly from the model's assumptions that the cost of studying technical fields is decreasing in ability and that technical fields have higher values of the in-school productivity term $F_j S^*$. We test this prediction using data on ability and college major choice from the NLSY.

4. *High ability workers sort out of high Δ_j careers over time*—Many other studies have found that STEM majors are positively selected on ability (e.g. Altonji, Blom and Meghir 2012, Kinsler and Pavan 2015, Arcidiacono et al. 2016). A less obvious prediction of the model is that high ability workers who start in STEM careers are *more* likely to switch out of STEM careers over time. Intuitively, the *relative* return to ability is higher in careers where the gains from on-the-job learning accumulate more rapidly, and so higher-ability workers are more likely to pay the short-run cost of switching out of STEM in order to recoup longer-run gains. We can see this by taking the derivative of the expression for wages in year one with respect to a, which is equal to $(2 - \Delta_j)$.

This shows that the return to ability is always positive, but less so in high Δ_j careers. The Model Appendix proves this result and shows the intuition in Figure M.A1.

Section 4 presents empirical evidence that supports each of these predictions.

To develop some intuition for the model's results, Figure 3 presents a simple simulation of worker wage profiles, holding different elements of W_{jt} constant. Panel A shows the impacts of field of study and career choice at different points in the life cycle. The solid blue line represents a career with high initial productivity ($F_j S^* = 6$) and a relatively high rate of task change ($\Delta_j = 0.2$).[25] With high starting wages and a high rate of task change, we can think of the solid blue line as a STEM career.

The dashed red line shows the impact of reducing $F_j S^*$ by half, holding Δ_j constant. This leads to a large initial difference in wages that narrows over time, with the two curves converging as $t \to \infty$. Intuitively, tasks learned in school gradually disappear from the production function, leaving only the newer vintages and diminishing the impact of the initial schooling choice on earnings later in life.[26]

The dotted green line in Panel A considers a career with low initial productivity ($F_j S^* = 3$), but also with a low rate of task change ($\Delta_j = 0.15$). We can think of this as a non-STEM career. This career has higher earnings growth, because on-the-job learning of a relatively constant share of initial tasks means that knowledge accumulates more rapidly.[27]

The tradeoff between high starting wages and slower earnings growth suggests that workers in high Δ_j fields might switch careers at some point to maximize lifetime earnings. Panel B provides an illustration of the determinants of career switching. The solid blue line and

[25] We fix $a = 2$ in all three scenarios.

[26] In the long run, ability is the most important determinant of earnings. Our model yields a similar result to Altonji and Pierret (2001), who find that education is a more important determinant of earnings early in life, while ability is more important in the long-run. In Altonji and Pierret (2001) this is true because education signals ability to employers without directly affecting productivity. In our model, education is productive but becomes less important over time as the tasks learned in school disappear from the production function.

[27] The worker's earnings trajectory in career j is a horse race between the gains from on-the-job learning (which is increasing in ability) and the losses from obsolescence. Total wages increases as long as the gains outweigh the losses, i.e. when $\frac{a}{(F_j S^* + a)} > \Delta_j$.

the dotted green line are the same cases as Panel A, with $F_j S^* = 6, \Delta_j = 0.2$ (the STEM career) and $F_j S^* = 3, \Delta_j = 0.15$ (the non-STEM career) respectively. The dashed red line shows earnings in the non-STEM career for workers of higher ability. An increase in ability (and thus the rate on-the-job learning) moves the optimal switching year forward from $t = 5$ to $t = 3$. This is because higher-ability workers can exploit their learning advantage more fully in careers that change less over time.

4 Results

4.1 Labor Market Data and Descriptive Statistics

Our main data source is the 2009–2016 American Community Surveys (ACS), extracted from the Integrated Public Use Microdata Series (IPUMS) 1 percent samples (Ruggles et al. 2017). The ACS has collected data on college major since 2009. Following Peri et al. (2015), we adopt the definition of STEM major used by the U.S. Department of Homeland Security in determining visitor eligibility for an F-1 Optional Practical Training (OPT) extension.[28] This definition is relatively restrictive and excludes majors such as psychology, economics and nursing used in past work (e.g. Carnevale et al. 2011). We further classify STEM majors into two groups—“applied” science, which includes computer science, engineering and engineering technologies, and “pure” science, which includes biology, chemistry, physics, environmental science, mathematics and statistics. We use the 2010 Census Bureau definition of STEM occupations in all of our analyses.[29]

We also use data from the 1993–2013 waves of the National Survey of College Graduates (NSCG), a survey administered by the National Science Foundation (NSF). The NSCG is a stratified random sample of college graduates which employs the decennial Census as an

[28] https://www.ice.gov/sites/default/files/documents/Document/2016/stem-list.pdf. Peri et al. (2015) create a crosswalk between these codes and those collected by the ACS. We use their crosswalk, except we further exclude Psychology and some Health Science and Agriculture-related majors.

[29] The list can be found here: https://www.census.gov/topics/employment/industry-occupation/guidance/code-lists.html.

initial frame, while oversampling individuals in STEM majors and occupations. The major classifications in the NSCG are very similar to the ACS, and we use a consistent definition of STEM major across the two data sources. For some analyses, we also use data from the Annual Social and Economic Supplement (ASEC) of the Current Population Survey (CPS). The CPS covers a longer time period than the ACS, but does not collect data on college major.

Our main outcome of interest in the ACS is the natural log of wage and salary income for workers who are employed at the time of the survey and report working at least 40 weeks in the previous year. The NSCG only asks about annual salary in the current job, and asks workers who are not paid a salary to estimate their annual earnings. However, the NSCG does ask about (current) full-time employment, and we restrict the sample to full-time employed workers in our main results. In both samples we adjust earnings to constant 2017 dollars using the Consumer Price Index (CPI).

We restrict the main analysis sample to men with at least a bachelor's degree between the ages 23 to 50 in the ACS and CPS, and ages 25–50 in the NSCG.[30] We are interested in studying the life-cycle profile of returns to STEM degrees, and large changes across birth cohorts in educational attainment for women, as well as cohort differences in the age profile of female labor force participation make comparisons over time difficult (e.g. Goldin et al. 2006, Black et al. 2017).[31] To maximize consistency across data sources, we restrict the sample to non-veteran US-born citizens who are not living in group quarters and not currently enrolled in school. Our ACS results are not sensitive to these sample restrictions.

We supplement these two large, cross-sectional data sources with the 1979 and 1997 waves of the National Longitudinal Survey of Youth (NLSY), two nationally representative

[30]The sample design of the NSCG resulted in very few college graduates age 23–24, so we exclude this small group from our analysis.

[31]From 1995 to 2015, the share of women age 25+ with a BA or higher grew from 20.2 percent to 32.7 percent, more than double the rate of growth for men (Digest of Education Statistics, 2017). Appendix Figures A1 and A2 present results for women, which are broadly similar to results for men over the 23–35 age period. Hunt (2016) finds that women are especially likely to leave engineering over time, mostly due to their dissatisfaction with pay and promotion opportunities.

longitudinal surveys which include detailed measures of pre-market skills, schooling experiences and wages. The NLSY-79 starts with a sample of youth ages 14 to 22 in 1979, while the NLSY-97 starts with youth age 12–16 in 1997. The NLSY-79 was collected annually from 1979 to 1993 and biannually thereafter, whereas the NLSY-97 was always biannual. We restrict our NLSY analysis sample to ages 23–34 to exploit the age overlap across waves. We use respondents' standardized scores on the Armed Forces Qualifying Test (AFQT) to proxy for ability, following many other studies (e.g. Neal and Johnson 1996, Altonji, Bharadwaj and Lange 2012).[32] Our main outcome is the real log hourly wage (in constant 2017 dollars), and we trim values of the real hourly wage that are below 3 and above 200, following Altonji, Bharadwaj and Lange (2012). We follow the major classification scheme for the NLSY used by Altonji, Kahn and Speer (2016). Finally, we generate consistent occupation codes (and STEM classifications) across NLSY waves using the Census occupation crosswalks developed by Autor and Dorn (2013).

4.2 Declining Life-Cycle Returns to STEM

We begin by documenting life-cycle returns to STEM careers. Table 4 presents population-weighted descriptive statistics by college major and age, using the ACS. The odd-numbered columns show average earnings, while the even-numbered columns show share working in a STEM occupation. Columns 1 and 2 show results for all non-STEM majors, while Columns 3-4 and 5-6 show pure" and applied science majors respectively. Earnings increase substantially over the life-cycle for all college graduates regardless of major. However, STEM majors earn substantially more at labor market entry and experience slower wage growth over the first decade of working life.

The age pattern of earnings is starkly different by STEM major type. Applied science majors such as computer science and engineering earn the highest starting salaries, yet they

[32] Altonji, Bharadwaj and Lange (2012)construct a mapping of the AFQT score across NLSY waves that is designed to account for differences in age-at-test, test format and other idiosyncracies. We take the raw scores from Altonji, Bharadwaj and Lange (2012) and normalize them to have mean zero and standard deviation one.

also experience the flattest wage growth. The earnings premium for an applied science major relative to a non-STEM major is 44 percent at age 24, but drops to 14 percent by age 35.[33] In contrast, pure science majors such as biology, chemistry, physics and mathematics earn a relatively small initial wage premium that grows with time.

This pattern of flatter wage growth for applied science majors closely matches their exit from STEM occupations over time. The share of applied science majors holding STEM jobs declines from 63 percent at age 24 to 48 percent at age 35, and continues to decline to about 40 percent by age 50. The share of pure science majors in STEM jobs declines more modestly, from 29 percent at age 24 to 21 percent at age 35 and is flat thereafter. The share of non-STEM majors in STEM jobs stays constant at around 6-7 percent.

To examine these patterns more systematically, we estimate regressions of the following general form:

$$\ln y_{it} = \alpha_{it} + \sum_{a}^{A} \beta_a A_{it} + \sum_{a}^{A} \gamma_a \left(A_{it} * AS_{it}\right) + \sum_{a}^{A} \delta_a \left(A_{it} * PS_{it}\right) + \zeta X_{it} + \theta_t + \epsilon_{it} \qquad (10)$$

where a_{it} is an indicator variable that is equal to one if respondent i in year t is either age in two year bins a, going from ages 23–24 to ages 49–50. $a_{it}*AS_{it}$ and $a_{it}*PS_{it}$ are interactions between age bins and indicators for applied science or pure science majors respectively. The γ and δ coefficients can be interpreted as the wage premium for applied science and pure science majors relative to all other college majors, for each age group. The X vector includes controls for race and ethnicity and years of completed education, θ_t represents year fixed effects, and ϵ_{it} is an error term.

Figure 4 presents population-weighted estimates of equation (10) for full-time working men ages 23–50 with at least a bachelor's degree. Panel A presents results using the ACS,

[33] The ACS does not collect information about the type of college attended. Thus one explanation for part of the high initial earnings premium for STEM majors is that they are drawn heavily from more selective colleges, which also have higher on-time graduation rates and (by implication) full-time workers by age 23 (e.g. Hoxby 2017).

and Panel B presents results using the NSCG. Each point in Figure 4 is a γ or δ coefficient and associated 95 percent confidence interval. The ACS and NSCG are both nationally representative, but for different years, with the ACS covering 2009–2016 and the NSCG covering 1993–2013.

We find a strong life-cycle pattern in the labor market payoff to applied science degrees. In the ACS, college graduates with degrees in engineering and computer science earn about 39 percent more than non-STEM degree holders at ages 23–24. This earnings premium declines to about 26 percent by age 30 and 17.5 percent by age 40, leveling off thereafter. In contrast, the return to a pure science degree is near zero initially but start to grow beginning in the mid 30s, reaching 12 percent at 40 and 16 percent at age 50. This is largely explained by the high rate of graduate degree attainment—52 percent by age 35, compared to 28 percent and 32 percent for applied science and non-STEM degrees respectively.[34]

Panel B shows very similar patterns in the NSCG sample. Applied science majors earn a premium of about 46 percent at ages 25–26. This declines to 27 percent by age 30 and 21 percent by age 40, and again levels off over the next decade. The returns to a pure science degree in the NSCG are initially near zero but grow modestly over time. In results not reported, we find no significant differences over time or across cohorts in the share of college graduates acquiring STEM degrees, alleviating concerns about supply-driven differences in returns (e.g. Freeman 1976, Card and Lemieux 2001).

Overall, the payoff to Engineering and Computer Science degrees is initially very high, but declines by more than 50 percent in the first decade of working life.

The results in Figure 4 are robust to a variety of alternative specifications and sample definitions.[35] Appendix Figures A4, A5 and A6 present results that include part-time workers,

[34]Appendix Figure A3 shows that excluding workers with graduate degrees flattens the return to pure science degrees, suggesting that part of the growth in Figure 4 reflects selection into graduate school over time. Appendix Table A4 studies selection into graduate school using the NLSY. We find that while graduate school attendance is overall more common in later years, selection into graduate school by ability has not changed over time. While high-ability college graduates are more likely to attend graduate school, this is modestly less true for STEM majors.

[35]Hanson and Slaughter (2016) document the rising share of high-skilled immigrants in U.S. STEM fields. Hunt (2015) finds a wage penalty for immigrants relative to natives within engineering that is linked to En-

that add industry fixed effects, and that separate out engineering and computer science respectively. These all yield very similar results.

Figure 5 presents estimates of equation (10) where age is interacted with indicators for working in a STEM *occupation*, using the ACS, the NSCG and the CPS (which does not include information on college major). Despite the fact that each data source spans different years and has a different sampling frame, each shows the same pattern of declining life-cycle returns to working in a STEM occupation.

Is declining returns an inherent feature of STEM jobs, or is it something about the characteristics of students who choose to major in STEM? To disentangle majors from occupations, we estimate a version of equation (10) that adds interactions between age categories and indicators for being employed in a STEM occupation, as well as three-way interactions between age, an applied science major and STEM employment.[36] This allows us to separately estimate the relative earnings premia for applied science degree-holders working in non-STEM jobs, for other majors working in STEM jobs, and for applied science majors in STEM jobs.

The results are in Figure 6. Declining relative returns to STEM is a feature of the job, not the major. Applied science degree holders working in non-STEM occupations earn around 15 percent more than those with other majors, and this premium is relatively constant throughout their working life. The STEM major premium could reflect differences in unobserved ability across majors, or differences in other job characteristics (e.g. Kinsler and Pavan 2015).[37]

glish language proficiency, and argues that imperfect English may be a barrier to occupational advancement. To the extent that immigrants are a better substitute for younger workers, rising immigration over time will tend to depress relative wages for younger workers, which works against our findings. Additionally, we find that the share of college graduates in STEM fields has not changed very much over the cohorts we study in the ACS.

[36]The results for applied science are very similar when we also include similar interactions for pure science majors and STEM occupations, although we exclude these interactions for simplicity. Unfortunately, the measures of occupation are too coarse and non-standard in the NSCG to estimate equation (2) in a way that is comparable to the ACS.

[37]Appendix Figure A7 adds industry fixed effects to the results in Figure 6, which produces generally similar results except that the return to applied science majors in non-STEM occupations drops by about 50 percent.

In contrast, we find a strong life-cycle earnings pattern for STEM workers with other majors. The earnings premium for non-STEM majors in STEM occupations is about 32 percent at ages 23–24 but declines rapidly to 7.5 percent within a decade. The pattern is similar for applied science majors in STEM jobs, with earnings premia declining from 59 percent to around 17 percent by age 40. Within a decade of college graduation, Applied science majors have similar earnings in STEM and non-STEM occupations.

Figure 6 yields three key insights. First, STEM jobs pay relatively higher wages to younger workers, and this is true for applied science degree holders but also for other majors as well. Second, this benefit dissipates within 10–15 years after labor market entry, after which time there is little or no payoff to working in a STEM job regardless of one's college major. Third, the flatter age-earnings profile holds for STEM occupations, not STEM majors.

Where do STEM majors go when they exit STEM occupations? Figure 7 shows results from two estimates of equation (10), restricting the sample to applied science majors and with indicators for working in STEM and management occupations as the outcome variables. At ages 23–24, 62.5 percent of applied science majors are working in STEM occupations. By age 50 this has declined to about 41 percent, with about half of the decline occurring in the first 10 years after college. Over the same period, the share of applied science majors in management occupations increases from 6.5 percent to 27.5 percent, again with about half of the increase occuring in the first decade. Thus all of the declining employment in STEM occupations for STEM majors is accounted for by a shift into management.[38]

Non-STEM majors also shift into management over time, with the share increasing from 10 percent at ages 23–24 to 26 percent at ages 49–50. Overall, the mix of jobs held by STEM and non-STEM majors looks more and more similar as they age.

[38]Appendix Figure A8 presents a parallel set of results using the smaller NLSY sample, where we can control for ability. We find that the share of applied science majors working in STEM drops by 36 percentage points between the ages of 25–26 and ages 49–50. This is closely paralleled by a 37 percentage point increase in employment in management occupations over the same period.

4.3 Job Skill Change and Life-Cycle Earnings

The results in Section 4.2 are consistent with the predictions of the model. College students majoring in applied STEM fields such as computer science and engineering have higher starting wages than non-STEM majors, but they also experience slower wage growth over time. Next we show that our measure of job skill change ($SkillChange_o$, as measured in the BG data discussed in Section 2.4, corresponding to Δ_j in the model) directly predicts wage growth across occupations. We estimate:

$$\ln{(earn)}_{it} = \alpha_{it} + \sum_{a}^{A} \beta_a a_{it} + \sum_{a}^{A} \gamma_a \left(a_{it} * SkillChange^o_{it}\right) + \delta X_{it} + \theta_t + \epsilon_{it} \qquad (11)$$

This follows a similar format to equation (10) and Figure 6, except that instead of using indicators for STEM major we directly interact $SkillChange_o$ with two-year age bins. The results are in Figure 8. As in Figure 4, the γ coefficients can be interpreted as the relative earnings return to jobs with higher rates of technological change, for each age group.

Jobs with higher rates of skill change have flatter age-earnings profiles. The estimates imply that occupations with a one standard deviation higher value of $SkillChange_o$ (1.14) pay 24 percent higher wages at ages 23–24 but only 13 percent higher wages at ages 39–40. Appendix Figures A9 and A10 present the results separately for STEM and non-STEM occupations. While the levels are different, the same declining life-cycle pattern holds in both cases. Thus the relationship between technological change and higher relative wages for recent college graduates appears to be a general phenomenon that is not limited to STEM.

Figure 9 tests the second prediction of the model by studying occupational sorting directly. We estimate:

$$SkillChange^o_{it} = \alpha_{it} + \sum_{a=23,24}^{a=49,50} \beta_a a_{it} + \delta X_{it} + \theta_t + \epsilon_{it} \qquad (12)$$

Occupations with higher values of $SkillChange_o$ have younger workforces. The estimates imply that workers age 23–24 are in jobs that are about 0.2 standard deviations higher on average in terms of $SkillChange_o$ than workers age 39–40. In results not reported, we also find that this pattern holds separately for STEM workers vs. all other professional occupations. Overall, we find strong evidence of higher employment and relative wages for young workers in jobs with higher rates of skill change.

One concern with this analysis is that other features of STEM jobs might by systematically correlated with $SkillChange_o$. For example, employers may not create career ladders for STEM workers because they see them as lacking managerial training, or because of the availability of high-skilled immigrants from other countries. More generally, the patterns we show above may be due to some other factor that is highly correlated with job skill change.

While we cannot fully address this concern, we can explore whether our results are predicted by a different measure—the amount of skill change that occurs within-careers, but *between jobs with different experience requirements.* In other words, how similar is the skill mix of an entry level job in a given field, compared to a more senior position? To test this, we construct an alternative measure of $SkillChange_o$ as in equation (1), except with the absolute value of the difference in job skill shares between vacancies in an occupation that require 0–2 years versus 6 or more years of experience in 2017.

We indeed find that STEM occupations have *lower* rates of skill change across experience categories, which is consistent with the evidence shown in Figure 2. To see whether this matters for our results, we re-estimate the models in equations (11) and (12) while also controlling for occupation-level differences in skill change by years of experience. The results are in Appendix Figures A11 and A12. Our main results are robust to controlling for skill change by years of experience, even though this measure strongly predicts age patterns in wages and employment as well.

4.4 Accounting for Ability Differences by Major

We find that STEM majors are positively selected on ability, in both waves of the NLSY.[39] This suggests that the high labor market return to a STEM degree might be confounded by differences in academic ability across majors (e.g. Arcidiacono 2004, Kinsler and Pavan 2015). To account for ability differences, we estimate regressions of log wages on major choice, using microdata from both waves of the NLSY:

$$\ln{(earn)}_{it} = \alpha_{it} + \beta AS_i + \gamma PS_i + \delta X_{it} + \epsilon_{it} \tag{13}$$

The X_{it} vector includes controls for race, years of completed education, an indicator variable for NLSY wave, and age and year fixed effects. The unit of observation in the NLSY is a person-year, with standard errors clustered at the individual level. The sample is restricted to ages 23–34 to ensure comparability across survey waves.

Column 1 of Table 5 presents results from the basic model in equation (13). Applied science majors earn about 18 percent more per year than non-STEM majors, while pure science majors earn 10 percent less. Column 2 adds controls for cognitive skills (i.e. AFQT score), social skills and "non-cognitive" skills.[40] While each skill measure strongly and independently predicts wages, adding them as controls does notchange the earnings premia for both types of STEM majors. This suggests that higher wages in STEM careers cannot be explained only by ability sorting.

Column 3 adds an indicator variable for employment in a STEM occupation. Earnings are about 24 percent higher for STEM workers, regardless of major. Controlling for occupation choice lowers the return to holding an applied science degree from 18 percent to 7 percent. Column 4 adds industry fixed effects, which further shrinks the premium for applied science majors to 3.4 percent.

[39] Appendix Table A5 presents results that regress AFQT score on indicators for major type and major interacted with NLSY wave. We find that STEM majors of both type score about 0.08 standard deviations higher on the AFQT than non-STEM majors, but that this has not changed significantly across NLSY waves.

[40] We adopt the measures of social and "non-cognitive" skills from Deming (2017).

Column 5 adds interactions between STEM majors and STEM occupations. After controlling for ability, applied science majors in non-STEM jobs earn only about 1.3 percent more than non-STEM majors, and the difference is statistically insignificant. Non-STEM majors in STEM jobs continue to earn a premium of about 12 percent ($p<0.001$), compared to 19 percent for applied science majors in STEM jobs. The interaction term is statistically insignificant, suggesting that wages in STEM jobs are similar for workers with different majors. Finally, Column 6 estimates the return to college major controlling for ability and occupation-by-industry fixed effects, yielding coefficients on both STEM major types that are statistically indistinguishable from zero. Our results are consistent with Lemieux (2014) and Kinsler and Pavan (2015), who show that most of the return to a science major is driven by the higher return to working in a closely-related job.

We also test whether the pattern of declining returns for STEM majors shown in Figures 4–6 holds when controlling for worker skills. The results are in Figure 10. Across both NLSY waves, applied science majors earn about 21–24 percent more than non-STEM majors at ages 23–26, compared to only about 5–12 percent at ages 31–34, a difference that is jointly significant at the 5 percent level ($p=0.041$) despite the relatively small sample sizes in the NLSY.

4.5 High ability workers sort out of STEM over time

The final prediction of the model is that high-ability workers will sort out of STEM careers over time. The intuition is that the return to being a fast learner is greater in jobs with *lower* rates of skill change. Put another way, jobs with high rates of skill change erode the advantage gained by learning more skills in each period on the job. Empirically, we should observe high ability workers sorting into STEM careers initially, but sorting out of STEM careers later in life. We test this by using the NLSY to estimate regressions of the form:

$$y_{it} = \alpha_{it} + AGE_{it} + \beta STEM_i + \gamma AFQT_i + \theta AGE_i * AFQT_i + \delta X_{it} + \epsilon_{it} \qquad (14)$$

where AGE_{it} is a linear age control for worker i in year t (scaled so that age 23=0, for ease of interpretation), $STEM_i$ is an indicator for STEM major, and $AGE_i * AFQT_i$ is the interaction between age and cognitive ability. The X_{it} vector includes controls for race, years of completed education, an indicator variable for NLSY wave, year fixed effects and cognitive, social and non-cognitive skills. As with other results using the NLSY, the age range is 23–34, observations are in person-years and we cluster standard errors at the individual level.

The results are in Table 6. The outcome in Column 1 is an indicator for working in a STEM occupation. Column 1 presents the baseline estimate of equation (14). We find a positive and statistically significant coefficient on $AFQT_i$ but a negative and statistically significant coefficient on the interaction term $AGE_i * AFQT_i$. This confirms the prediction that high-ability workers sort into STEM jobs initially but sort out over time. The results imply that a worker with cognitive ability one standard deviation above average is 8.4 percentage points more likely to work in STEM at age 23, but only 3 percentage points more likely to be working in an STEM job by age 34.

Columns 2 and 3 of Table 6 repeat the pattern above, except with log wages as the outcome. Column 2 shows that there is a positive overall return to ability and that it is increasing in age, consistent with the basic framework of the model. Column 3 adds the interactions above. We find that the the coefficient on the key triple interaction term $AGE_{it} * STEM_i * AFQT_i$ is large and negative, implying that the return to ability is much flatter over time for STEM majors.

Summing the coefficients in Column 3 suggests that for a worker with cognitive ability one standard deviation above average, STEM majors earn about 21 percent more than average at age 23 and 40 percent more at age 35. In contrast, non-STEM majors of equal ability earn a 2 percent return at age 23 that grows rapidly to a 39 percent premium at age 35, completely erasing the earnings advantage for STEM majors. Similar computations for $AFQT_i > 1$ imply an earlier crossing point, an empirical result that is predicted by the stylized model simulation in Figure 3B.

Thus the results in Table 6 confirm the fourth prediction of the model that high-ability college graduates will choose STEM fields initially and exit for lower Δ_j careers over time.

5 Job Skill Change in Earlier Periods

Our model predicts that increases in the rate of skill change Δ_j should flatten the age-earnings profile of careers. Section 4 compares earnings over time in STEM and non-STEM careers, but the prediction should also hold within careers over time. Specifically, periods of relatively rapid technological change such as the IT revolution of the 1980s should correspond to an increase in the rate of skill change and a rising relative return for young workers in STEM careers.

The BG data only allow us to calculate detailed measure of job skill changes for the 2007–2017 period. We study the impact of technological change in earlier years using data from Atalay et al. (2018). Atalay et al. (2018) assemble the full text of job advertisements in the *New York Times, Wall Street Journal* and *Boston Globe* between 1940 and 2000, and they create measures of job skill content and relate job title to SOC codes using a text processing algorithm. They then map words and phrases to widely-used existing skill content measures such as the Dictionary of Occupational Titles (DOT) and the Occupational Information Network (O*NET), as well as the job task classification schema used in past studies such as Autor et al. (2003), Spitz-Oener (2006), Firpo et al. (2011) and Deming and Kahn (2018).

We estimate a version of $SkillChange_o$ from equation (2) using the Atalay et al. (2018) data and job skill classifications.[41] Since there is no natural mapping between our BG data and the classified ads collected by Atalay et al. (2018), we cannot create a directly comparable measure. Our preferred approach is to use all of the skill measures computed by Atalay et al. (2018), although the results are not sensitive to other choices. We calculate $SkillChange_o$ for 5 year periods starting with 1973–1978 and ending with 1993–1998. Finally, to account

[41] The data and programs can be found on the authors' public data page—https://occupationdata.github.io/

for fluctuations in the data we smooth each beginning and end point into a 3 year moving average (e.g. 1998 is actually 1997–1999). 5 year bins starting with 1973–1978 and through 1993–1998.

We calculate $SkillChange_o$ for each time period and occupation (6 digit SOC code), and then compute the vacancy-weighted average in each period for STEM and non-STEM occupations. The results—in Panel A of Figure 11—show three main findings. First, the rate of skill change for non-STEM occupations is relatively constant at around 0.4 in each period.

Second, the rate of skill change in STEM occupations fluctuates markedly, with peaks that occur during the technological revolution of the 1980s. The $SkillChange_o$ measure more than doubles from 0.26 to 0.53 between the 1973–1978 and 1978–1983 periods, and then increases again to 0.73 for 1983–1988 before falling again during the 1990s. Card and DiNardo (2002) date the beginning of the "computer revolution" to the introduction of the IBM-PC in 1981, and Autor et al. (1998) document a rapid increase in computer usage at work starting in the 1980s.

Third, while 2007–2017 cannot be easily compared to earlier periods in levels due to differences in the data, it is notable that the relatively higher value of $SkillChange_o$ for STEM occupations holds for the 2007–2017 period and the 1980s, but not the late 1970s or 1990s. This suggests that new technologies may diffuse first through STEM occupations before spreading gradually throughout the rest of the economy.

Our model predicts that periods with higher rates of skill change will yield relatively higher labor market returns for younger workers, especially in STEM occupations. We test this by lining up the evidence in Panel A of Figure 11 with wage trends for young workers in STEM jobs over the same period, using the CPS for years 1974–2016. We estimate population-weighted regressions of the form:

$$\ln(earn)_{it} = \alpha_{it} + \sum_{c}^{C} \gamma_c (c_{it} * Y_{it}) + \sum_{c}^{C} \zeta_c (c_{it} * ST_{it}) + \sum_{c}^{C} \eta_c (c_{it} * Y_{it} * ST_{it}) + \delta X_{it} + \epsilon_{it} \quad (15)$$

where c_{it} is an indicator variable that is equal to one if respondent i is in each of the five-year age bins starting with 1974–1978 and extending to 2009–2016 (with the last period being slightly longer to maximize overlap with the BG data). Y_{it} is an indicator variable that is equal to one if the respondent is "young", defined as between the ages of 23 and 26 in the year of the survey, and ST_{it} is an indicator for whether the respondent is working in a STEM occupation. The X vector includes controls for race and ethnicity, years of completed education, and age and year fixed effects, as well as controls for the main effects c_{it} and $STEM_{it}$. Thus the γ and ζ coefficients represent the wage premium for young workers and older STEM workers relative to the base period of 1974–1978, while the η coefficients represent the earnings premium for young STEM workers relative to older STEM workers in each period.

The results are in Panel B of Figure 11. Each bar displays coefficients and 95% confidence intervals for estimates of γ, ζ and η in equation (15). Comparing the timing to Panel A, we see that the relative return to STEM for young workers is highest in periods with the highest rate of skill change. The premium for STEM workers age 23–26 relative to ages 27–50 is small and close to zero during the 1974–1978 period (when $SkillChange_o$ in Panel A was low), but jumps up to 18 percent and 24 percent in the 1979–1983 and 1983–1988 periods respectively. It then falls to 16 percent for 1989–1993 and 8 percent for 1994–1998, exactly when the rate of change falls again in Panel A.

The results in Figure 11 show that young STEM workers earn relatively higher wages during periods of rapid skill change.[42] In contrast, we do not find similar patterns of fluctuating wage premia for older STEM workers (the second set of bars) or for young workers in non-STEM occupations. The main effect of $STEM_{it}$ implies an overall wage premium of around 24 percent for STEM occupations, but this changes very little over the 1974–2016

[42] One limitation of the CPS is that we do not know college major, and so it is possible that the patterns we find are driven by selection of high-ability workers (including those who did not major in STEM) into STEM jobs. However, this would not by itself explain why selection would only occur among younger workers. Grogger and Eide (1995) show that about 25 percent of the rise in the college premium during the 1980s can be accounted for by an increase in the STEM skills acquired in college.

period.

Similarly, we find no consistent evidence that wages for young non-STEM workers move in any systematic way with the rate of occupational skill change. Finally, although we do not have the data to calculate $SkillSChange_o$between 2000 and 2007, we find that a very high return for young STEM workers during the 1999–2003 period, which coincides with the technology boom of the late 1990s (e.g. Beaudry et al. 2016).

6 Conclusion

This paper studies the impact of changing skill demands on the life-cycle returns to STEM careers. STEM graduates earn higher starting wages because they have learned job-relevant skills in school. Yet over time, employers require new skills and older skills become obsolete. This leads to flatter wage growth among more experienced STEM graduates, who eventually exit the STEM workforce.

In addition to providing important evidence on employment and wage profiles for STEM careers, this paper also contributes to the broader literature on how technology affects labor markets. We show how job vacancy data—with detailed measures of employer skill demands—can be used to study the process by which technology changes the returns to skills learned in school. Future research can use vacancy data to understand other changes in job skill requirements at a much more detailed level than has previously been possible. For example, our approach uncovers the rapid increase in skill requirements for new artificial intelligence technologies.

We formalize the key mechanism of job skill change with a simple model of education and career choice. Intuitively, on-the-job learning is more difficult in careers where the job functions themselves are constantly changing. Although STEM majors gain an initial earnings advantage because they learn job-relevant skills in school, the advantage is eroded over time. Our model predicts that the highest-ability individuals will major in STEM and enter

STEM careers initially, but that they will be more likely to exit STEM over time. We find strong support for this prediction using longitudinal data from the NLSY.

Using historical data on job vacancies collected by Atalay et al. 2018, we test the predictions of our framework in earlier periods such as the IT revolution of the 1980s. We find large increases in the rate of skill change for STEM jobs during the 1980s, a period that coincides closely with important technological developments such as the introduction of the personal computer. We also show that relative wages spiked during this period for young STEM workers.

This paper contributes to the ongoing policy debate over the "STEM shortage" by showing that it is the new job-relevant *skills* that are scarce, not necessarily the STEM workers themselves. In fact, faster technological progress contributes directly to the perception of shortage by hastening skill obsolescence among older workers.

Finally, our results inform policy tradeoffs between investment in specific and general education. The high-skilled vocational preparation provided by STEM degrees paves a smoother transition for college graduates entering the workforce. Yet at the same time, rapid technological change can lead to a short shelf life for technical skills. The rise of coding bootcamps, stackable credentials and other attempts at "lifelong learning" can be seen as a market response to anticipated skill obsolescence. This tradeoff between technology-specific and general skills is an important consideration for policymakers and colleges seeking to educate the workers of today, while also building the skills of the next generation.

References

Acemoglu, D. and Autor, D.: 2011, Skills, tasks and technologies: Implications for employment and earnings, *Handbook of labor economics*, Vol. 4, Elsevier, pp. 1043–1171. 1, 3.1

Altonji, J. G., Arcidiacono, P. and Maurel, A.: 2016, The analysis of field choice in college and graduate school: Determinants and wage effects, *Handbook of the Economics of Education*, Vol. 5, Elsevier, pp. 305–396. 2, 5

Altonji, J. G., Bharadwaj, P. and Lange, F.: 2012, Changes in the characteristics of american youth: Implications for adult outcomes, *Journal of Labor Economics* **30**(4), 783–828. 4.1, 32

Altonji, J. G., Blom, E. and Meghir, C.: 2012, Heterogeneity in human capital investments: High school curriculum, college major, and careers, *Annu. Rev. Econ.* **4**(1), 185–223. 2, 5, 4

Altonji, J. G., Kahn, L. B. and Speer, J. D.: 2016, Cashier or consultant? entry labor market conditions, field of study, and career success, *Journal of Labor Economics* **34**(S1), S361–S401. 4.1

Altonji, J. G. and Pierret, C. R.: 2001, Employer learning and statistical discrimination, *The Quarterly Journal of Economics* **116**(1), 313–350. 26

Arcidiacono, P.: 2004, Ability sorting and the returns to college major, *Journal of Econometrics* **121**(1-2), 343–375. 2, 1, 4.4

Arcidiacono, P., Aucejo, E. M. and Hotz, V. J.: 2016, University differences in the graduation of minorities in stem fields: Evidence from california, *American Economic Review* **106**(3), 525–62. 5, 1, 4

Arora, A., Branstetter, L. G. and Drev, M.: 2013, Going soft: How the rise of software-based innovation led to the decline of japan's it industry and the resurgence of silicon valley, *Review of Economics and Statistics* **95**(3), 757–775. 2.3

Atalay, E., Phongthiengtham, P., Sotelo, S. and Tannenbaum, D.: 2018, The evolving us occupational structure. 1, 5, 6

Aubert, P., Caroli, E. and Roger, M.: 2006, New technologies, organisation and age: firm-level evidence, *The Economic Journal* **116**(509). 1

Autor, D. and Dorn, D.: 2013, The growth of low-skill service jobs and the polarization of the us labor market, *American Economic Review* **103**(5), 1553–97. 4.1

Autor, D. H., Katz, L. F. and Krueger, A. B.: 1998, Computing inequality: have computers changed the labor market?, *The Quarterly Journal of Economics* **113**(4), 1169–1213. 5

Autor, D. H., Levy, F. and Murnane, R. J.: 2002, Upstairs, downstairs: Computers and skills on two floors of a large bank, *ILR Review* **55**(3), 432–447. 3, 1

Autor, D. H., Levy, F. and Murnane, R. J.: 2003, The skill content of recent technological change: An empirical exploration, *The Quarterly journal of economics* **118**(4), 1279–1333. 1, 2.2, 5

Bartel, A., Ichniowski, C. and Shaw, K.: 2007, How does information technology affect productivity? plant-level comparisons of product innovation, process improvement, and worker skills, *The quarterly journal of Economics* **122**(4), 1721–1758. 3, 1

Beaudry, P., Green, D. A. and Sand, B. M.: 2016, The great reversal in the demand for skill and cognitive tasks, *Journal of Labor Economics* **34**(S1), S199–S247. 5

Berman, E., Bound, J. and Griliches, Z.: 1994, Changes in the demand for skilled labor within us manufacturing: evidence from the annual survey of manufactures, *The Quarterly Journal of Economics* **109**(2), 367–397. 1

Black, S. E., Schanzenbach, D. W. and Breitwieser, A.: 2017, The recent decline in women's labor force participation, *Driving Growth through Women's Economic Participation* p. 5. 4.1

Branstetter, L. G., Drev, M. and Kwon, N.: 2018, Get with the program: Software-driven innovation in traditional manufacturing, *Management Science* . 2.3

Bresnahan, T. F., Brynjolfsson, E. and Hitt, L. M.: 2002, Information technology, workplace organization, and the demand for skilled labor: Firm-level evidence, *The Quarterly Journal of Economics* **117**(1), 339–376. 3, 1

Brynjolfsson, E., Mitchell, T. and Rock, D.: 2018, What can machines learn, and what does it mean for occupations and the economy?, *AEA Papers and Proceedings*, Vol. 108, pp. 43–47. 2.2

Cappelli, P. H.: 2015, Skill gaps, skill shortages, and skill mismatches: Evidence and arguments for the united states, *ILR Review* **68**(2), 251–290. 1

Card, D. and DiNardo, J. E.: 2002, Skill-biased technological change and rising wage inequality: Some problems and puzzles, *Journal of labor economics* **20**(4), 733–783. 1, 5

Card, D. and Lemieux, T.: 2001, Can falling supply explain the rising return to college for younger men? a cohort-based analysis, *The Quarterly Journal of Economics* **116**(2), 705–746. 4.2

Carnevale, A. P., Cheah, B. and Strohl, J.: 2012, *College Majors, Unemployment and Earnings: Not all college degrees are created equal*, Georgetown University Center on Educaiton and the Workforce. 2, 1

Carnevale, A. P., Smith, N. and Melton, M.: 2011, Stem: Science technology engineering mathematics., *Georgetown University Center on Education and the Workforce* . 1, 4.1

Caselli, F.: 1999, Technological revolutions, *American economic review* **89**(1), 78–102. 1, 3.3

Chari, V. V. and Hopenhayn, H.: 1991, Vintage human capital, growth, and the diffusion of new technology, *Journal of political Economy* **99**(6), 1142–1165. 1, 7, 3.3

Deming, D. J.: 2017, The growing importance of social skills in the labor market, *The Quarterly Journal of Economics* **132**(4), 1593–1640. 1, 2.2, 40

Deming, D. and Kahn, L. B.: 2018, Skill requirements across firms and labor markets: Evidence from job postings for professionals, *Journal of Labor Economics* **36**(S1), S337–S369. 2.1, 11, 5

Firpo, S., Fortin, N. and Lemieux, T.: 2011, Occupational tasks and changes in the wage structure. 1, 5

Freeman, R. B.: 1976, A cobweb model of the supply and starting salary of new engineers, *ILR Review* **29**(2), 236–248. 4.2

Friedberg, L.: 2003, The impact of technological change on older workers: Evidence from data on computer use, *ILR Review* **56**(3), 511–529. 1

Galenson, D. W. and Weinberg, B. A.: 2000, Age and the quality of work: The case of modern american painters, *Journal of Political Economy* **108**(4), 761–777. 9

Galor, O. and Tsiddon, D.: 1997, Technological progress, mobility, and economic growth, *The American Economic Review* pp. 363–382. 1, 3.3

Goldin, C. and Katz, L. F.: 2007, The race between education and technology: the evolution of us educational wage differentials, 1890 to 2005, *Technical report*, National Bureau of Economic Research. 1

Goldin, C., Katz, L. F. and Kuziemko, I.: 2006, The homecoming of american college women: The reversal of the college gender gap, *Journal of Economic perspectives* **20**(4), 133–156. 4.1

Golsteyn, B. H. and Stenberg, A.: 2017, Earnings over the life course: General versus vocational education, *Journal of Human Capital* **11**(2), 167–212. 2

Gould, E. D., Moav, O. and Weinberg, B. A.: 2001, Precautionary demand for education, inequality, and technological progress, *Journal of Economic Growth* **6**(4), 285–315. 7

Griliches, Z.: 1957, Hybrid corn: An exploration in the economics of technological change, *Econometrica, Journal of the Econometric Society* pp. 501–522. 1

Griliches, Z.: 1992, Introduction to" output measurement in the service sectors", *Output measurement in the service sectors*, University of Chicago Press, pp. 1–22. 1

Grogger, J. and Eide, E.: 1995, Changes in college skills and the rise in the college wage premium, *Journal of Human Resources* pp. 280–310. 42

Hanson, G. H. and Slaughter, M. J.: 2016, High-skilled immigration and the rise of stem occupations in us employment, *Technical report*, National Bureau of Economic Research. 35

Hanushek, E. A., Schwerdt, G., Woessmann, L. and Zhang, L.: 2017, General education, vocational education, and labor-market outcomes over the lifecycle, *Journal of Human Resources* **52**(1), 48–87. 2, 1

Hastings, J. S., Neilson, C. A. and Zimmerman, S. D.: 2013, Are some degrees worth more than others? evidence from college admission cutoffs in chile, *Technical report*, National Bureau of Economic Research. 5

Hershbein, B. and Kahn, L. B.: 2018, Do recessions accelerate routine-biased technological change? evidence from vacancy postings, *American Economic Review* **108**(7), 1737–72. 2.1, 2.3

Hunt, J.: 2015, Are immigrants the most skilled us computer and engineering workers?, *Journal of Labor Economics* **33**(S1), S39–S77. 35

Hunt, J.: 2016, Why do women leave science and engineering?, *ILR Review* **69**(1), 199–226. 31

Ichniowski, C. and Shaw, K. L.: 2009, Insider econometrics: Empirical studies of how management matters, *Technical report*, National Bureau of Economic Research. 3

Jones, B. F.: 2009, The burden of knowledge and the “death of the renaissance man”: Is innovation getting harder?, *The Review of Economic Studies* **76**(1), 283–317. 6

Jones, C. I.: 1995, R & d-based models of economic growth, *Journal of political Economy* **103**(4), 759–784. 1

Jovanovic, B. and Nyarko, Y.: 1996, Learning by doing and the choice of technology, *Econometrica* **64**(6), 1299–1310. 1

Katz, L. F. and Murphy, K. M.: 1992, Changes in relative wages, 1963–1987: supply and demand factors, *The quarterly journal of economics* **107**(1), 35–78. 1

Kinsler, J. and Pavan, R.: 2015, The specificity of general human capital: Evidence from college major choice, *Journal of Labor Economics* **33**(4), 933–972. 2, 4, 5, 1, 4, 4.2, 4.4, 4.4

Kirkeboen, L. J., Leuven, E. and Mogstad, M.: 2016, Field of study, earnings, and self-selection, *The Quarterly Journal of Economics* **131**(3), 1057–1111. 2, 5

Kredler, M.: 2014, Experience vs. obsolescence: A vintage-human-capital model, *Journal of Economic Theory* **150**, 709–739. 1, 7

Krueger, D. and Kumar, K. B.: 2004, Skill-specific rather than general education: A reason for us–europe growth differences?, *Journal of economic growth* **9**(2), 167–207. 1

Leighton, M. and Speer, J.: 2017, Labor market returns to college major specificity. 5

Lemieux, T.: 2014, Occupations, fields of study and returns to education, *Canadian Journal of Economics/Revue canadienne d'économique* **47**(4), 1047–1077. 4, 4.4

MacDonald, G. and Weisbach, M. S.: 2004, The economics of has-beens, *Journal of Political Economy* **112**(S1), S289–S310. 1, 9

Malamud, O.: 2010, Breadth versus depth: the timing of specialization in higher education, *Labour* **24**(4), 359–390. 2

Malamud, O. and Pop-Eleches, C.: 2010, General education versus vocational training: Evidence from an economy in transition, *The review of economics and statistics* **92**(1), 43–60. 2

McDowell, J. M.: 1982, Obsolescence of knowledge and career publication profiles: Some evidence of differences among fields in costs of interrupted careers, *The American Economic Review* **72**(4), 752–768. 8

Moretti, E.: 2012, *The new geography of jobs*, Houghton Mifflin Harcourt. 6

Neal, D.: 1999, The complexity of job mobility among young men, *Journal of Labor Economics* **17**(2), 237–261. 3.1

Neal, D. A. and Johnson, W. R.: 1996, The role of premarket factors in black-white wage differences, *Journal of political Economy* **104**(5), 869–895. 4.1

Nelson, R. R. and Phelps, E. S.: 1966, Investment in humans, technological diffusion, and economic growth, *The American economic review* **56**(1/2), 69–75. 3.3

Neuman, S. and Weiss, A.: 1995, On the effects of schooling vintage on experience-earnings profiles: Theory and evidence, *European economic review* **39**, 943–955. 8

Parente, S. L.: 1994, Technology adoption, learning-by-doing, and economic growth, *Journal of economic theory* **63**(2), 346–369. 1

Pavan, R.: 2011, Career choice and wage growth, *Journal of Labor Economics* **29**(3), 549–587. 2, 3.1

Peri, G., Shih, K. and Sparber, C.: 2015, Stem workers, h-1b visas, and productivity in us cities, *Journal of Labor Economics* **33**(S1), S225–S255. 1, 4.1, 28

Ransom, T.: 2016, Selective migration, occupational choice, and the wage returns to college majors. 5

Rosen, S.: 1975, Measuring the obsolescence of knowledge, *Education, income, and human behavior*, NBER, pp. 199–232. 1

Ruggles, S., Genadek, K., Goeken, R., Grover, J. and Sobek, M.: 2017, Integrated public use microdata series: Version 6.0 [dataset]. minneapolis: University of minnesota, 2015. 4.1

Ryan, P.: 2001, The school-to-work transition: a cross-national perspective, *Journal of economic literature* **39**(1), 34–92. 1

Silos, P. and Smith, E.: 2015, Human capital portfolios, *Review of Economic Dynamics* **18**(3), 635–652. 5

Spence, M.: 1978, Job market signaling, *Uncertainty in Economics*, Elsevier, pp. 281–306. 3.2

Spitz-Oener, A.: 2006, Technical change, job tasks, and rising educational demands: Looking outside the wage structure, *Journal of labor economics* **24**(2), 235–270. 5

Stephan, P. E.: 1996, The economics of science, *Journal of Economic literature* **34**(3), 1199–1235. 6

Thompson, P.: 2003, Technological change and the age–earnings profile: Evidence from the international merchant marine, 1861–1912, *Review of Economic Dynamics* **6**(3), 578–601. 8

Tinbergen, J.: 1975, *Income distribution: Analysis and policies.* 1

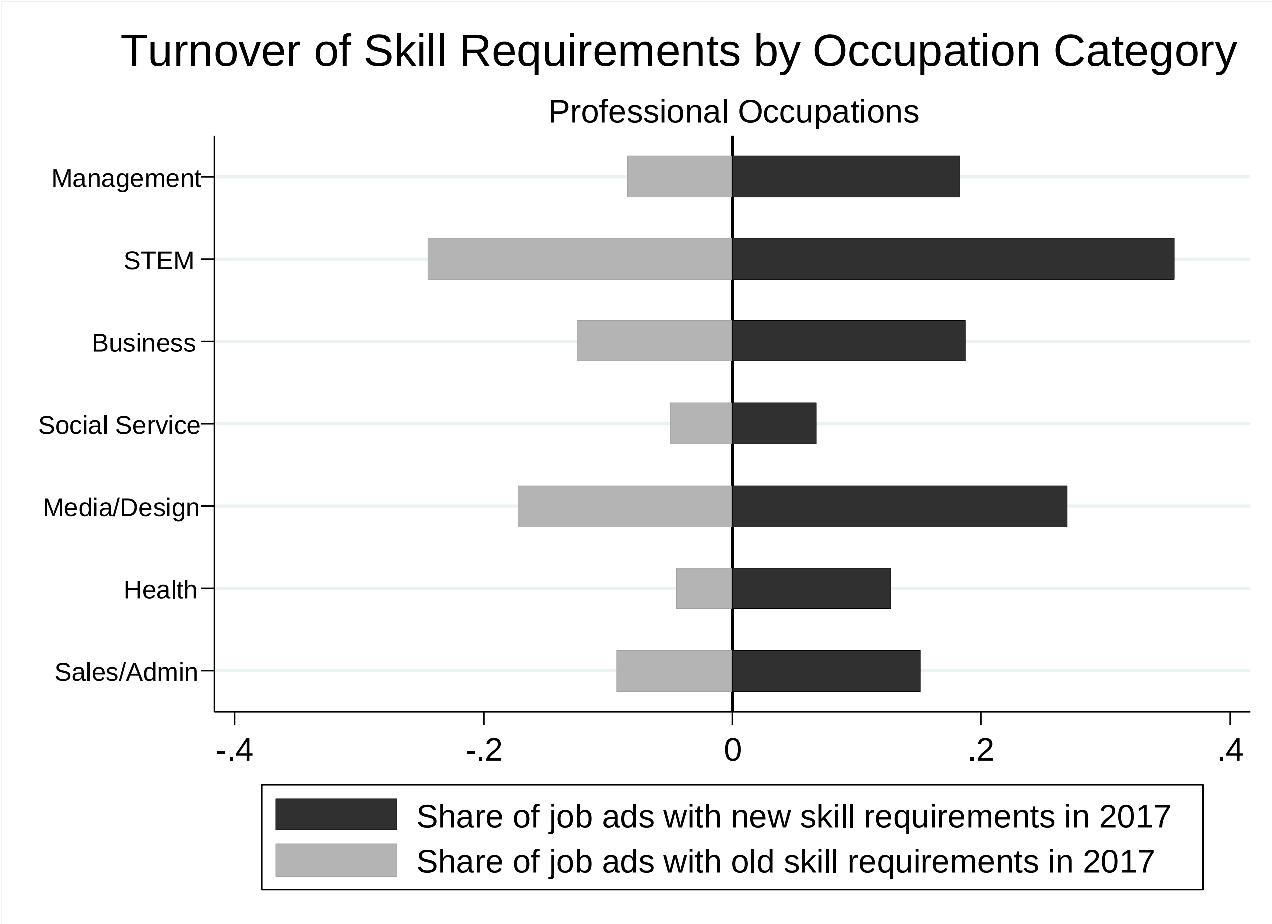
Violante, G. L.: 2002, Technological acceleration, skill transferability, and the rise in residual inequality, *The Quarterly Journal of Economics* **117**(1), 297–338. 1

Webber, D. A.: 2014, The lifetime earnings premia of different majors: Correcting for selection based on cognitive, noncognitive, and unobserved factors, *Labour economics* **28**, 14–23. 5

Weinberg, B. A.: 2004, Experience and technology adoption. 1

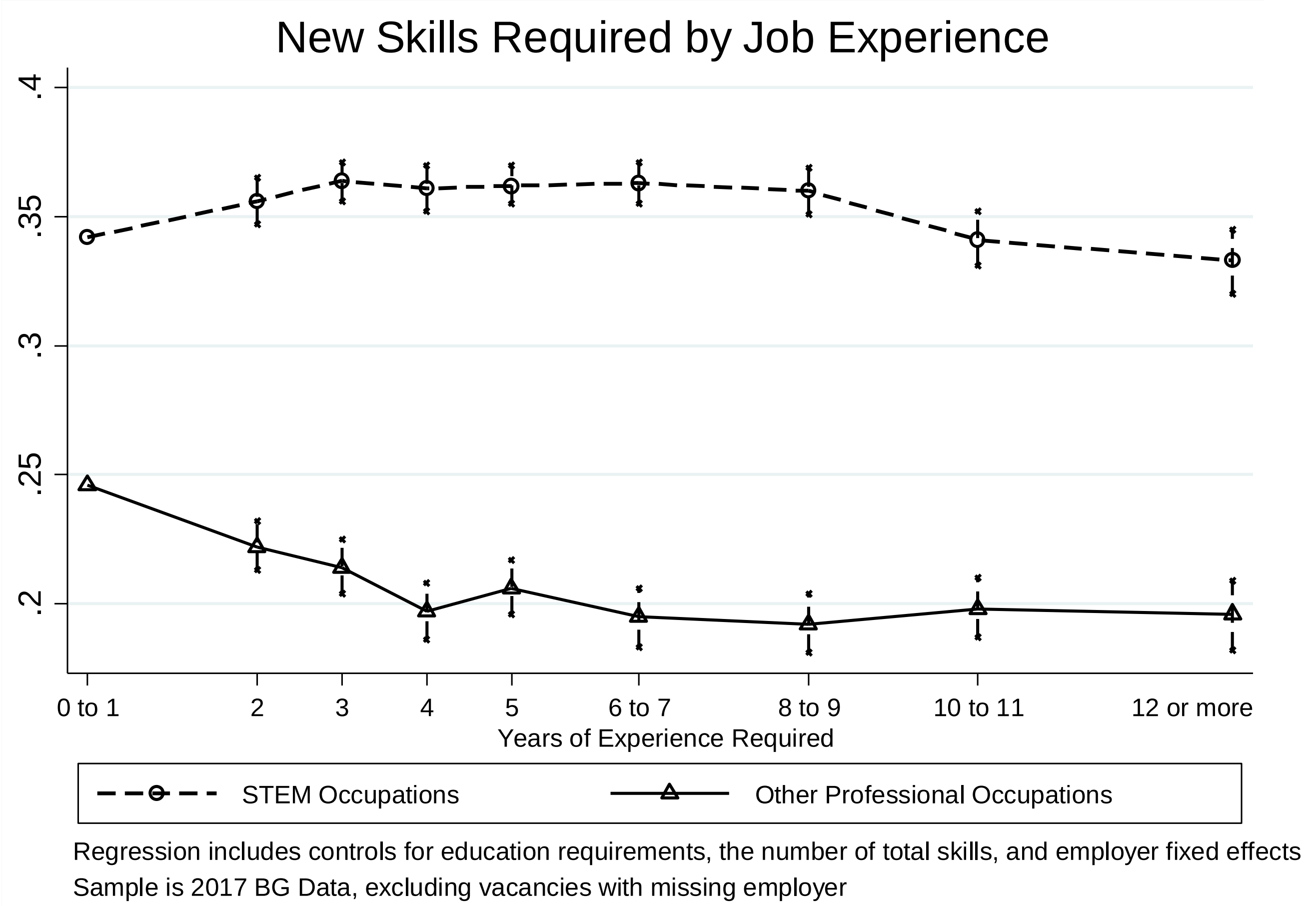
Wuchty, S., Jones, B. F. and Uzzi, B.: 2007, The increasing dominance of teams in production of knowledge, *Science* **316**(5827), 1036–1039. 6

Figure 1



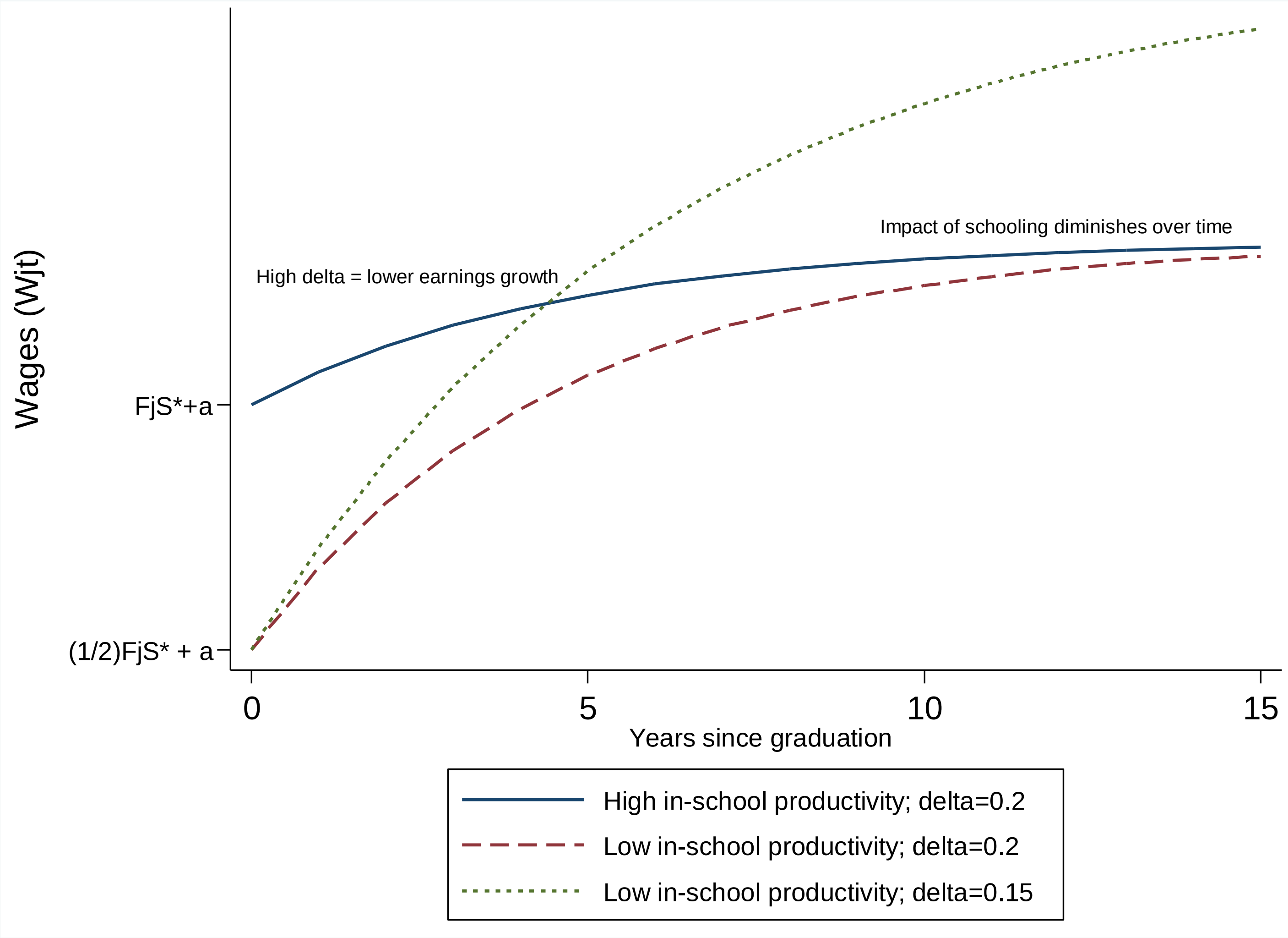
Notes: The bars show the share of jobs in each occupation category that required an “old” skill in 2007 (the light gray bars) and a “new” skill in 2017 (the dark gray bars). Old skills are defined as those with at least 1,000 appearances in 2007 but are either five times less frequent or do not exist in 2017. New skills are defined as those with at least 1,000 appearances in 2017 that either did not exist in 2007 or are 20 times more frequent in 2017 than 2007. The values of each bar are coefficients from a vacancy-level regression of the frequency of old and new skill requirements on an indicator for the 2017 year, the total number of skills listed in each vacancy, education and experience requirements, and occupation-city-employer fixed effects.

Figure 2



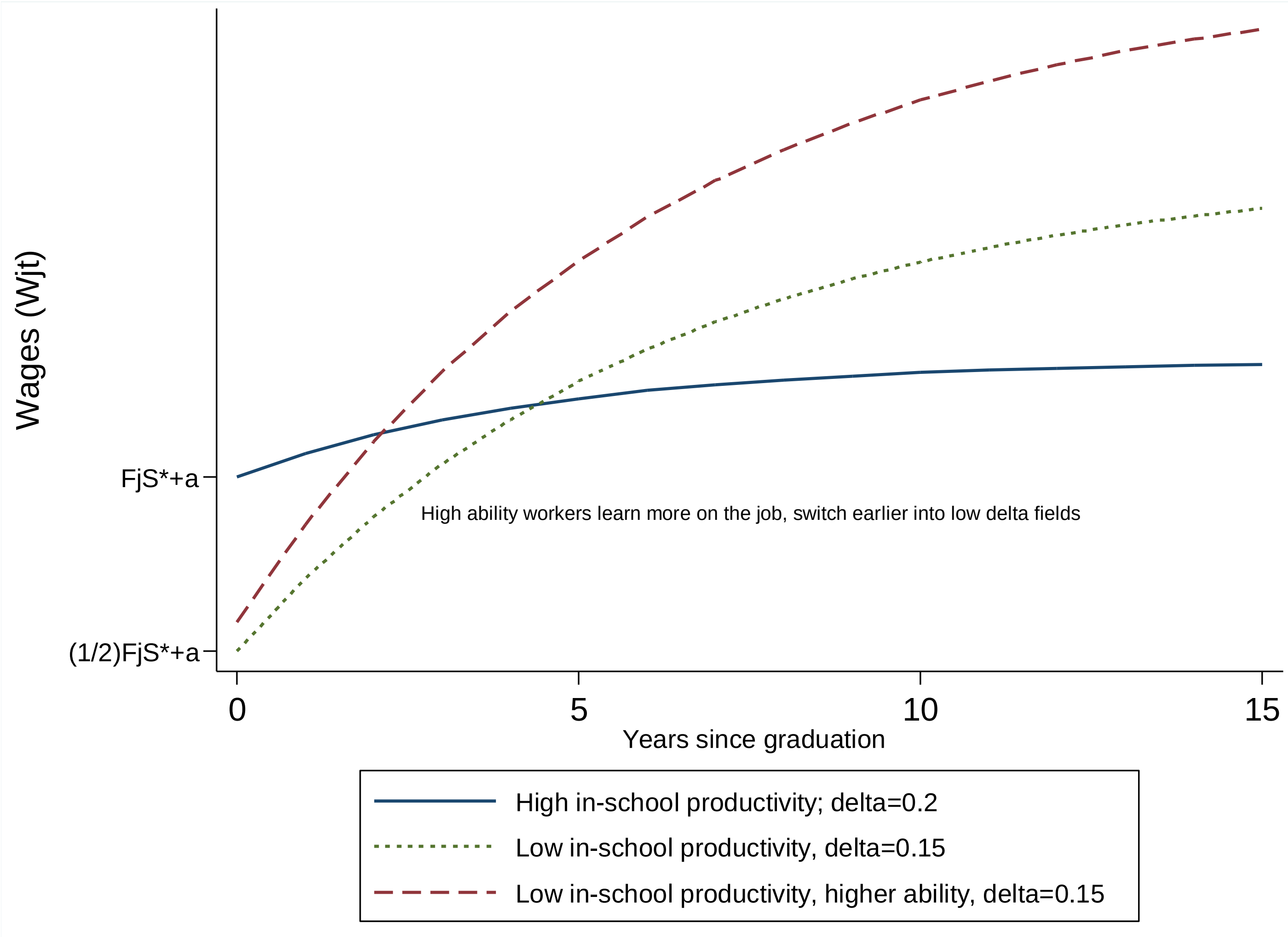
Notes: This figure shows how new skill requirements change along with required years of experience – in STEM, compared to other professional occupations. Each point in the figure is the coefficient (and associated 95 percent confidence interval) on the relevant experience category from a vacancy-level regression of the frequency of new skill requirements on experience categories, the total number of skills listed in the vacancy, education requirements, and employer-by-MSA fixed effects. New skills are defined as those with at least 1,000 appearances in 2017 that either did not exist in 2007 or are 20 times more frequent in 2017 than 2007.

Figure 3A



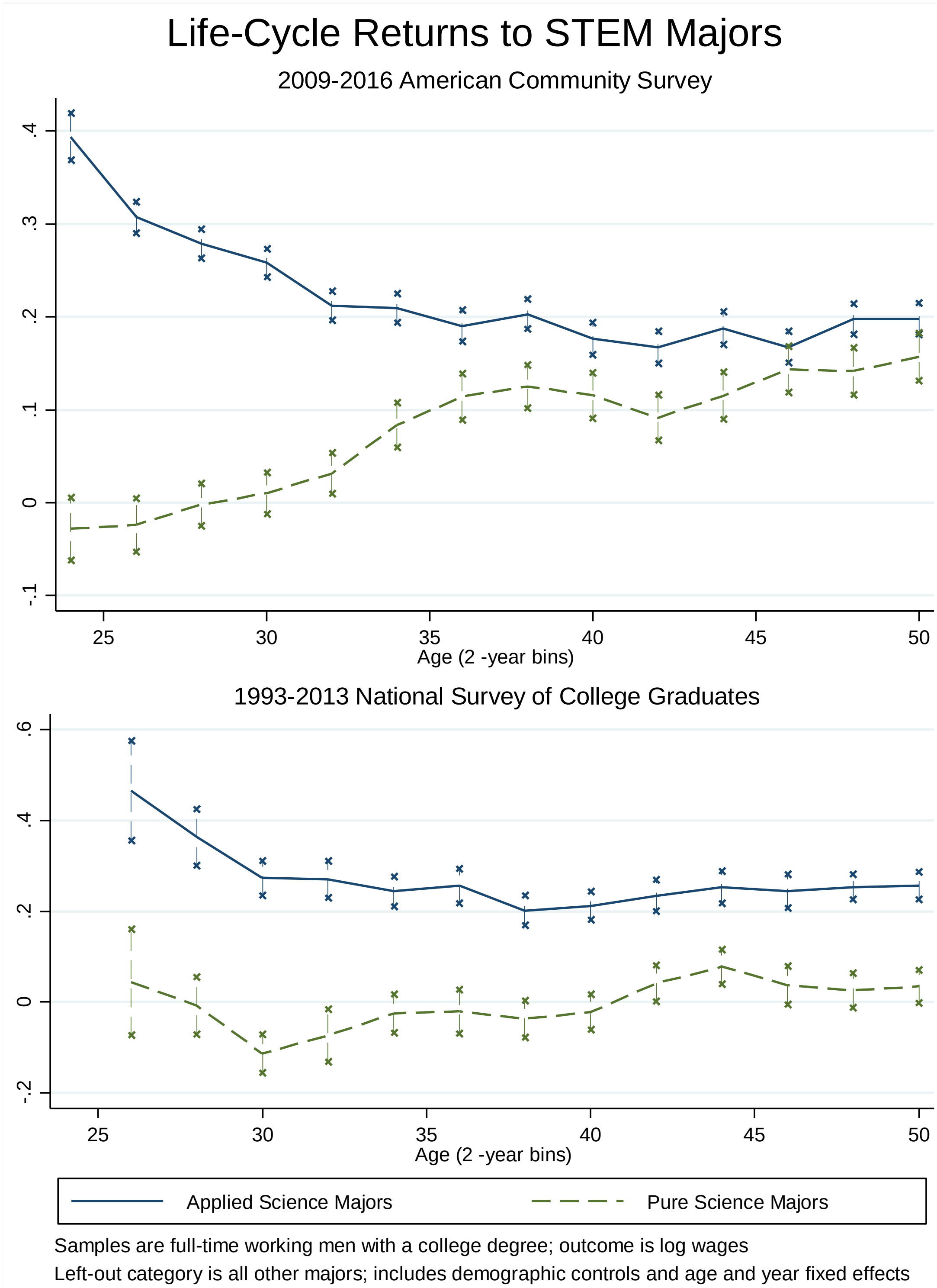
Notes: This Figure simulates earnings growth from the model in Section 3 of the paper when $F_j S^* = 6$ (high in-school productivity) or $F_j S^* = 3$ (low in-school productivity) and the rate of task change Δ_j is equal to 0.20 or 0.15. See the text for details.

Figure 3B



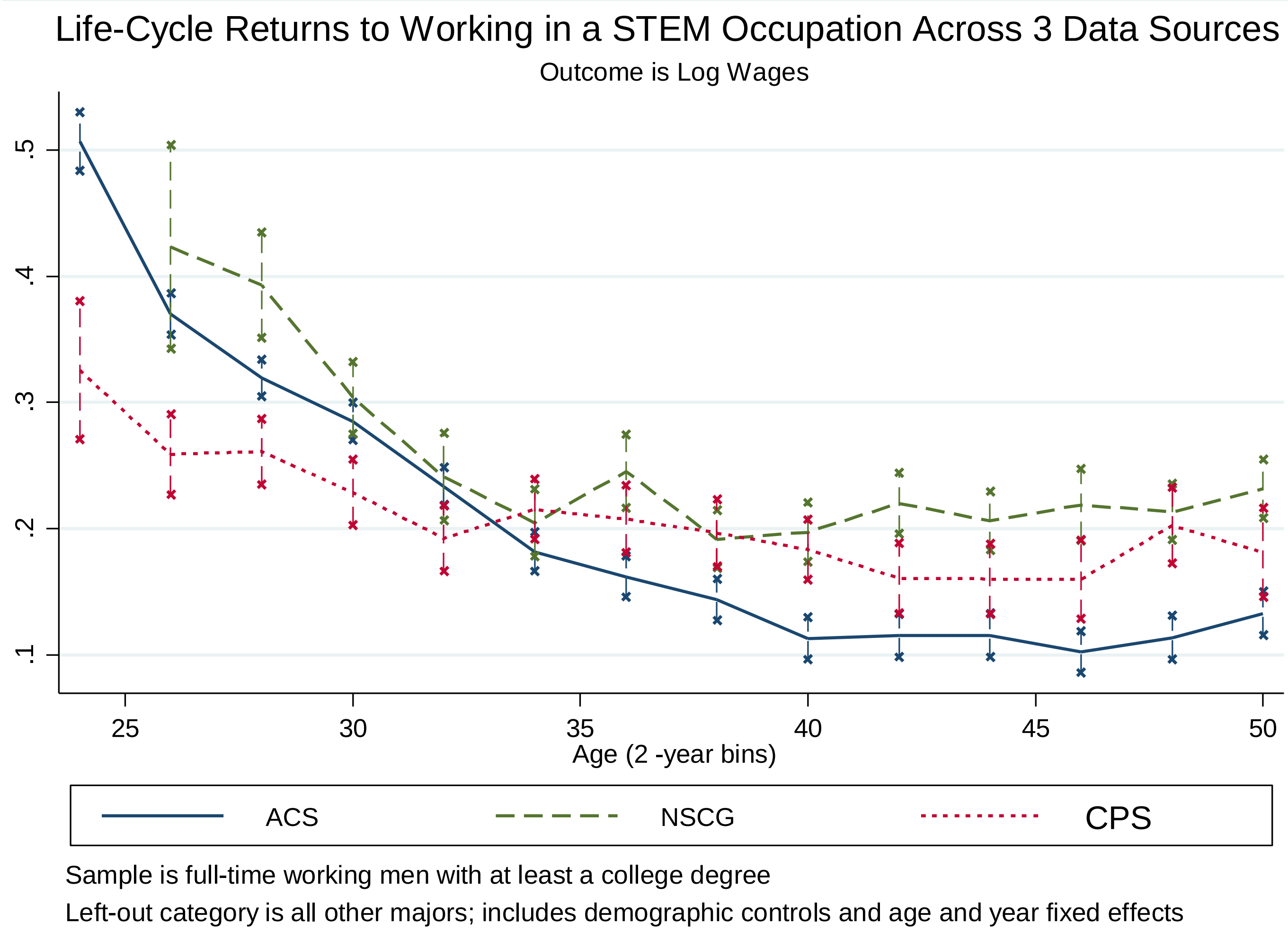
Notes: This Figure simulates earnings growth from the model in Section 3 of the paper when $F_j S^* = 6$ (high in-school productivity) or $F_j S^* = 3$ (low in-school productivity), the rate of task change Δ_j is equal to 0.20 or 0.15, and for a high vs. low ability worker. See the text for details.

Figure 4



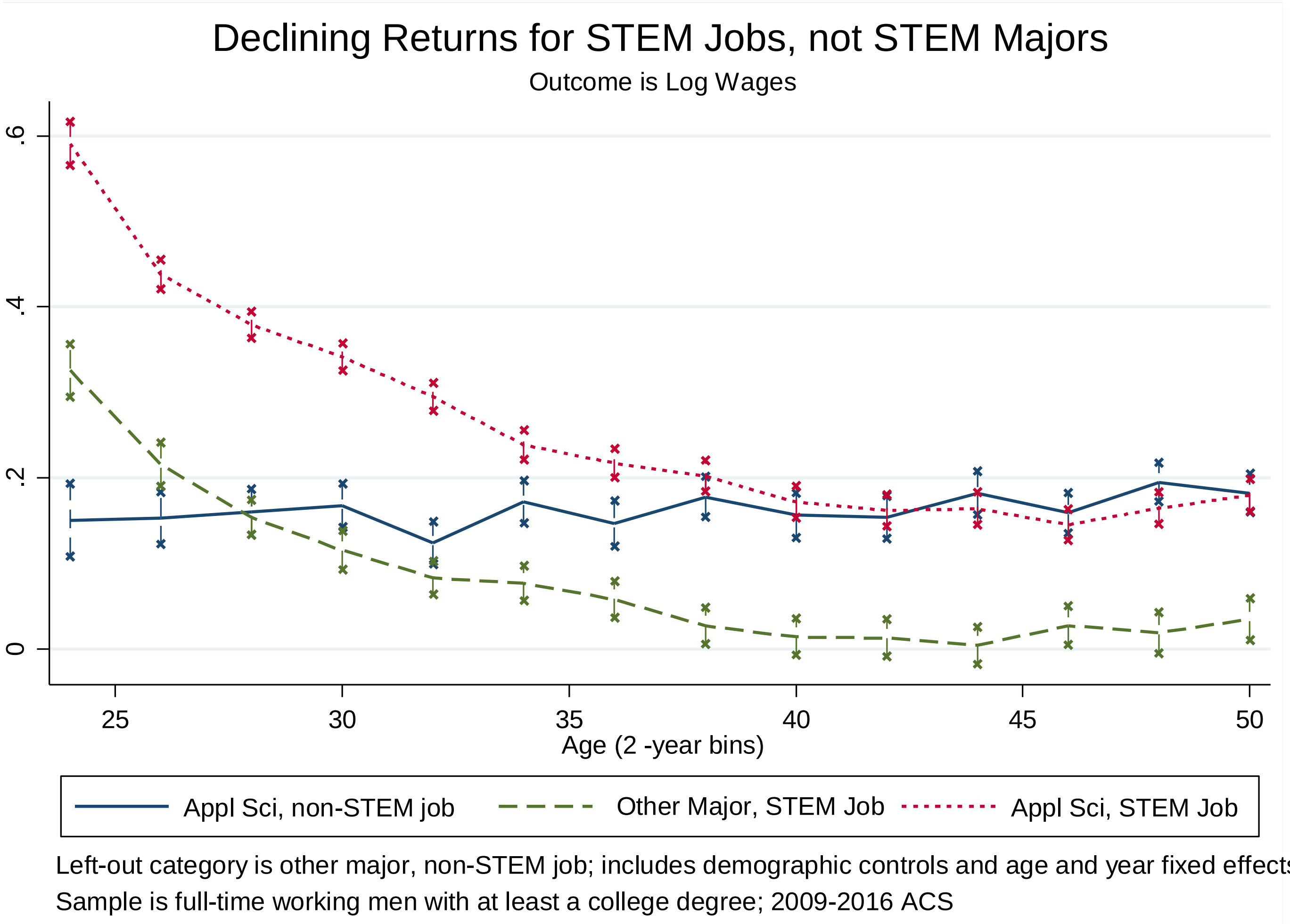
Notes: The figure plots coefficients and 95 percent confidence intervals from an estimate of the returns to majors over time, following equation (10) in the paper. "Pure" Science includes biology, chemistry, physics, mathematics and statistics, while "Applied" Science includes engineering and computer science.

Figure 5



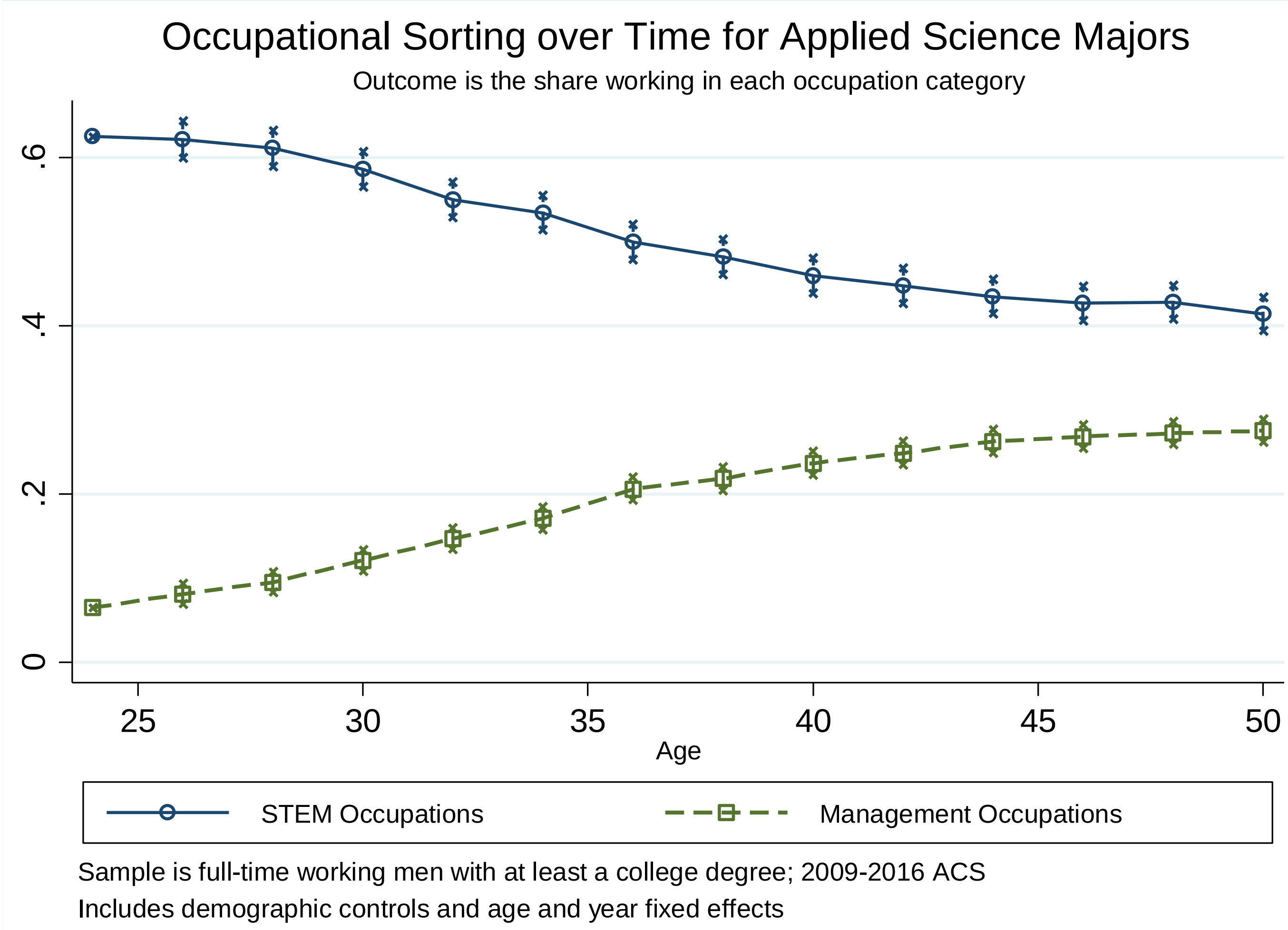
Notes: The figure plots coefficients and 95 percent confidence intervals from three separate estimates of equation (10) in the paper, except we interact age bins with indicators for working in a STEM occupation rather than earning a STEM degree. STEM occupations are defined using the 2010 Census Bureau classification. The three data sources are the 2009-2016 American Community Survey, the 1993-2013 National Survey of College Graduates, and the 1973-2016 Current Population Survey.

Figure 6



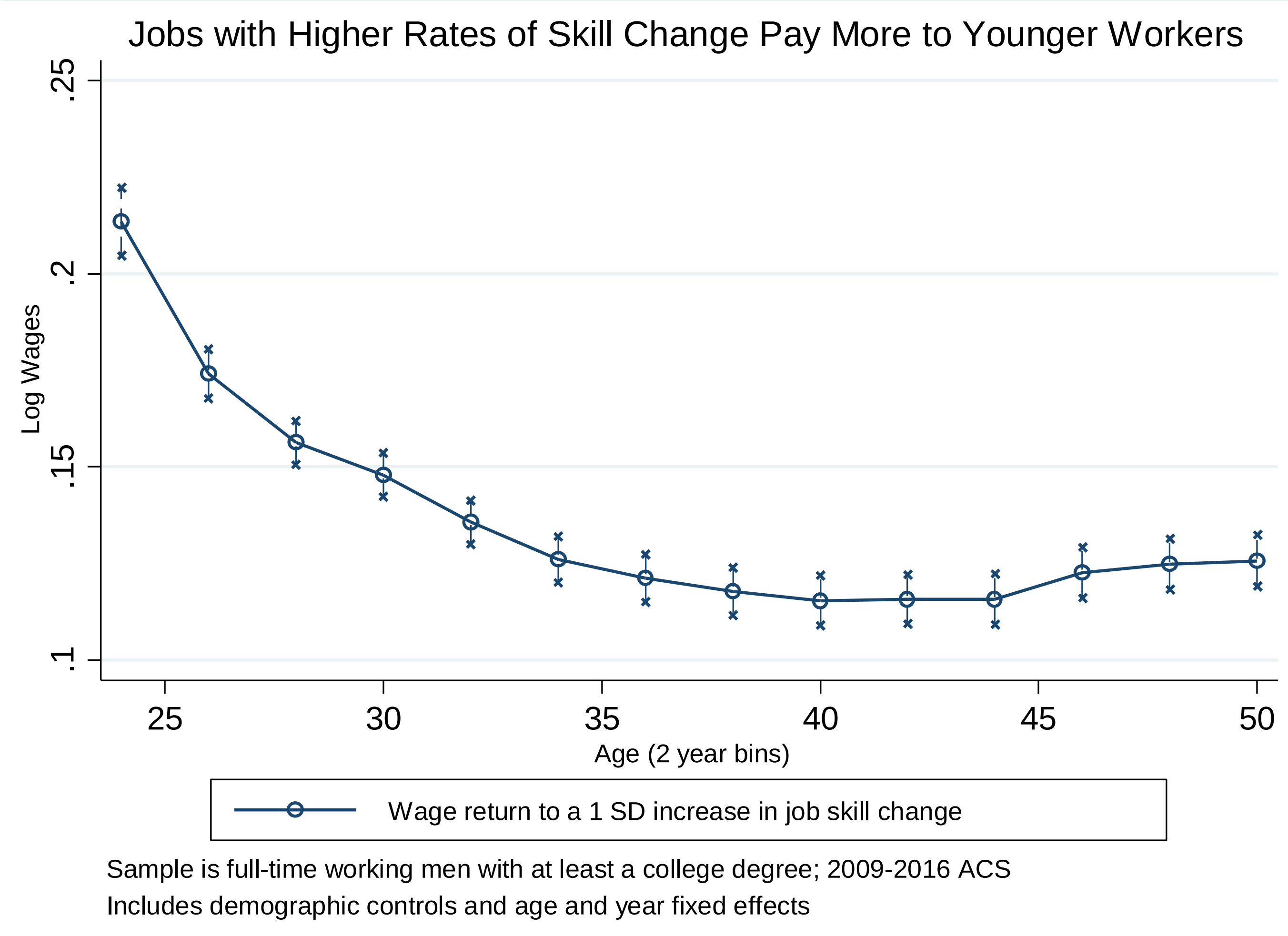
Notes: The figure plots coefficients and 95 percent confidence intervals from an estimate of the returns to majors over time, following equation (10) in the paper, but adding occupation and major interactions. "Applied" Science majors include engineering and computer science.

Figure 7



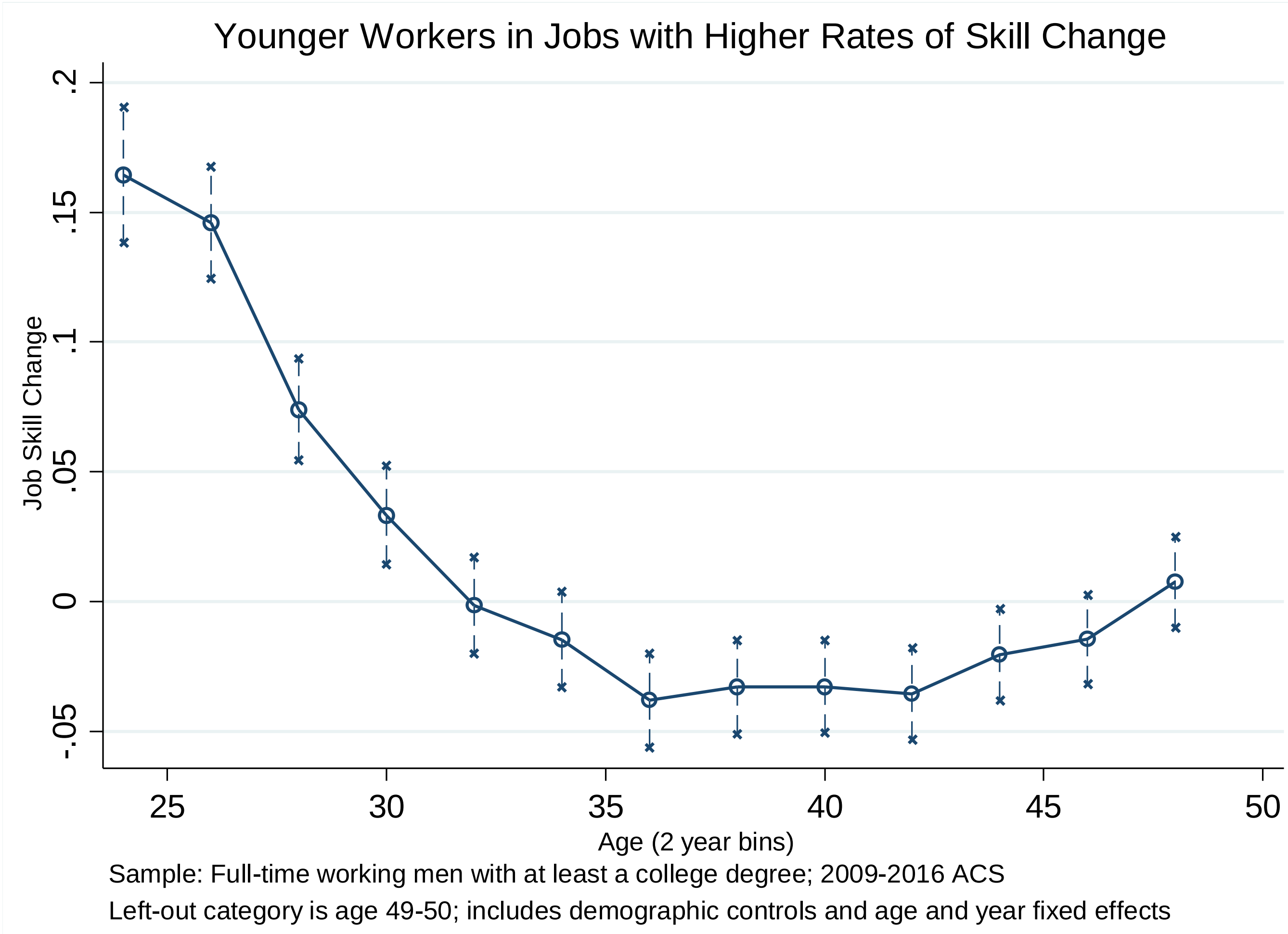
Notes: The figure plots coefficients and 95 percent confidence intervals from two separate estimates of equation (10) in the paper, restricting the sample to Applied Science majors and with indicators for working in STEM and management occupations as the outcome variables. STEM occupations are defined using the 2010 Census Bureau classification.

Figure 8



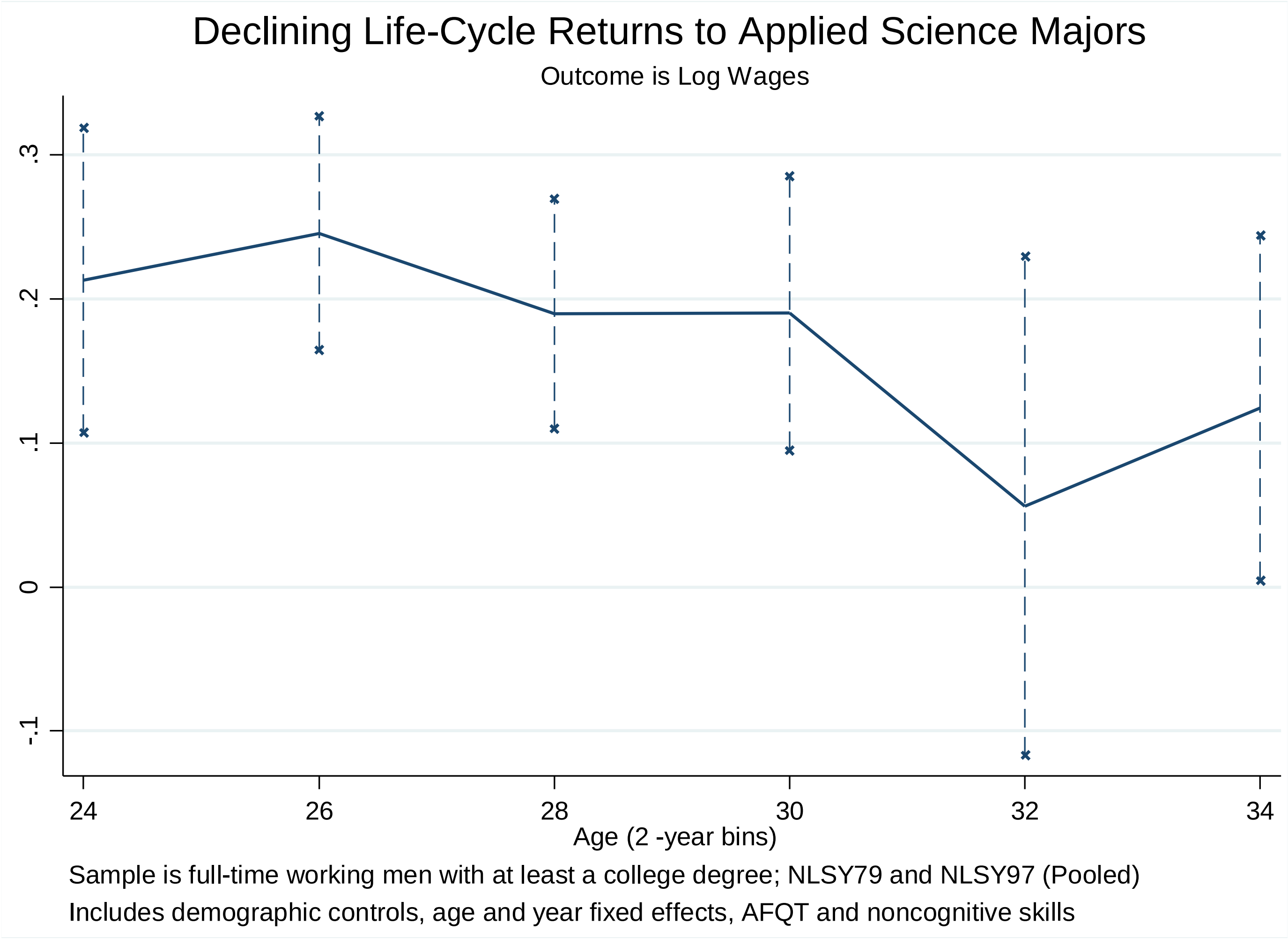
Notes: The figure plots coefficients and 95 percent confidence intervals from an estimate of equation (11) in the paper, a regression of log wages on interactions between two-year age bins and the skill change measure Δ_j that is estimated using 2007-2017 online job vacancy data from Burning Glass Technologies. The standard deviation of Δ_j is 1.14, indicating that jobs with a 1 SD higher skill change pay 24 percent higher wages at ages 23-24 but only 13 percent higher at ages 49-50. STEM occupations are defined using the 2010 Census Bureau classification. See the text for details.

Figure 9



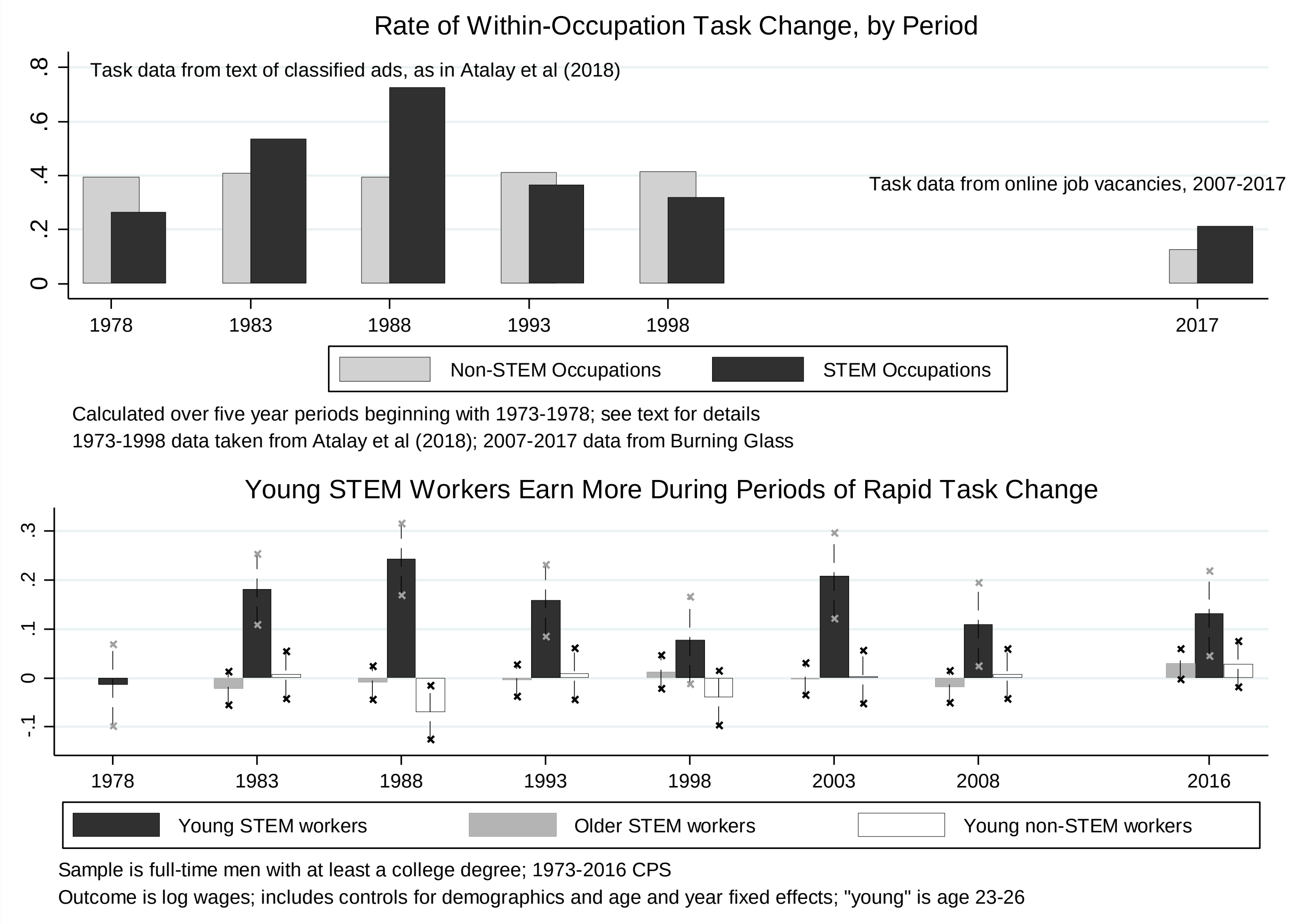
Notes: The figure plots coefficients and 95 percent confidence intervals from an estimate of equation (12) in the paper, a regression of the task change measure Δ_j (which is constructed using 2007-2017 online job vacancy data from Burning Glass Technologies) on occupation by age group interactions. The standard deviation of Δ_j is 1.14, indicating that workers age 23-24 are in jobs that score about 0.2 standard deviations higher on the job skill change measure than workers age 49-50. STEM occupations are defined using the 2010 Census Bureau classification. See the text for details.

Figure 10



Notes: The figure plots coefficients and 95 percent confidence intervals from an estimate of equation (10) in the paper, which regresses log wages on major-by-age group interactions. "Applied" Science includes engineering and computer science majors. The regression is estimated at the person-year level and standard errors are clustered at the individual level. The sample is restricted to ages 23-34 to ensure comparability across NLSY waves.

Figure 11



Notes: Panel A presents estimates of the task change measure Δ_j calculated using data from Atalay et al (2018) on the text of classified job ads between the years of 1977 and 1999. Panel B presents coefficients and 95 percent confidence intervals from a regression of log wages on age (23-26 vs. 27-50) by STEM occupation interactions for successive five year periods that match the job ad data, using the CPS. STEM occupations are defined using the 2010 Census Bureau classification. See the text for details.

Table 1: Skill Requirements by Occupation Category in 2007

Panel A	Social (1)	Cognitive (2)	Character (3)	Creativity (4)	Writing (5)	Management (6)	Finance (7)
Management	0.606	0.421	0.453	0.077	0.172	0.382	0.402
STEM	0.540	0.536	0.345	0.063	0.208	0.170	0.167
Business	0.651	0.551	0.463	0.100	0.182	0.258	0.475
Social Science / Service	0.362	0.356	0.220	0.062	0.158	0.147	0.081
Art/Design/Media	0.585	0.397	0.502	0.256	0.465	0.138	0.160
Health	0.331	0.238	0.190	0.021	0.063	0.136	0.053
Sales and Admin	0.626	0.321	0.423	0.073	0.127	0.180	0.222
Total	0.566	0.458	0.386	0.077	0.177	0.213	0.269

Panel B	Business Systems	Customer Service	Office Software	Technical Support	Data Analysis	Specialized Software	ML and AI
Management	0.243	0.315	0.296	0.115	0.057	0.209	0.005
STEM	0.260	0.207	0.254	0.328	0.092	0.593	0.039
Business	0.272	0.340	0.394	0.123	0.083	0.260	0.006
Social Science / Service	0.045	0.134	0.151	0.053	0.023	0.094	0.003
Art/Design/Media	0.125	0.195	0.337	0.153	0.029	0.396	0.009
Health	0.022	0.392	0.139	0.037	0.026	0.048	0.002
Sales and Admin	0.193	0.763	0.331	0.126	0.040	0.156	0.011
Total	0.218	0.354	0.296	0.177	0.067	0.320	0.017

Notes: Each cell in this table presents the share of postings in an occupation category that requires at least one skill in the categories indicated in each column. The occupations are grouped based on 2010 Standard Occupation Classification (SOC) codes. Data come from online job vacancies collected by Burning Glass Technologies in 2007. See the Data Appendix for detailed descriptions of how each skill category is constructed.

Table 2: Skill Requirements by Occupation Category in 2017

Panel A	Social (1)	Cognitive (2)	Character (3)	Creativity (4)	Writing (5)	Management (6)	Finance (7)
Management	0.715	0.515	0.552	0.117	0.221	0.447	0.461
STEM	0.659	0.644	0.448	0.112	0.252	0.208	0.189
Business	0.766	0.642	0.606	0.147	0.243	0.299	0.487
Social Science / Service	0.516	0.382	0.336	0.096	0.197	0.184	0.080
Art/Design/Media	0.700	0.476	0.610	0.365	0.497	0.162	0.189
Health	0.438	0.299	0.284	0.032	0.070	0.163	0.051
Sales and Admin	0.758	0.444	0.613	0.098	0.173	0.235	0.312
Total	0.661	0.531	0.489	0.114	0.214	0.253	0.278

Panel B	Business Systems	Customer Service	Office Software	Technical Support	Data Analysis	Specialized Software	ML and AI
Management	0.292	0.363	0.370	0.094	0.084	0.253	0.021
STEM	0.304	0.220	0.284	0.329	0.170	0.679	0.180
Business	0.362	0.397	0.488	0.092	0.119	0.351	0.029
Social Science / Service	0.043	0.157	0.190	0.040	0.049	0.110	0.015
Art/Design/Media	0.136	0.195	0.372	0.105	0.055	0.472	0.024
Health	0.031	0.558	0.154	0.028	0.040	0.099	0.005
Sales and Admin	0.274	0.760	0.429	0.076	0.058	0.237	0.016
Total	0.249	0.381	0.335	0.145	0.104	0.367	0.065

Notes: Each cell in this table presents the share of postings in an occupation category that requires at least one skill in the categories indicated in each column. The occupations are grouped based on 2010 Standard Occupation Classification (SOC) codes. Data come from online job vacancies collected by Burning Glass Technologies in 2017. See the Data Appendix for detailed descriptions of how each skill category is constructed.

Table 3: Occupations with the Highest and Lowest Rates of Task Change

Panel A: Fastest-Changing Professional Occupations (3-digit)

SOC code	Occupation Title	Rate of Task Change
172	Engineers	3.53
192	Physical Scientists	3.48
191	Life Scientists	3.25
151	Computer Occupations	3.24
113	Operations Specialties Managers	3.20
152	Mathematical Scientists	3.19
171	Architects and Surveyors	3.13
112	Advertising, Marketing and Sales Managers	3.00
132	Financial Specialists	2.71
173	Drafters and Engineering Technicians	2.61

Panel B: Fastest-Changing Professional Occupations (6-digit)

SOC code	Occupation Title	Rate of Task Change
151131	Computer Programmers	6.69
151133	Software Developers, Systems Software	5.99
172081	Environmental Engineers	5.49
151142	Network / Computer Systems Administrators	4.71
173013	Mechanical Drafters	4.49
172041	Chemical Engineers	4.37
152041	Statisticians	4.29
151141	Database Administrators	3.98
151134	Web Developers	3.96
151152	Computer Network Support Specialists	3.77

Panel C: Slowest-Changing Professional Occupations (3-digit)

SOC code	Occupation Title	Rate of Task Change
252	Pre-K, Primary and Secondary School Teachers	0.74
253	Other Teachers and Instructors	0.79
291	Health Diagnosing and Treating Practitioners	0.86
272	Entertainers and Performers	1.12
259	Other Education, Training and Library Occupations	1.15
292	Health Technologists and Technicians	1.29
251	Postsecondary Teachers	1.36
193	Social Scientists and Related Workers	1.40
211	Counselors and Social Workers	1.51
274	Media / Communications Equipment Workers	1.76

Panel D: Slowest-Changing Professional Occupations (6-digit)

SOC code	Occupation Title	Rate of Task Change
291021	Dentists	0.32
291066	Psychiatrists	0.38
193031	Clinical Psychologists	0.41
291069	Physicians and Surgeons, All Other	0.41
291062	Family and General Practitioners	0.41
291171	Nurse Practitioners	0.44
252059	Special Education Teachers, All Other	0.46
252031	Secondary School Teachers	0.51
292052	Pharmacy Technicians	0.54
272022	Coaches and Scouts	0.63

Notes: This table uses online job vacancy data from Burning Glass Technologies (BG) to calculate the rate of skill change between 2007 and 2017 for each 3- and 6-digit Standard Occupational Classification (SOC) code. The average value of the task change measure is 2.10 - see the text for details. Professional Occupations are SOC codes that begin with a 1 or a 2.

Table 4: Life-Cycle Earnings and Employment for STEM Majors

Age	Non-STEM Major		"Pure" Science		"Applied" Science	
	Wages	Share in STEM Job	Wages	Share in STEM Job	Wages	Share in STEM Job
	(1)	(2)	(3)	(4)	(5)	(6)
23	32,236	0.074	32,840	0.269	47,007	0.616
24	36,632	0.076	35,909	0.286	52,727	0.631
25	43,354	0.076	44,849	0.258	58,188	0.620
26	46,918	0.075	49,472	0.282	61,558	0.616
27	51,722	0.075	53,181	0.247	66,286	0.626
28	54,856	0.074	57,243	0.231	69,590	0.585
29	58,389	0.073	62,651	0.238	73,765	0.584
30	62,787	0.074	69,109	0.224	76,309	0.569
31	67,567	0.074	79,274	0.220	80,546	0.539
32	71,933	0.074	79,894	0.212	83,536	0.536
33	74,608	0.072	91,085	0.211	89,109	0.525
34	79,971	0.069	98,442	0.206	91,542	0.515
35	85,897	0.069	105,914	0.205	98,291	0.482
36	89,875	0.070	111,807	0.198	99,114	0.487
37	93,259	0.073	114,927	0.206	103,804	0.472
38	94,453	0.072	117,943	0.194	108,081	0.463
39	99,481	0.065	121,372	0.189	110,477	0.461
40	99,952	0.069	123,224	0.199	111,678	0.429
41	103,447	0.066	123,281	0.187	113,388	0.425
42	104,068	0.067	122,578	0.199	113,511	0.439
43	106,122	0.068	132,626	0.194	120,005	0.422
44	108,777	0.064	129,115	0.194	122,278	0.419
45	111,802	0.061	136,001	0.204	121,420	0.427
46	111,235	0.062	141,341	0.179	121,746	0.399
47	112,430	0.060	136,539	0.199	125,350	0.418
48	112,002	0.058	136,772	0.206	126,601	0.410
49	112,347	0.059	139,118	0.204	126,111	0.403
50	111,754	0.060	137,439	0.204	126,606	0.399

Notes: This table presents population-weighted average annual wage and salary income and employment shares in Science, Technology, Engineering and Mathematics (STEM) occupations by age, using the 2009-2016 American Community Survey Integrated Public Use Microdata Series (IPUMS, Ruggles et al 2017). The sample is restricted to men with at least a college degree who were employed at the time of the survey and worked at least 40 weeks during the year. Earnings are in constant 2016 dollars. STEM majors are defined following Peri, Shih and Sparber (2015), and STEM jobs are defined using the 2010 Census Bureau classification. "Pure" Science includes biology, chemistry, physics, mathematics and statistics, while "Applied" Science includes engineering and computer science.

Table 5: Labor Market Returns to STEM Majors in the NLSY

Outcome is Log Hourly Wage (2016$)	(1)	(2)	(3)	(4)	(5)	(6)
Applied Science Major	0.179***	0.180***	0.072*	0.034	0.013	0.046
	[0.035]	[0.036]	[0.037]	[0.034]	[0.041]	[0.044]
Pure Science Major	-0.099	-0.103	-0.141*	-0.107*	-0.110	-0.037
	[0.079]	[0.074]	[0.073]	[0.058]	[0.067]	[0.063]
STEM Occupation			0.241***	0.143***	0.119***	
			[0.028]	[0.027]	[0.029]	
Applied Science * STEM Occupation					0.057	
					[0.051]	
Pure Science * STEM Occupation					0.031	
					[0.112]	
Cognitive Skills (AFQT, standardized)		0.129***	0.113***	0.076***	0.076***	0.063
		[0.025]	[0.024]	[0.021]	[0.021]	[0.031]
Social Skills (standardized)		0.042***	0.048***	0.033***	0.033***	0.009
		[0.015]	[0.014]	[0.012]	[0.012]	[0.015]
Noncognitive Skills (standardized)		0.060***	0.058***	0.045***	0.045***	0.041
		[0.016]	[0.016]	[0.013]	[0.013]	[0.016]
Demographics and Age/Year FE	X	X	X	X	X	X
Industry Fixed Effects				X	X	
Occupation-by-Industry Fixed Effects						X
R-squared	0.225	0.244	0.259	0.397	0.397	0.649
Number of Observations	8,634	8,634	8,634	8,634	8,634	8,634

Notes: Each column reports results from a regression of real log hourly wages on indicators for college major, occupation and/or industry (in columns 3 through 5), individual skills, indicator variables for race and years of completed education, age and year fixed effects, and additional controls as indicated. The data source is the National Longitudinal Survey of Youth (NLSY) 1979 and 1997, and the sample is restricted to men with at least a college degree. The waves are pooled and an indicator for sample wave is included in the regression. Science, Technology, Engineering and Mathematics (STEM) occupations are defined using the 2010 Census Bureau classification. "Pure" Science majors include biology, chemistry, physics, mathematics and statistics, while "Applied" Science includes engineering and computer science. Cognitive skills are measured by each respondent's score on the Armed Forces Qualifying Test (AFQT). We normalize scores across NLSY waves using the crosswalk developed by Altonji, Bharadwaj and Lange (2012). Social and noncognitive skill definitions are taken from Deming (2017). All skill measures are normalized to have a mean of zero and a standard deviation of one. Person-year is the unit of observation, and all standard errors are clustered at the person level. The sample is restricted to ages 23-34 to maximize comparability across survey waves. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table 6: STEM Majors, Relative Wages and Ability Sorting in the NLSY

	In a STEM Job	Ln (Wages)	
	(1)	(2)	(3)
STEM Major	0.352***	0.116***	0.005
	[0.035]	[0.034]	[0.120]
AFQT (Standardized)	0.084***	0.063*	0.017
	[0.016]	[0.033]	[0.032]
Age (Linear)	0.002	0.013	0.007
	[0.005]	[0.008]	[0.009]
Age * AFQT	-0.005**	0.013***	0.024***
	[0.002]	[0.005]	[0.005]
Age * STEM Major			0.027*
			[0.014]
STEM Major * AFQT			0.187*
			[0.097]
STEM Major * AFQT * Age			-0.041***
			[0.013]
R-squared	0.183	0.237	0.242
Number of Observations	11,214	8,685	8,685

Notes: Each column reports results from a regression of indicators for working in a STEM occupation (Column 1) or real log hourly wages (Columns 2 and 3) on indicators for majoring in a Science, Technology, Engineering and Mathematics (STEM) field, cognitive, social and noncognitive skills, indicator variables for race and years of completed education, year fixed effects, and additional controls as indicated. The data source is the National Longitudinal Survey of Youth (NLSY) 1979 and 1997, and the sample is restricted to men with at least a college degree. The waves are pooled and an indicator for sample wave is included in the regression. STEM majors are defined following Peri, Shih and Sparber (2015), and STEM occupations are defined using the 2010 Census Bureau classification. Cognitive skills are measured by each respondent's score on the Armed Forces Qualifying Test (AFQT). We normalize scores across NLSY waves using the crosswalk developed by Altonji, Bharadwaj and Lange (2012). Social and noncognitive skill definitions are taken from Deming (2017). All skill measures are normalized to have a mean of zero and a standard deviation of one. Person-year is the unit of observation, and all standard errors are clustered at the person level. The sample is restricted to ages 23-34 to maximize comparability across survey waves. *** p<0.01, ** p<0.05, * p<0.10.