

Earnings Dynamics, Changing Job Skills, and STEM Careers

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Abstract

This paper studies the impact of changing job skills on career earnings dynamics for college graduates. We measure changes in the skill content of occupations between 2007 and 2019 using detailed job descriptions from a near-universe of online job postings. We then develop a simple model where the returns to work experience are a race between on-the-job learning and skill obsolescence. Obsolescence lowers the return to experience, flattening the age-earnings profile in faster-changing careers. We show that the earnings premium for college graduates majoring in technology-intensive subjects such as Computer Science, Engineering and Business declines rapidly, and that these graduates sort out of faster-changing occupations as they gain experience.

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1 Introduction

A vast body of work in economics finds that technological change increases relative demand for educated workers, which leads to rising wage inequality when the supply of skills grows more slowly (e.g. [Katz and Murphy 1992](#), [Berman et al. 1994](#), [Autor et al. 2003](#), [Acemoglu and Autor 2011](#)). This race between education and technology (RBET) framework does a good job of explaining changes in the economic return to different levels of education in the U.S. over the last century ([Goldin and Katz 2008](#), [Autor et al. 2020](#)).¹ Yet the RBET literature typically abstracts away from heterogeneity in the curricular content of college majors and in returns to field of study.² There is little direct evidence linking changes in skill demands to the specific human capital learned in school, and the *process* of skill-biased technological change remains mostly a “black box”.

In this paper, we study the impact of changing job skills on the labor market returns to field of study over a worker’s career.³ Using online job vacancy data collected between 2007 and 2019 by the employment analytics firm Burning Glass Technologies (BG), we show that many job ads in 2019 required skills that did not exist or were highly infrequent in 2007. Similarly, some skills required in 2007 became obsolete by 2019. How do new job skill requirements affect earnings for workers who learned older skills in school?

We construct a new measure of job skill change using the BG data. Science, Technology, Engineering and Math (STEM) occupations have the highest rates of change, followed by some technology-intensive business occupations in fields such as Advertising, Market Research and Logistics. We then combine our occupation-level measure with the actual jobs held by early-career college graduates to construct a *college major-specific* measure of job skill change. College grad-

¹[Acemoglu and Autor \(2011\)](#) extend the RBET framework to accommodate non-neutral technological progress, such as technology leading to polarization and declining relative demand for middle-skilled workers.

²There is 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 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](#)).

³[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.

uates majoring in applied subjects such as Computer Science, Engineering and Business work in occupations with much faster rates of job skill change than graduates majoring in broader fields like Biology, Economics, Political Science and History.

We develop a simple model that explores the implications of job skill change for returns to field of study and work experience over time. In our model, careers vary in the rate at which new job tasks replace old job tasks. Workers learn career-specific skills in school but can also learn on-the-job, and experience performing a particular task increases productivity in that task. Workers have higher productivity in older-vintage tasks, but must learn new tasks from scratch. Rapidly changing careers require workers to learn many new tasks each year. This diminishes the gains from learning and lowers the return to experience. The result is a flatter age-earnings profile and a relatively high exit rate of college graduates from fast-changing careers.

We test the model's predictions using data from the 2009-2017 American Community Survey (ACS). College graduates in all fields experience rapid earnings growth. Yet the relative earnings advantage for graduates majoring in applied subjects such as Computer Science, Engineering and Business is highest at labor market entry and declines rapidly over time. Flatter wage growth for technology-intensive majors coincides with their faster exit from career-specific occupations. This basic pattern holds in multiple data sources and subsamples, and is robust to controlling for academic ability and to different assumptions about dynamic selection into full-time work and graduate school.

We also find that STEM majors with higher scores on the Armed Forces Qualifying Test (AFQT) - a widely used proxy for academic aptitude - leave STEM careers more often and at younger ages. 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 5 percentage points more likely to work in STEM at age 24, but no more likely to work in STEM by 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 skill change using a historical dataset of classified job ads assembled by [Atalay et al. \(2018\)](#). The computer and IT revolution of the 1980s coincided with higher rates of technological change in STEM jobs, and young STEM workers were also paid relatively high wages during this same period. This matches the pattern of evidence for the 2007–2019 period and confirms that the relationship between job skill change and age-earnings profiles is not specific to the most recent decade.

This paper makes three main contributions. First, we present new evidence on declining life-cycle returns to career-oriented fields of study, and we connect this descriptive pattern to the novel mechanism of job skill change.⁴ Applied majors such as computer science, engineering and business teach vintage-specific skills that become less valuable as new skills are introduced to the workplace over time.⁵

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 them indirectly from changes in relative wages and skill supplies ([Card and DiNardo 2002](#)).⁶

Third, our results provide an empirical foundation for work on vintage capital and technology

⁴[Weiss and Lillard \(1978\)](#) and [Lillard and Weiss \(1979\)](#) compare scientists with similar levels of work experience and find greater earnings growth for graduates of a more recent vintage.

⁵Most 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.

⁶Our 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 ([Stephan 1996](#), [Moretti 2012](#)).

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 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.

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 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 certain fields of study in U.S. four-year colleges. Four-year degrees in applied subjects provide high-skilled vocational education, which pays off in the short-run because it is at the technological frontier. However, technological progress erodes the value of

⁷In [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. In [Gould et al. \(2001\)](#), workers make precautionary investments in general education to insure against obsolescence of technology-specific skills.

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.

⁹Similarly, [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.

these skills over time. Thus the long-run payoff to career-oriented majors is still high, but smaller than short-run comparisons suggest.

The remainder of the paper proceeds as follows. Section 2 describes the data. Section 3 documents changes in job skill requirements and introduces our measurement approach. Section 4 presents a simple model and a set of empirical predictions. Section 5 presents the main results. Section 6 studies job task change in earlier periods. Section 7 concludes.

2 Data

2.1 Job Vacancies

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 translates key words and phrases from job ads 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 2007–2019 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.

Following [Hershbein and Kahn \(2018\)](#) we exclude vacancies with missing employers. This leaves us with a total sample of 22,683,822 vacancies in the years 2007 and 2019 combined. About

80 percent come from 2019, due to the overall increase in online job posting, as well as a higher share of vacancies with non-missing employers and education requirements. There are 15,003 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.

Appendix Tables A1 and A2 show baseline rates of job skill requirements in 2007 and 2019, by broad occupation groups.¹⁰ 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). 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. Sales and Administrative support occupations are more likely to require customer service. STEM jobs are much more likely than other categories to require technical skills such as data analysis, machine learning and artificial intelligence, as well as specific software such as Python or AutoCAD.

2.2 Employment and Earnings

Our main data source for employment and earnings is the 2009–2017 American Community Surveys (ACS), extracted from the Integrated Public Use Microdata Series (IPUMS) 1 percent samples ([Ruggles et al. 2017](#)). We classify occupations according to the Standard Occupational Classification (SOC) system, and use the 2010 Census Bureau definition of STEM occupations.

We also use data from the 1993–2017 waves of the National Survey of College Graduates (NSCG) and the 1971-2019 Annual Social and Economic Supplement (ASEC) of the Current

¹⁰Comparing Table A1 to Table A2 shows how job skill requirements have changed over a ten year period. There are especially large increases in the share of vacancies requiring machine learning and artificial intelligence. 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 20.4 percent in 2019, consistent with the rapid diffusion of automation technologies documented by [Brynjolfsson et al. \(2018\)](#).

Population Survey (CPS). The NSCG is a stratified random sample of college graduates which employs the decennial Census as an initial frame, while oversampling individuals in STEM majors and occupations. The CPS covers the longest time period but does not collect data on college major.

Finally, we include data from the 1979 and 1997 waves of the National Longitudinal Survey of Youth (NLSY), two nationally representative 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.

Our main outcome in each data source is the natural log of inflation-adjusted annual wage and salary income, although our results are not sensitive to alternative approaches such as using data on hours worked to compute wage rates. 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](#)).¹¹ We follow the major classification scheme for the NLSY used by [Altonji, Kahn and Speer \(2016\)](#), and we generate consistent occupation codes across NLSY waves using the Census occupation crosswalks developed by [Autor and Dorn \(2013\)](#). Due to the lack of consistent coding of occupations in the NLSY across waves, we are unable to measure skill change for detailed occupation codes with the same precision as in the ACS.

¹¹[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 idiosyncrasies. We take the raw scores from [Altonji, Bharadwaj and Lange \(2012\)](#) and normalize them to have mean zero and standard deviation one.

3 The Changing Skill Requirements of Work

3.1 Descriptive Patterns of Job Change, 2007–2019

Vacancy data are ideal for measuring the changing skill requirements of jobs. Vacancies directly measure employer demand for specific skills, and vacancy data are sufficiently detailed to measure 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 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.

One natural way to measure job skill change is to study the appearance of new skills and the disappearance of old skills over time. We define old skills as those with at least 1,000 appearances in 2007 and that either no longer exist or are one fifth as frequent in 2019. Similarly, we define new skills as those with at least 1,000 appearances in 2019, and that either did not exist in 2007 or were 20 times more frequent in 2019 compared to 2007. These thresholds are arbitrary, but the results are not sensitive to different choices.

Figure 1 shows the change in the share of job ads that requested old skills and new skills in 2019, by two digit SOC codes.¹² To account for changes over time in the sample of jobs and firms that post vacancies online, we estimate vacancy-level regressions of the frequency of each skill category on an indicator for the 2007 or 2019 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.

There are three main lessons from Figure 1. First, the overall rate of skill turnover is high.

¹²To conserve space, we group SOC codes 21 and 23 together as “Legal, Community and Social Service”, codes 31 through 39 together as “Health, Protective and Personal Services”, codes 41 and 43 as “Sales and Administrative Support” and codes 47 to 53 as “Construction, Production, Transportation”.

Among vacancies posted by the same firm for the same 6 digit occupation, about 29 percent contained at least one new skill requirement in 2019.

Second, occupations vary systematically in the amount of skill turnover. 47 percent of Computer and Mathematical jobs required at least one new skill in 2019, compared to less than 20 percent for jobs in fields such as Education, Law, and Community and Social Services. Other job categories with high rates of skill change include Design/Media, Business, and Management. Third, jobs with high share of new skills also experience faster skill obsolescence. About 16 percent of Computer and Mathematical job vacancies in 2007 listed a skill that had become obsolete by 2019. Design/Media and Business also have relatively high rates of skill obsolescence, and Education and Healthcare the lowest.

Software-intensive jobs have the highest rates of skill turnover, and indeed about a third of the overall changes shown in Figure 1 are driven by changes in requirements for specific software.¹³ 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. The fastest-growing software skills between 2007 and 2019 include Python, R, Apache Hadoop, Scrum and Revit. Software that was relatively common in 2007 but obsolete by 2019 includes QwarkXpress, Adobe Flash, ActionScript, Solaris and IBM Websphere.¹⁴

Another important contributor to job change is skills that are not specific software but are clearly related to technological change. For Business and Management occupations, the non-software skills that are growing most rapidly include Digital Marketing, Social Media and Software

¹³[Dillender and Forsythe \(2019\)](#) show that when firms adopt new software requirements in online job vacancies for office and administrative support occupations, they also increase education and skill requirements. 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.

¹⁴[Horton et al. \(2019\)](#) study the impact of Apple's announcement that they would no longer support Adobe Flash, and find that demand for the skill died quickly but that programmer wages did not suffer because they quickly picked up other technical skills.

as a Service (SaaS). For technology-intensive jobs, we see rapid increases in skills such as Data Science, Machine Learning, Artificial Intelligence and DevOps. In healthcare, Electronic Medical Records and ICD-10 (a classification system for medical billing that changed in 2015) are important contributors, and Point of Sale System for sales jobs. Likewise, the obsolete non-software skills include job functions that are being replaced by technology, such as Print Advertising, Category Management (a concept in retail sales that aligns product categories between retailers and suppliers), Technical Translation and Analog Design.

3.2 Measuring Changes in the Skill Content of Jobs

We next construct a formal measure of changes in the skill content of jobs between 2007 and 2019. 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 2019 or that existed in 2007 but then disappeared altogether. 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

$$SkillChange_o = \sum_{s=1}^S \left\{ Abs \left[\left(\frac{Skill_o^s}{JobAds_o} \right)_{2019} - \left(\frac{Skill_o^s}{JobAds_o} \right)_{2007} \right] \right\} \quad (1)$$

Conceptually, equation (1) measures the amount of net skill change in an occupation.

Table 1 presents the 3 digit (SOC) occupation codes with the highest and lowest measures of $SkillChange_o$. Appendix Table A3 presents the same results, but for all 3-digit SOC codes. Appendix Table A4 shows results for 6-digit SOC codes. We restrict the sample to 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 3.01, and the standard deviation for 6 (3)

¹⁵To 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 2019, 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.

digit occupations is 1.03 (0.93).

The jobs with the highest rates of skill change include Computer Occupations, Engineers, Scientists and Science Technicians, Business and Financial Specialists, and Managers in technology-intensive fields such as Advertising, Marketing and Operations. The jobs with the least amount of skill change include drivers, teachers, and food preparation and personal service workers.

The professional, high-skilled jobs with the lowest rates of change are almost entirely in education and healthcare. 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. Our approach may understate job change in these cases. However, the main results are robust to excluding education and healthcare jobs entirely.

Table 1 suggests that workers in technology-intensive fields 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. The occupation-level correlation between the two measures is 0.94.

Second, we directly study changes in job skill requirements by work experience. Figure 2 presents results from a regression of new skills (defined as in Section 3.1 above) on years of experience required, controlling for education requirements, the number of skills in each posting (since ads for more experienced workers might be longer and more complex), and firm-occupation-MSA fixed effects. This shows how job skill requirements change with work experience, across vacancies listed by the same firm in the same labor market. We compare Computer, Mathematical, Engineering and Architecture jobs to all other occupations.

As in Figure 1, technology-intensive jobs are more likely than others to require new skills. However, the pattern by experience requirements is quite different. The share of technology-

intensive jobs requiring new skills is roughly constant at around 41 percent, for entry level jobs as well as jobs requiring 12 or more years of experience. This means that experienced STEM workers seeking employment in 2019 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 jobs requiring new skills declines from 29 percent for entry level jobs to 24 percent for jobs that require 4 or more years of experience.

3.3 College Majors and Career Paths

Job skills change much faster in technology-intensive careers. What is the role of education in teaching new, highly-demanded skills? We study career choices using data from the ACS, which has collected information on the major field of study for bachelor's degree recipients since 2009. Figure 3 presents information on the early-career occupations of college graduates by major. We restrict the sample to full-time workers between the ages of 23 and 26 with non-missing occupations.

Panel A shows the distribution of occupations for Computer Science majors. 58 percent of them work in a computer-related occupation, compared to only 3 percent for the second and third most common jobs (Business Operations Specialists and Other Management Occupations). This suggests that Computer Science majors learn specific skills in school that are relevant in computer-related jobs. Panel B shows similar results for Engineering majors. 42 percent of them work in Engineering jobs, and another 13 percent in Computer occupations. In contrast, Life Sciences and Social Sciences majors (Panel C and D respectively) go into a broad range of jobs, with no single 3 digit occupation code accounting for more than 10 percent of graduates in either case. Appendix Figure A1 shows results for other major categories. Business and Education majors are concentrated in a small number of occupations, whereas other majors such as Psychology and Humanities are dispersed across a wide range of jobs.

Figure 3 shows that college majors vary in their specificity, with some offering narrow preparation for a few careers and some being much broader. We can combine this information on career

paths with our measure $SkillChange_o$ in equation (1) to compute a data-driven measure of expected job skill change by college major. As above, we restrict the ACS sample to full-time workers ages 23-26 with non-missing occupations, and then construct a weighted average of $SkillChange_o$ by college major (which we call $\overline{SkillChange_o^M}$), based on the actual jobs held by early career graduates.

The results from this calculation are in Table 2. For ease of presentation we restrict the sample to majors with at least 1,000 respondents. The two majors with the fastest rate of skill change are Computer Science and Engineering, followed by Business, Communications and Architecture. Figure 3 shows that students who major in these subjects go into a narrow range of technology-intensive careers with high rates of change (as shown in Table 1). At the same time, less than 50 percent of Engineering majors work in Engineering occupations. This follows other recent evidence showing that STEM graduates work in a wide range of different occupations and careers ([National Academies of Engineering 2019](#)).

In contrast, while Life Scientist itself is a fast-changing career, only a small number of Life Science majors actually become scientists, leading to a major ranking around the sample average. This is also true of majors such as social science, history and psychology, where students pursue a broad range of careers. Education majors rank at the bottom, because most education majors become teachers and teaching is a slowly changing career.

The patterns of career choice by college major suggest that some college graduates - particularly Computer Science and Engineering majors - learn specific skills that are in high demand but also changing rapidly over time. In the next section we present a conceptual model that explores the implications of job skill change for life-cycle earnings and career trajectories.

4 Model

Consider a perfectly competitive labor market with many careers j (we can think of these as industry-occupation pairs, following [Neal \(1999\)](#) and [Pavan \(2011\)](#)). Each career contains a large

number of identical profit-maximizing firms which produce a single final good Y_{jt} in each year by aggregating output over many tasks. Labor is the only factor of production. Workers are paid their marginal product and supply one unit of labor in each year t to a career j in order to maximize earnings.

Two features distinguish our framework from a standard approach. First, worker productivity is determined by a *learning function* over job tasks. Workers choose a field of study, which corresponds to a unique career j . Workers then choose a sequence of careers j^* over their lifetime to maximize lifetime earnings. Workers learn some job tasks for career j^* in school, but they also learn on-the-job.

Second, the production function for career j varies by year according to an *obsolescence parameter*, which we call Δ_j . We can think of $\Delta_j \in [0, 1]$ as the share of job tasks in career j that are new in each year.

We can express a worker's year t earnings in their chosen career j^* as the product of gains from learning and losses from obsolescence:

$$w_{j^*} \left[\underbrace{\left(H_{j^*} + (t-1)a \right)}_{\text{Learning}} \underbrace{\left((1 - \Delta_{j^*})^{t-1} \right)}_{\text{Obsolescence}} \right] \quad (2)$$

Each career pays an exogenous time-invariant wage w_j , which may reflect differences in product market demand or other factors. H_{j^*} is the stock of human capital that each worker initially learns in school, so the first period wage is just $w_{j^*} H_{j^*}$. Workers become more productive in year $t+1$, and their productivity gain is increasing in ability a . For simplicity, we assume that ability is linear in t , although our results generalize to a broader class of functions where ability augments learning.

All of our key empirical predictions can be illustrated with a two-period, two-career model where initial human capital is exogenous, so we focus on that simple case here. The Model Appendix develops the N career, T period case and endogenous sorting into college majors.

In the two-period, two-career case we can write the worker's maximization problem as:

$$\max_{j^1, j^2} w_{j^1} H_{j^1} + w_{j^2} (H_{j^2} + a)(1 - \Delta_{j^2})$$

where j^t represents an individual's career choice in period t .¹⁶ Workers are exogenously assigned an initial vector of human capital $\vec{H} = (H_1, H_2)$. Let j^{1*} and j^{2*} represent the optimal career choice in period 1 and 2, which gives us the following career "demand" functions:

$$j^{1*} = \begin{cases} 1 & \text{if } H_1 w_1 > H_2 w_2 \\ 2 & \text{if } H_1 w_1 \leq H_2 w_2 \end{cases},$$

$$j^{2*} = \begin{cases} 1 & \text{if } w_1(H_1 + a)(1 - \Delta_1) > w_2(H_2 + a)(1 - \Delta_2) \\ 2 & \text{if } w_1(H_1 + a)(1 - \Delta_1) \leq w_2(H_2 + a)(1 - \Delta_2) \end{cases}.$$

Our first prediction is that *wage growth is lower in careers with higher rates of skill change* Δ_j . To see this, define the ratio of second period earnings between two careers as $\frac{w_1(H_1 + a)(1 - \Delta_1)}{w_2(H_2 + a)(1 - \Delta_2)}$. The derivative of this expression with respect to the ratio of skill change between careers $\frac{\Delta_1}{\Delta_2}$ is:

$$\frac{d \frac{w_1(H_1 + a)(1 - \Delta_1)}{w_2(H_2 + a)(1 - \Delta_2)}}{d \frac{\Delta_1}{\Delta_2}} = - \frac{w_1(H_1 + a)}{w_2(H_2 + a)} < 0 \quad (3)$$

Equation (3) shows that the earnings gain from working in career 1 relative to career 2 is decreasing in the relative rate of skill change between careers $\frac{\Delta_1}{\Delta_2}$.¹⁷ Intuitively, careers with high rates of obsolescence require workers to learn many new tasks each year, which diminishes learning gains and lowers the returns to experience. We measure Δ_j empirically using *SkillChange_o* from equation (1) above.

Slower wage growth in higher Δ_j careers suggests that some workers might switch careers

¹⁶We implicitly assume that on-the-job learning is perfectly transferable. This is purely for convenience, and all of our key predictions are robust to assuming partial transferability of learning across careers.

¹⁷Another way to see this is by differentiating the period 2 earnings equation with respect to Δ_j , which yields $\frac{dw_{j^2}(H_{j^2} + a)(1 - \Delta_{j^2})}{d\Delta_j} = -w_{j^2}(H_{j^2} + a) < 0$.

between periods 1 and 2. Formally, switching from career 1 to career 2 between periods 1 and 2 will happen when $w_1 H_1 > w_2 H_2$ but $[w_1(H_1 + a)(1 - \Delta_1)] < [w_2(H_2 + a)(1 - \Delta_2)]$.

Thus our second prediction is that *some workers will switch from fast-changing to slow-changing careers, and switchers are positively selected on ability*. To see this, let $H_1 = H_2 = \bar{H}$, so that workers have the same human capital in each career. In this case, switching from 1 to 2 will occur when $w_1 > w_2$ and $[w_1(\bar{H} + a)(1 - \Delta_1)] < [w_2(\bar{H} + a)(1 - \Delta_2)]$. Rearranging terms, we can combine these inequalities into a single expression:

$$\frac{1 - \Delta_2}{1 - \Delta_1} > \frac{w_1}{w_2} > 1 \quad (4)$$

Equation (4) shows that a worker with equal endowments of initial human capital will switch from career 1 to career 2 in period 2 *if and only if* career 1 has both a higher rate of skill change Δ_j and a higher first period wage offer. The difference in the rate of skill change between careers 1 and 2 also needs to be large enough to offset exogenous wage differences across fields.¹⁸

While we do not explicitly model preferences, heterogeneity in preferences for non-wage amenities across fields would cause some workers to switch into a different career despite receiving a lower wage offer. More generally, endogenous sorting means that observed wage differences across fields will be smaller than the true difference in skills. Thus sorting across careers will tend to compress measured wage differences.

To see why switchers are positively selected on ability, note that:

$$\lim_{a \rightarrow 0} \frac{w_1(H_1 + a)(1 - \Delta_1)}{w_2(H_2 + a)(1 - \Delta_2)} = \frac{w_1 H_1 (1 - \Delta_1)}{w_2 H_2 (1 - \Delta_2)} \quad (5)$$

$$\lim_{a \rightarrow \infty} \frac{(H_1 + a)(1 - \Delta_1)}{(H_2 + a)(1 - \Delta_2)} = \frac{(1 - \Delta_1)}{(1 - \Delta_2)} \quad (6)$$

Equation (5) and (6) show that wages and initial human capital become a less important deter-

¹⁸This result easily generalizes to cases where $H_1 > H_2$. The necessary inequalities instead become $\frac{w_1 H_1}{w_2 H_2} > 1$ and $\frac{1 - \Delta_2}{1 - \Delta_1} > \frac{w_1(H_1 + a)}{w_2(H_2 + a)}$. In this case, switching from career 1 to career 2 requires Δ_1 to be greater than Δ_2 by enough to offset any initial wage or human capital advantage for $w_1 H_1$ relative to $w_2 H_2$.

minant of career switching as ability increases. In the limit, very high ability workers will always switch from a fast-changing career with higher initial wages to a slow changing career with lower initial wages, regardless of their human capital endowments.¹⁹

In the model, high ability workers are faster learners in all fields. However, the relative return to ability is actually *lower* in faster-changing careers, because learning gains do not accumulate. Thus, among workers initially in fast-changing careers, those with higher ability will be more likely to switch into slower-changing careers.²⁰ We test this prediction empirically using longitudinal data from the NLSY and direct measures of worker ability.

Our stylized model highlights the importance of skill obsolescence for earnings dynamics, but does not consider other determinants of wage growth across careers such as heterogeneous career ladders across occupations or differences in training opportunities across fields. These factors surely also contribute to some of the patterns we document below.

5 Results

5.1 Earnings Growth in Rapidly Changing Careers

The first prediction of our framework is that wage growth will be relatively slower in careers with higher rates of job skill change. We test this prediction in the ACS data by estimating:

$$\ln(earn)_{it} = \alpha_{it} + \sum_a^A \beta_a a_{it} + \sum_a^A \gamma_a \left(a_{it} * \overline{SkillChange_O^M} \right) + \delta X_{it} + \theta_t + \epsilon_{it} \quad (7)$$

where $\overline{SkillChange_O^M}$ is taken directly from Table 2, and is the weighted average value of

¹⁹Another way to see this is to differentiate the period 2 earnings equation by Δ_j and a , which yields $\frac{d^2 w_{j2} (H_{j2} + a)(1 - \Delta_{j2})}{d\Delta_j da} = -w_{j2} < 0$.

²⁰The model does not take a stand on differences in the initial wage premium across careers. Some careers might pay higher wages to new graduates because they are in industries with high labor demand, which would lead to endogenous sorting of high-ability workers into these careers. 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](#)). The Model Appendix explicitly works through the case of ability selection into majoring in STEM.

$SkillChange_o$ in the occupations held by early career college graduates in each major field of study. 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.

The γ coefficients can be interpreted as the wage premium to working in a faster-changing occupation at any given age. The X vector includes controls for sex-by-age indicators, race and ethnicity, citizenship, veteran status and an indicator for having any graduate school education. θ_t represents year fixed effects, and ϵ_{it} is an error term.

Our main analysis sample includes all four-year college graduates between the ages 23 to 50 in the ACS and CPS, and ages 25–50 in the NSCG who are not living in group quarters and not currently enrolled in school.²¹

Figure 4 presents estimates of the γ coefficients by age and the associated 95 percent confidence intervals. Standard errors are clustered at the major-by-age level. The solid line shows results for the full sample. We find a gradual decline in the returns to majoring in a fast-changing subject. A major with a one standard deviation higher rate of skill-change pays 30 percent more at age 24, compared to 20 percent more at age 50. A one standard deviation difference in $\overline{SkillChange}_O^M$ is approximately equal to the difference between Computer Science and Engineering majors and more general majors such as Biology, History and English.

The dashed line in Figure 4 shows a much steeper life-cycle pattern when we exclude education majors. In this case, the returns to majoring in a faster-changing field decline from 52 percent at age 24 to 16 percent at age 50. While education majors constitute only 9 percent of our analysis sample, excluding them changes the results markedly for two reasons. First, teaching is by far the slowest-changing occupation in which most workers are college graduates (see Appendix Table A3 for details), and nearly two-thirds of Education majors become teachers. Second, age-earnings profiles for public school teachers are based on set salary scales rather than market forces, obscuring the economic impact of any true skill obsolescence for older workers.

Our results are robust to excluding outliers in both directions. The dotted line in Figure 4

²¹Results that include older workers are very similar. The sample design of the NSCG resulted in very few college graduates age 23–24, so we exclude this small group from our analysis.

shows that excluding all of the most “vocational” majors - engineering, computer science, health and education - leads to a very similar set of results when only education is excluded. Additionally, we find very similar results to the dashed and dotted lines when we restrict the sample to men only, who comprise only about 20 percent of education majors.

We can also study life-cycle earnings patterns directly by estimating returns to college major at different ages. We do this by estimating regressions of the general form:

$$\ln(earn)_{it} = \alpha_{it} + \sum_a^A \beta_a a_{it} + \sum_a^A \gamma_a (a_{it} * MAJOR_{it}) + \zeta X_{it} + \theta_t + \epsilon_{it} \quad (8)$$

with the same sample, controls and confidence intervals as above. Figure 5 shows results for four different types of college majors - 1) Computer Science and Engineering (combined); 2) Business; 3) Life and Physical Sciences; and 4) Social Sciences.²² Relative to all other major groups (including education), computer science and engineering majors earn about 45 percent more early in their career, but only 33 percent more by age 50. The earnings advantage for business majors declines from around 38 percent initially to 20 percent by age 50. In contrast, the earnings premium grows over time for life and physical sciences and social sciences majors.²³

This basic pattern of an initial earnings advantage but slower growth for fast-changing majors is robust to a variety of different specifications, samples and data sources.²⁴ Appendix Figure A3 presents similar results using the NSCG, which covers the 1993-2017 period.

²²Computer Science also includes Information Sciences. Engineering includes all sub-branches of engineering (Civil, Electrical, Mechanical, Chemical etc.). Business includes Accounting, Management, Finance, Marketing, Human Resources, Hospitality Management and others. Life Sciences is mostly Biology, but also includes Environmental Science, Zoology, Neuroscience and others. Physical Sciences includes Chemistry, Physics, Geology and similar subjects. Social Science includes Economics, Political Science, Sociology, International Relations, Geography and other similar majors.

²³The rapid growth in life-cycle earnings for life and physical sciences majors is partly due to their very high rate of graduate school attendance. When restricting the ACS sample to respondents with exactly a BA, we find similar results for the other three major groups (all of whom have similar rates of graduate school attendance) but slower growth for life and physical sciences majors.

²⁴Hunt (2015) finds a wage penalty for immigrants relative to natives within engineering that is linked to English 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. Appendix Figure A2 shows that our results are very similar when we exclude immigrants, or immigrants who came to the U.S. after age 18. Additionally, we find that the share of college graduates in different fields of study has not changed very much over the cohorts we study in the ACS.

Appendix Table A5 presents population-weighted mean earnings by college major and age in levels, using the ACS. In levels, earnings growth is rapid for all college graduates, regardless of major. However, while computer science, engineering and business majors are earning substantially more in their mid-twenties than life/physical sciences and social sciences majors, this advantage is greatly diminished by age 40.

Computer science and engineering majors score modestly higher on tests of academic ability than other majors.²⁵ 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](#)). However, Appendix Table A7 shows that controlling for AFQT directly in the NLSY barely changes the return to majoring in computer science or engineering.

One potential concern is that college graduates in fast-changing majors are more likely to work (or to work full-time) early in their careers, whereas others might choose to attend graduate school or take internships and other learning opportunities.²⁶ Self-selection could potentially overstate the early career returns to some majors, depending on which graduates choose to work and which choose other paths.

We attempt to bound the importance of self-selection by imputing missing wages for college graduates who are in school or working part-time, with a variety of assumptions about differential selection by college major.²⁷ The results from these imputations are in Figures A6 and A7.²⁸ Imputing very high early career earnings for other majors modestly flattens the life-cycle profile for

²⁵Appendix Table A6 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.

²⁶Appendix Figures A4 and A5 show that college graduates with technology-intensive majors are somewhat more likely to work full-time and somewhat less likely to attend graduate school.

²⁷We first collapse different moments of the earnings distribution in ACS data by age, year, race/ethnicity, gender, citizenship, veteran status, educational attainment and college major. We then impute these different moments for college graduates in the analysis above who are either not working at all, not working full-time, or currently enrolled in school.

²⁸Figure A6 imputes missing earnings for college graduates of all ages, but differently by major. Even if we assume that the college graduates who are enrolled in school or not working full-time had 25th percentile earnings in computer science, engineering or business and 90th percentile earnings for other majors, the basic pattern of declining returns does not change. Figure A7 presents imputations of dynamic selection, where we assume a different selection pattern by age. Our most demanding specification imputes 25th percentile earnings to fast-changing majors and 90th percentile earnings to all other majors before the age of 30, but median earnings for all graduates thereafter.

computer science and engineering majors, but the broad pattern still holds. The results for business degrees, however, are somewhat sensitive to assumptions about missing earnings.

5.2 Earnings Growth by Occupation

The results so far have focused exclusively on differences by college major. However, we can also study earnings patterns by age in the returns to working in different *occupations*, regardless of major.

Figure 6 presents estimates like equation (8), except that 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).²⁹ Standard errors are clustered at the occupation-by-age level. In all three data sources, we find that STEM jobs pay relatively higher wages to younger workers.

To disentangle majors from occupations, we estimate a version of equation (8) that adds interactions between age categories and indicators for being employed in a STEM, as well as three-way interactions between age, a Computer Science or Engineering major, and STEM employment. This allows us to separately estimate the relative earnings premia for Computer Science and Engineering degree-holders working in non-STEM jobs, for other majors working in STEM jobs, and then for the union of these two categories.

The results are in Figure 7. Declining relative returns is a feature of STEM jobs, not majors. The earnings premium for non-STEM majors in STEM occupations starts off near 40 percent, but declines to 20 percent within a decade. In contrast, the relative earnings advantage grows over time for Computer Science and Engineering majors working in non-STEM occupations. The STEM major premium could reflect differences in unobserved ability across majors, or differences in other job characteristics (e.g. [Kinsler and Pavan 2015](#)).

²⁹SOC codes are not consistent for the years covered by all three data sources. For this reason, we adopt the “occ1990dd” classification of occupations defined by [Autor and Dorn \(2013\)](#) and then use their crosswalk to map occupations to the 2010 Census Bureau classification of STEM jobs. This mapping back to the 1970s does not work as well for Business occupations, so we focus on STEM occupations in Figure 6.

5.3 Employment Patterns by College Major

The second prediction of the model is that college graduates in fast-changing careers will exit them over time, as their skills become obsolete. We can show this sorting pattern directly by looking at the occupations held by Computer Science, Engineering and Business majors at each age.

Figure 8 shows that the share of Computer Science and Engineering majors working in Computer and Engineering occupations declines from 59 percent at age 26 to 41 percent by age 50. This decline of 18 percentage points is almost entirely offset by increased employment in non-STEM management occupations.³⁰ Appendix Figure A8 shows the same pattern for Business majors, who shift into Management as they age.

Figure A9 tests the sorting prediction directly by estimating a version of equation (8) with $SkillChange_o$ as the outcome and major-by-age interactions. For computer science and engineering majors, the average rate of skill change in the jobs they hold drops by about 0.2 standard deviations from ages 26 to age 50. The drop for business majors is about 0.15 standard deviations over the same period. In contrast, there is no change at all for social science majors.

5.4 High ability workers sort out of STEM over time

The model also predicts that high-ability workers are more likely to sort out of fast-changing 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. We test this by using the NLSY to estimate regressions of the form:

$$y_{it} = \alpha_{it} + AGE_{it} + \beta STEM_i + \gamma AFQT_i + \theta AGE_i * AFQT_i + \delta X_{it} + \epsilon_{it} \quad (9)$$

where AGE_{it} is a linear age control for worker i in year t (scaled so that age 23=0, for ease

³⁰We classify Computer and Information Systems Managers (SOC 11-3021), Architectural and Engineering Managers (SOC 11-9041) and Natural Sciences Managers (11-9121) as STEM occupations in this Figure and all other results. Thus the shift into Management over time is not driven by STEM workers shifting into STEM-related management.

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. Observations are in person-years and we cluster standard errors at the individual level. Due to a lack of consistent coding of business occupations over time, we focus here only on computer science and engineering majors entering STEM occupations.

The results are in Table 3. The outcome in Column 1 is an indicator for working in a STEM occupation. Column 1 presents the baseline estimate of equation (10). 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 out of faster-changing STEM careers over time. The results imply that a worker with cognitive ability one standard deviation above average is 4.9 percentage points more likely to work in STEM at age 23, but only 1.6 percentage points more likely to be working in an STEM job by age 34.

Column 2 adds interactions between an indicator for majoring in STEM and age, STEM major and AFQT, and then the triple interaction $AGE_{it} * STEM_i * AFQT_i$. The coefficient on the triple interaction term is almost exactly zero, suggesting that ability sorting out of STEM majors over time happens at the same rate for STEM and non-STEM majors.

Columns 3 and 4 of Table 3 repeat the pattern above, except with log wages as the outcome. Column 3 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 4 adds the interactions above. The coefficient on the key triple interaction term $AGE_{it} * STEM_i * AFQT_i$ is negative, implying that the return to ability is much flatter over time for STEM majors.

Summing the coefficients in Column 4 suggests that a computer science or engineering major with one standard deviation higher cognitive ability earns 23.9 percent more at age 23 and 42.7 percent more at age 34. In contrast, high ability college graduates in other majors earn only 7 percent more at age 23, but 43.3 percent more at age 34. Thus for high ability college graduates, the advantage to majoring in STEM is completely erased by age 34.

6 Job Skill Change in Earlier Periods

The BG data only allow us to calculate detailed measure of job skill changes for the 2007–2019 period. However, we can 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 (9) using the [Atalay et al. \(2018\)](#) data and job skill classifications. 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. \(2018\)](#) and then to normalize the data so that the average over the entire 1968–1998 period is the same as the average over 2007–2019. The basic pattern of results is 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 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 9 —show three main findings. First, the rate of skill change for non-STEM occupations is relatively constant 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 between the 1973–1978 and 1978–1983 periods, and then increases again in 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 2007–2019 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 2007–2019 period and the 1980s, but not the late 1970s or 1990s.

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 9 with wage trends for young workers in STEM jobs over the same period, using the CPS for years 1974–2019. We estimate population-weighted regressions of the form:

$$\ln(earn)_{it} = \alpha_{it} + \sum_c^C \gamma_c (c_{it} * Y_{it}) + \sum_c^C \zeta_c (c_{it} * ST_{it}) + \sum_c^C \eta_c (c_{it} * Y_{it} * ST_{it}) + \delta X_{it} + \epsilon_{it} \quad (10)$$

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 2009–2019 (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 9. Each bar displays coefficients and 95% confidence intervals for estimates of γ , ζ and η in equation (11). 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 9 show that young STEM workers earn relatively higher wages during periods of rapid skill change. 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 1974–2019 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 $SkillChange_o$ 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](#)).

7 Conclusion

This paper studies the impact of changing skill demands on the career earnings dynamics of college graduates. We empirically measure changes in skill requirements across occupations over the course of a decade. Some jobs change much faster than others. College graduates majoring in career-oriented fields such as Computer Science, Engineering and Business earn higher starting wages because they learn job-relevant skills in school. Yet over time, employers in fast-changing occupations such as STEM jobs require new skills, and older skills become obsolete. This leads to flatter wage growth in careers with higher rates of job skill change, although most other majors never quite catch up.

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.

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. If workers with high academic ability are faster learners, the relative return to ability will be higher in careers that change less, because learning gains can accumulate more over time. This explains our finding that high ability college graduates exit STEM occupations earlier in their careers.

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.

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. 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.

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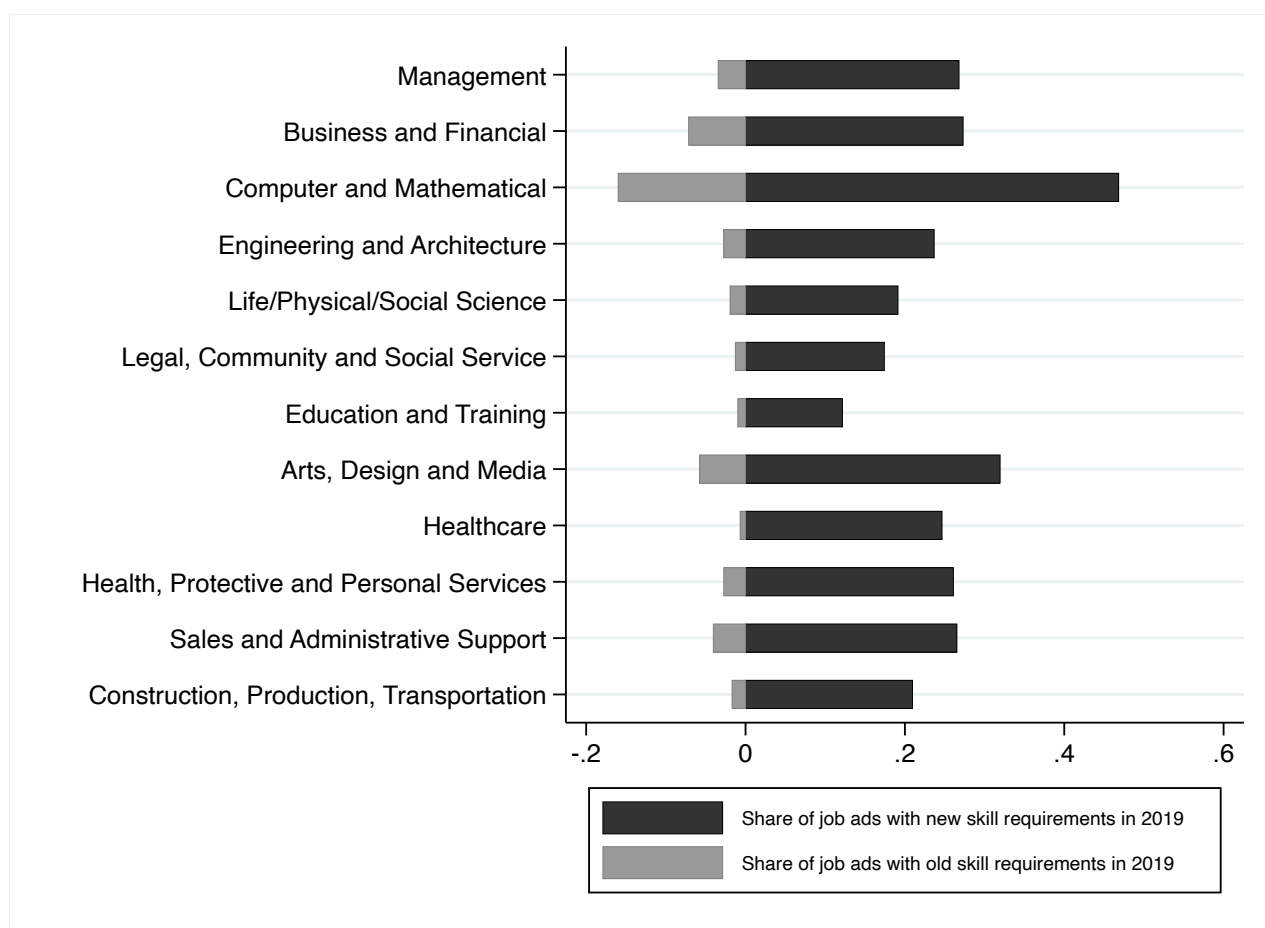
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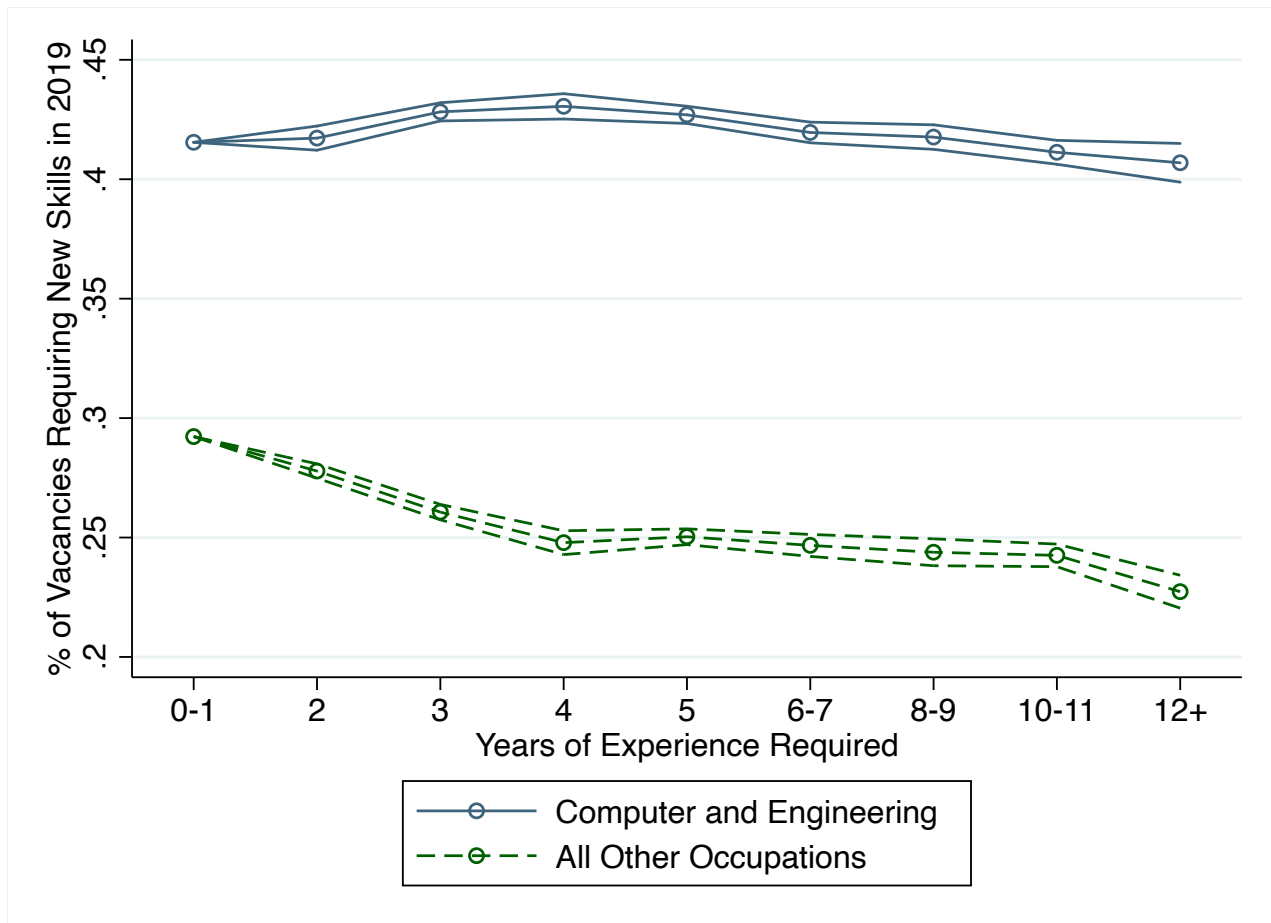
Figures

Figure 1: Turnover of Skill Requirements by Occupation Category



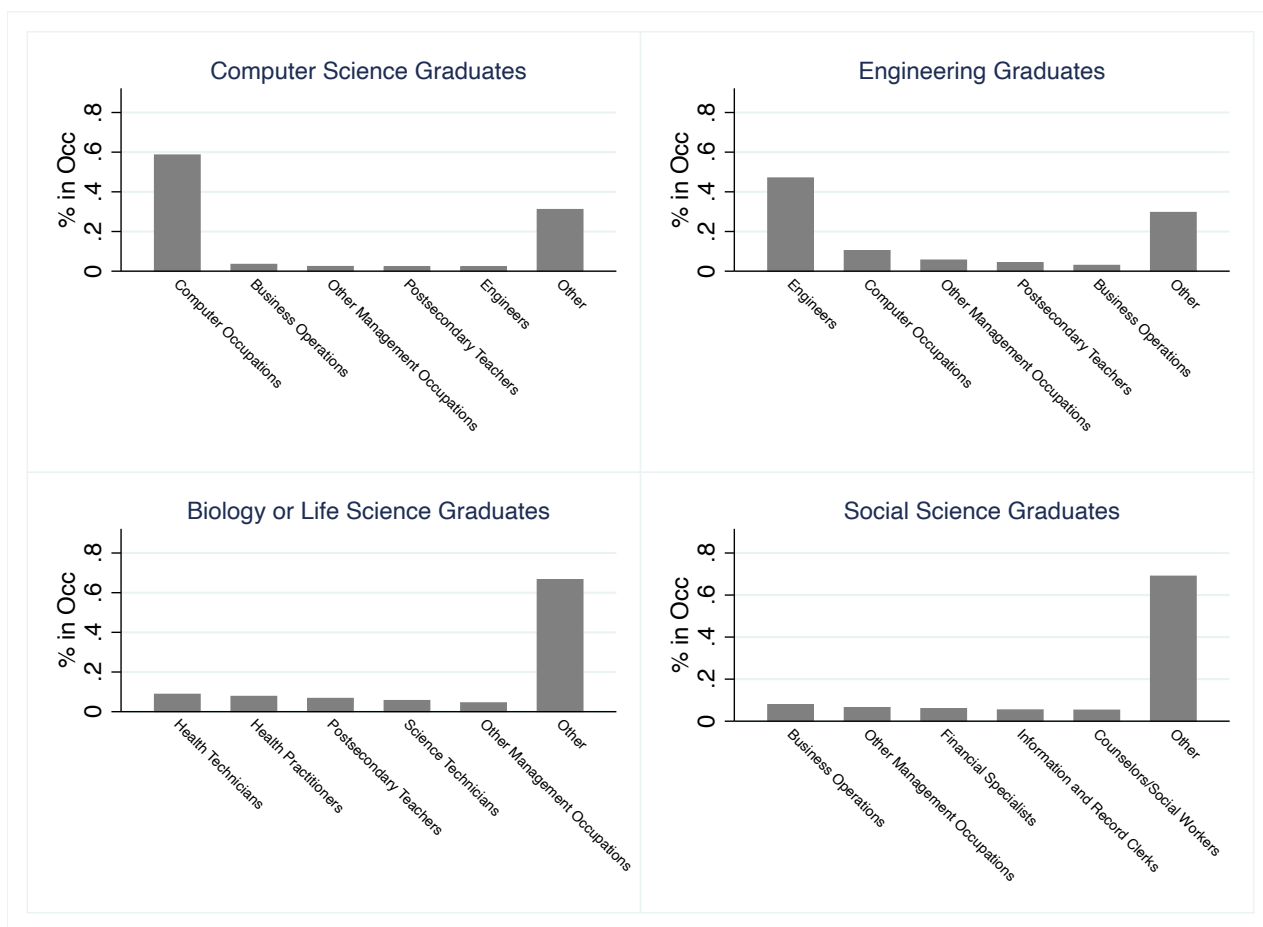
Notes: The bars show the share of jobs in each occupation category that required an “old” skill in 2007 (the light gray bars) and a “new” skill in 2019 (the dark gray bars). Old skills are defined as those with at least 1,000 appearances in 2007 but are either five times less frequent or do not exist in 2019. New skills are defined as those with at least 1,000 appearances in 2019 that either did not exist in 2007 or are 20 times more frequent in 2019 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 2019 year, the total number of skills listed in each vacancy, education and experience requirements, and occupation-city-employer fixed effects. Occupations are grouped according to 2-digit Standard Occupation Classification (SOC) codes. Some 2-digit SOC codes are grouped together to conserve space - see the text for details.

Figure 2: New Skills Required by Job Experience



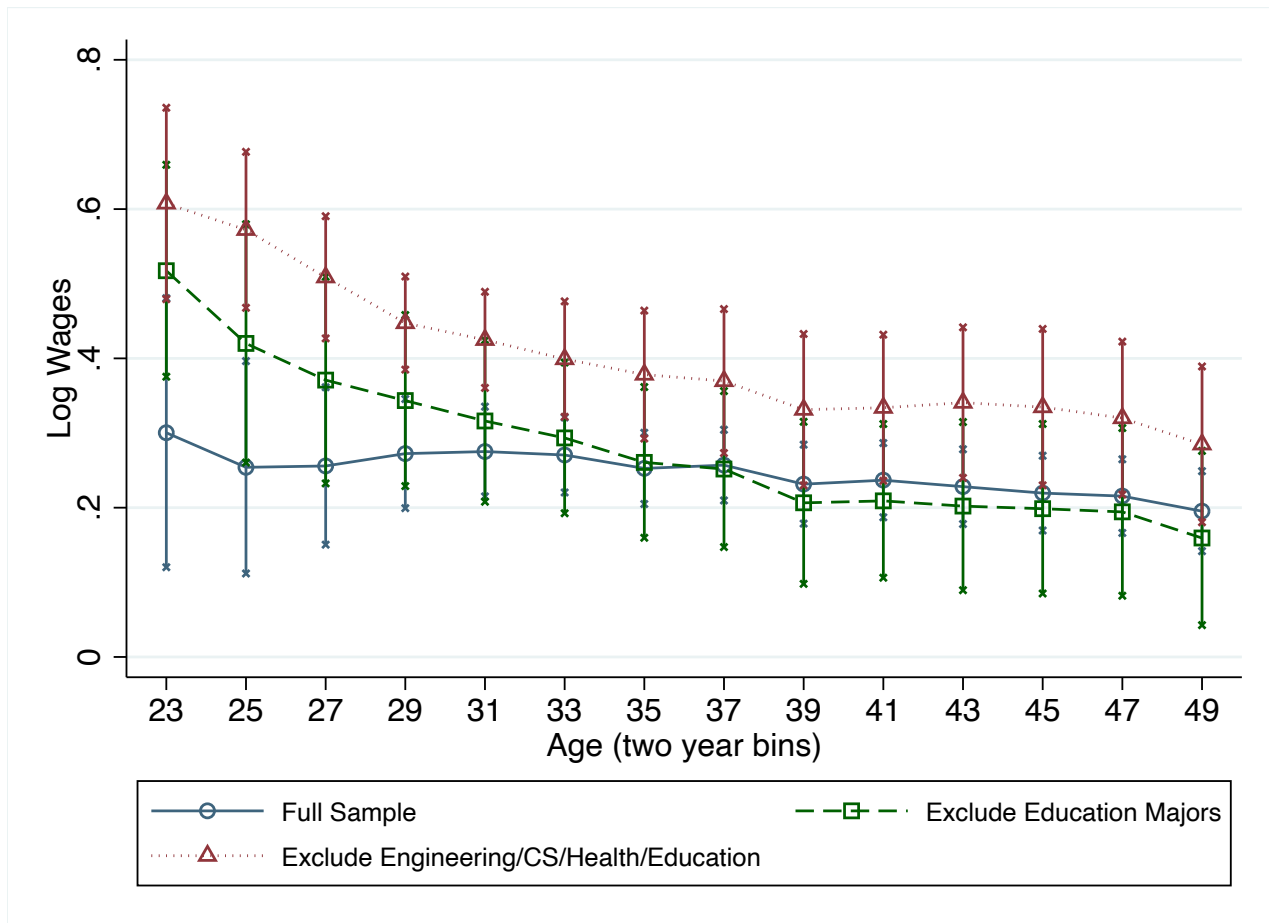
Notes: This figure shows how new skill requirements change along with required years of experience – in computer and engineering occupations (defined as Standard Occupation Classification (SOC) two digit codes 15 and 17), compared to all other occupations. Each point in the figure is the coefficient (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 2019 that either did not exist in 2007 or are 20 times more frequent in 2019 than 2007.

Figure 3: Early Career Occupations of College Graduates, by Major



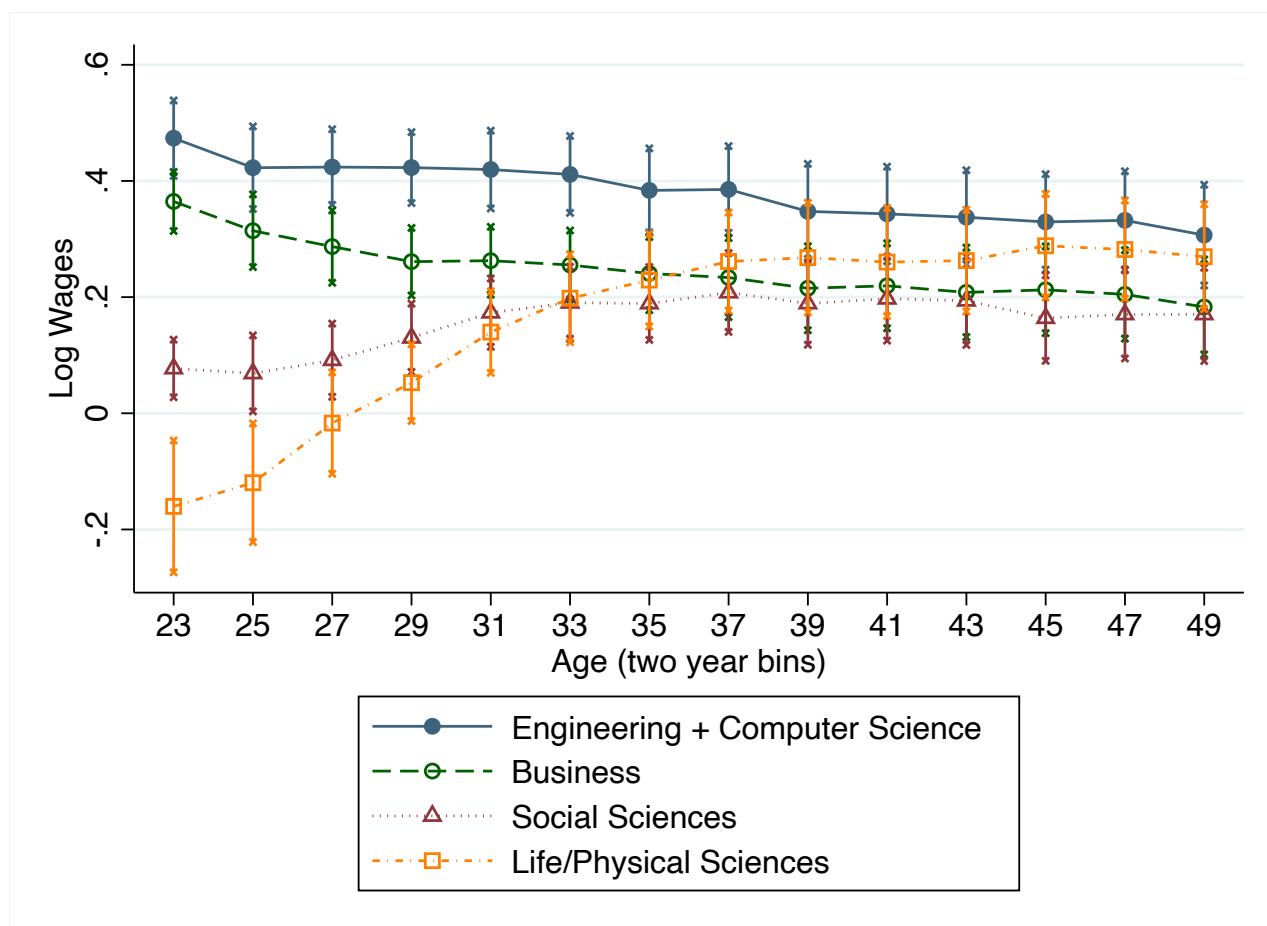
Notes: Each panel shows frequency distributions of the 5 most common occupations held by full-time working college graduates age 23-26 in the 2009-2017 waves of the American Community Survey who majored in the indicated subject. Occupations are defined here as 3-digit Standard Occupation Classification (SOC) codes. The “Other” category comprises all 3 digit SOC codes other than the top 5. Social Science majors are Economics, Political Science, Sociology and similar subjects.

Figure 4: Declining Wage Returns to Majoring in a Fast-Changing Field



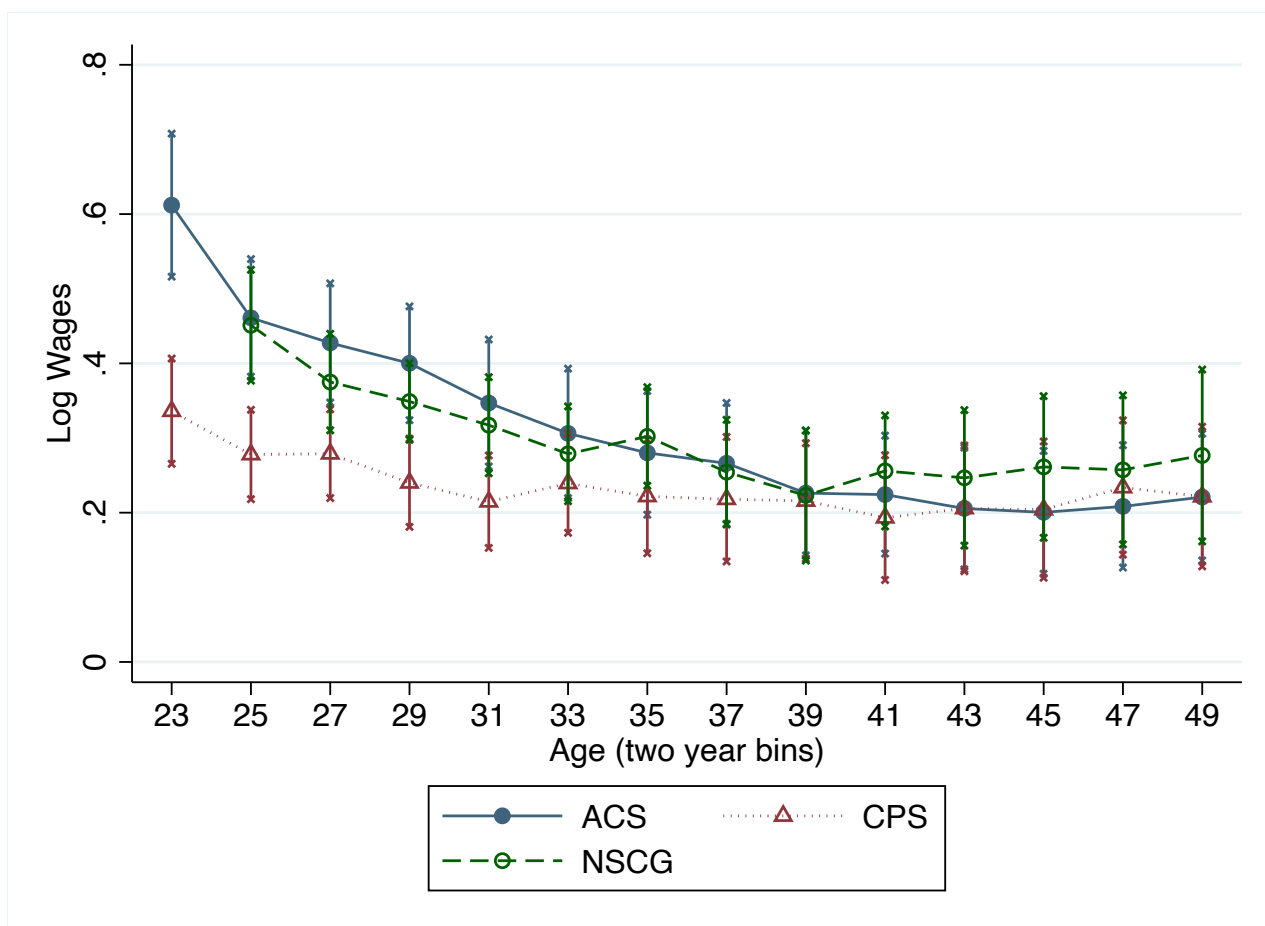
Notes: The figure plots coefficients and 95 percent confidence intervals from three separate estimates of equation (7) in the paper, a regression of log annual wage and salary income on interactions between two-year age bins and the average skill change measure Δ_j , which is computed for each college major using the occupation distribution for early career college graduates. The sample is all four-year college graduates ages 23-50 in the 2009-2017 American Community Survey, with some majors excluded as indicated in the legend. The skill change measure is constructed using 2007-2019 online job vacancy data from Burning Glass Technologies. See the text for details. The standard deviation of Δ_j is 1.01. The regression also includes controls for sex-by-age indicators, age and year fixed effects, race and ethnicity, citizenship, veteran status and an indicator for having any graduate school education. Standard errors are clustered at the major-by-age level.

Figure 5: Relative Wage Returns to College Majors over the Life Cycle



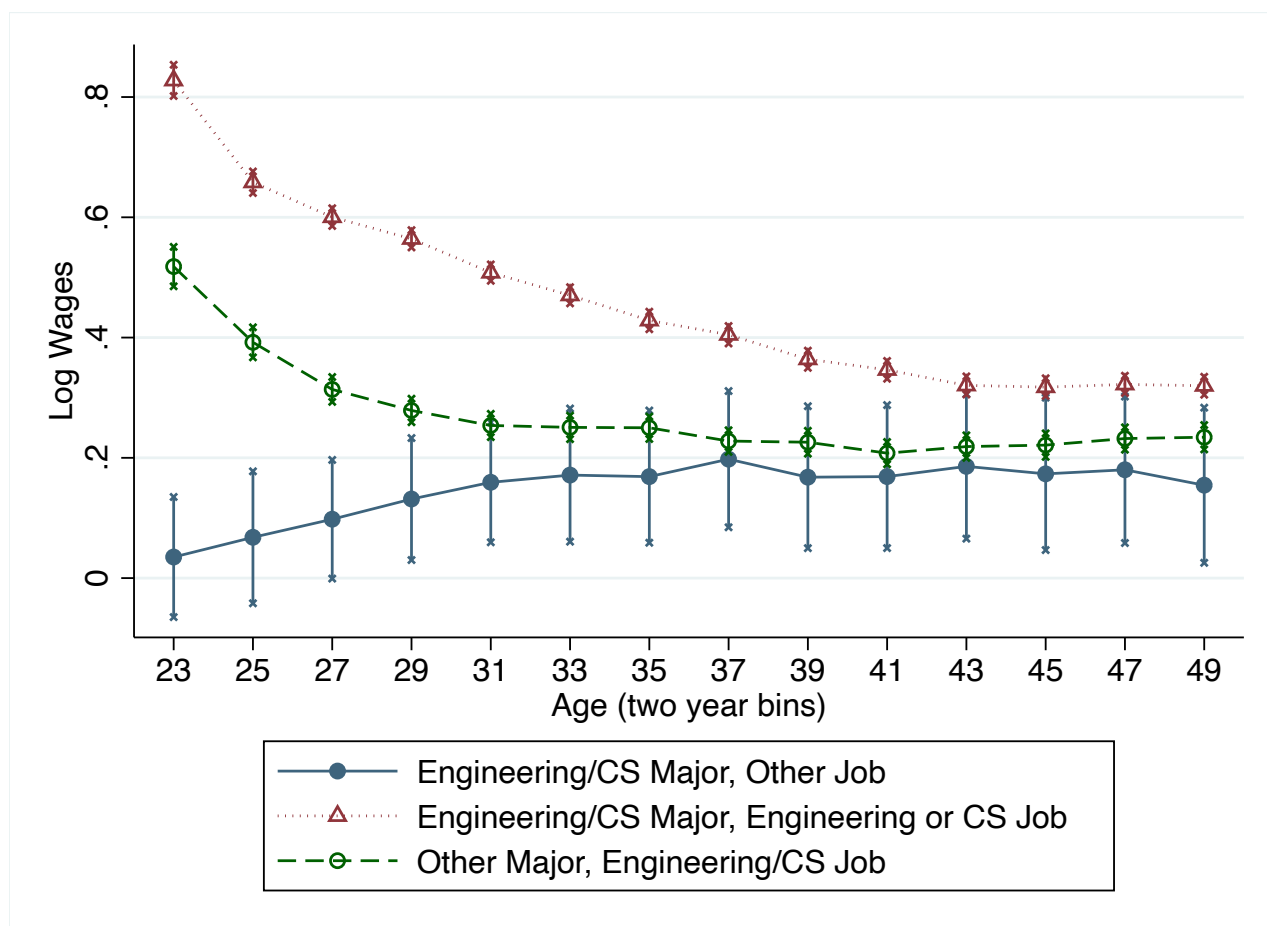
Notes: The figure plots coefficients and 95 percent confidence intervals from an estimate of equation (8) in the paper, a regression of log annual wage and salary income on interactions between two-year age bins and indicators for college major. The sample is all four-year college graduates ages 23-50 in the 2009-2017 American Community Survey. Life and Physical Science majors are Biology, Chemistry, Physics and similar subjects. Social Science majors are Economics, Political Science, Sociology and similar subjects. The left-out category is all other majors. The regression also includes controls for sex-by-age indicators, age and year fixed effects, race and ethnicity, citizenship, veteran status and an indicator for having any graduate school education. Standard errors are clustered at the major-by-age level.

Figure 6: Life-Cycle Returns to Working in a STEM Occupation Across 3 Data Sources



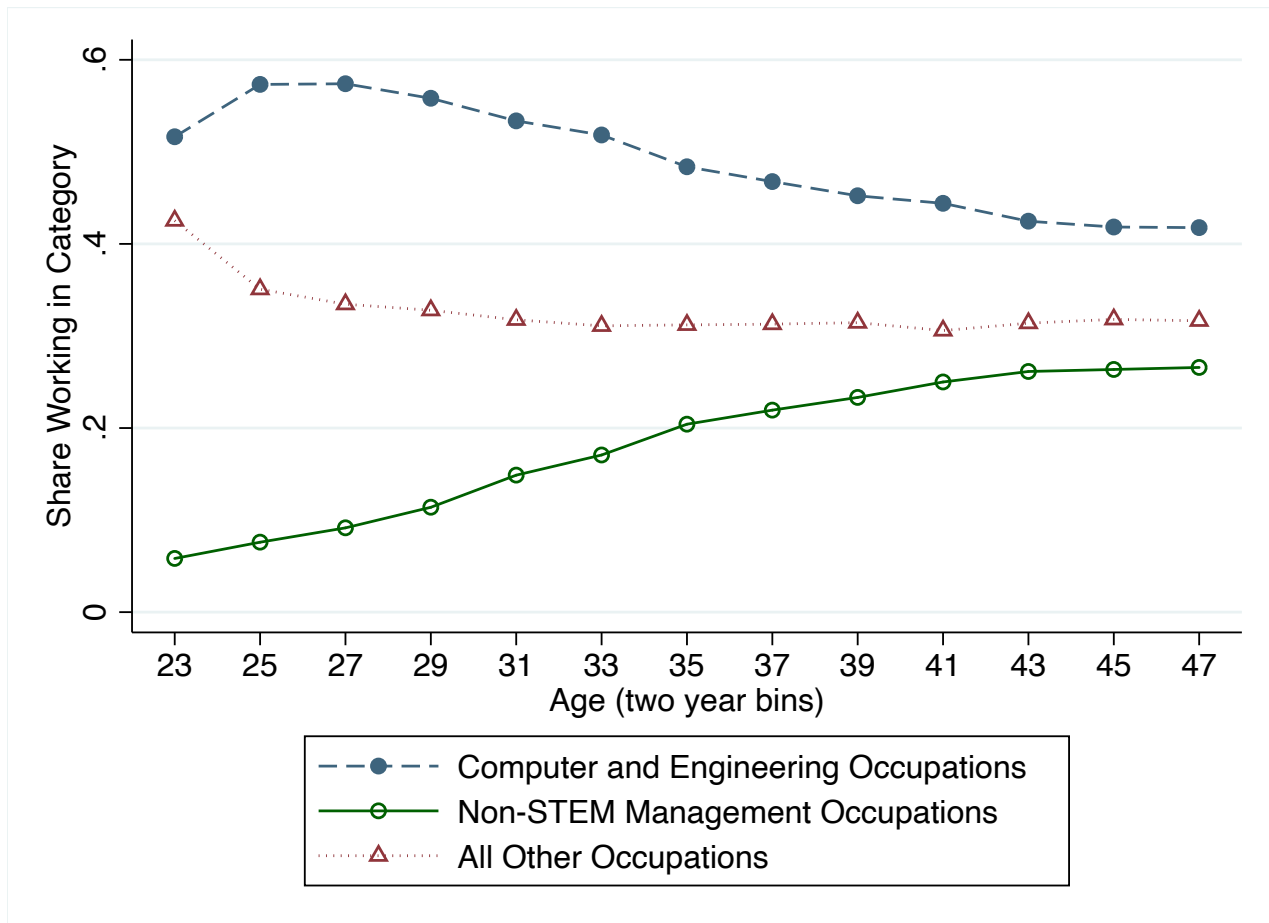
Notes: The figure plots coefficients and 95 percent confidence intervals from three separate regressions of log annual wage and salary income on interactions between two-year age bins and indicators for working in a STEM occupation. STEM occupations are defined using the 2010 Census Bureau classification, and we map backward to earlier years using the “occ1990dd” crosswalk developed by Autor and Dorn (2013). The three data sources are the 2009-2017 American Community Survey, the 1993-2017 National Survey of College Graduates, and the 1973-2019 Current Population Survey. The sample is all four-year college graduates ages 23-50 in the ACS and CPS, and ages 25-50 in the NSCG. The regression also includes controls for sex-by-age indicators, age and year fixed effects, race and ethnicity, citizenship, veteran status and an indicator for having any graduate school education. Standard errors are clustered at the occupation-by-age level.

Figure 7: Declining Returns for CS/Engineering jobs, not Majors



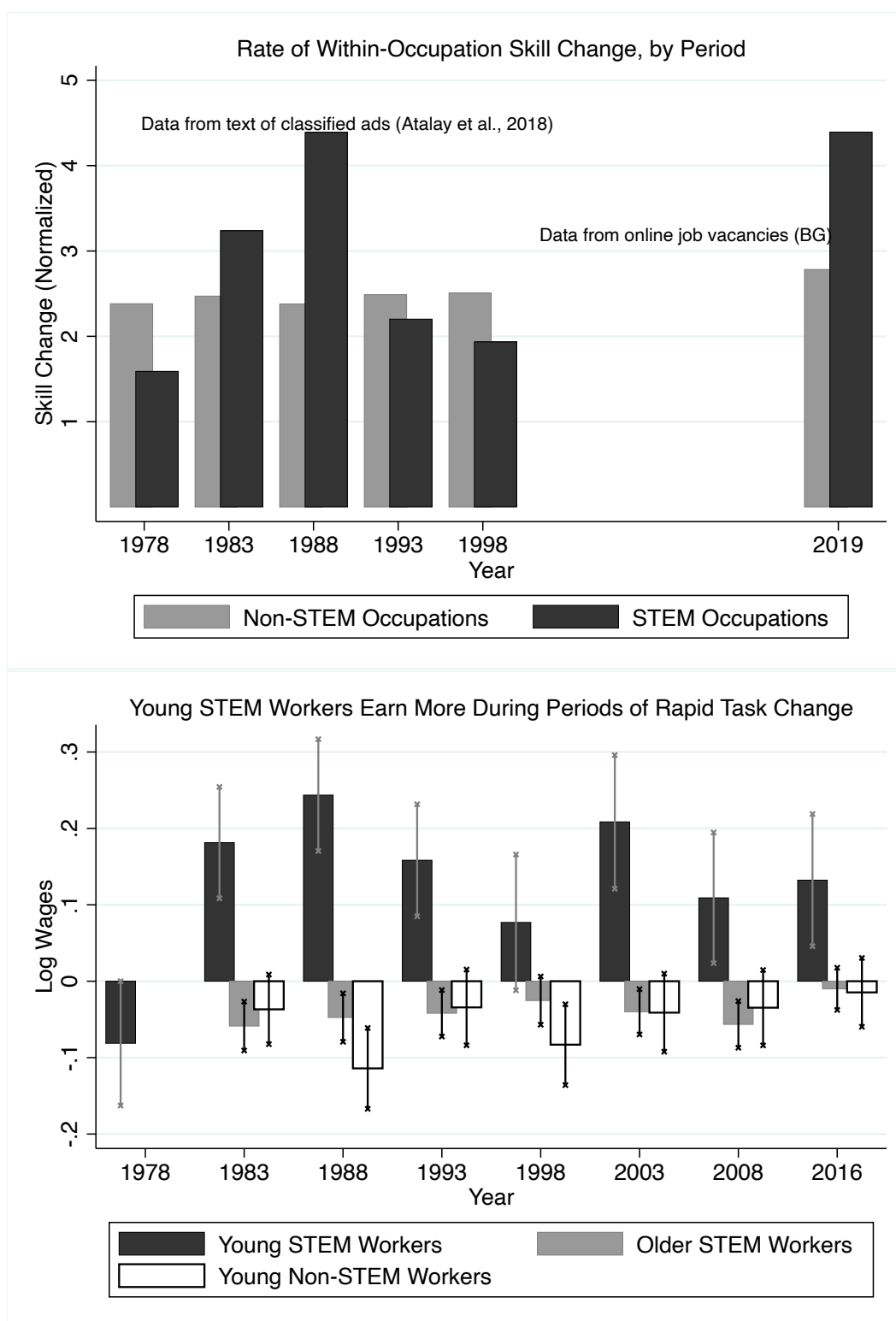
Notes: The figure plots coefficients and 95 percent confidence intervals from an estimate of equation (8) in the paper, a regression of log annual wage and salary income on interactions between two-year age bins and indicators for college major. The regression also adds major-by-occupation interactions (plotted above). The sample is all four-year college graduates ages 23-50 in the 2009-2017 American Community Survey. Computer and Engineering jobs are defined as Standard Occupation Classification (SOC) 2-digit codes 15 and 17. The regression also includes controls for sex-by-age indicators, age and year fixed effects, race and ethnicity, citizenship, veteran status and an indicator for having any graduate school education. Standard errors are clustered at the occupation-by-major-by-age level.

Figure 8: Occupational Sorting by Age for Engineering/CS Majors



Notes: The figure plots coefficients from three separate regressions of indicators for working in the labeled occupation category on two-year age bins plus controls for sex-by-age indicators, year fixed effects, race and ethnicity, citizenship, veteran status and an indicator for having any graduate school education. The sample is all full-time working four-year college graduates ages 23-50 in the 2009-2017 American Community Survey, who also majored in Computer Science or Engineering. Computer and Engineering occupations are 2-digit Standard Occupational Classification (SOC) codes 15 and 17. Non-STEM management is 2-digit SOC code 11, except a small number of codes indicating management in computer or engineering fields. See the text for details.

Figure 9: STEM Youth Premium and Skill Change in Earlier Periods



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 annual wage and salary income 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. Young Non-STEM workers and Older STEM workers in 1978 are the left-out categories. See the text for details.

Tables

Table 1: Occupations with the Highest and Lowest Rates of Skill Change

<i>Panel A</i>		<i>Fastest-Changing Professional Occupations</i>	
Occupation Title	SOC Code	Rate of Skill Change	
Computer Occupations	151	4.795	
Advertising, Marketing and Sales Managers	112	4.043	
Sales Representatives, Services	413	3.923	
Operations Specialties Managers	113	3.913	
Life, Physical, and Social Science Technicians	194	3.910	
Electronic Equipment Mechanics	492	3.828	
Engineers	172	3.772	
Financial Specialists	132	3.751	
Business Operations Specialists	131	3.666	
Supervisors of Installation, Maintenance, and Repair Workers	491	3.628	
Supervisors of Sales Workers	411	3.546	
Life Scientists	191	3.544	
Mathematical Science Occupations	152	3.511	
Top Executives	111	3.490	
Media and Communication Workers	273	3.469	
Supervisors of Office and Administrative Support Workers	431	3.451	
Secretaries and Administrative Assistants	436	3.435	
Physical Scientists	192	3.418	
<i>Panel B</i>		<i>Slowest-Changing Professional Occupations</i>	
Occupation Title	SOC Code	Rate of Skill Change	
Motor Vehicle Operators	533	1.269	
Other Food Preparation and Serving Related Workers	359	1.375	
Cooks and Food Preparation Workers	352	1.377	
Personal Appearance Workers	395	1.396	
Building Cleaning and Pest Control Workers	372	1.591	
Primary and Secondary School Teachers	252	1.639	
Food Processing Workers	513	1.715	
Baggage Porters, Bellhops, and Concierges	396	1.731	
Entertainment Attendants and Related Workers	393	1.747	
Material Moving Workers	537	1.749	
Food and Beverage Serving Workers	353	1.768	
Other Teachers and Instructors	253	1.781	
Grounds Maintenance Workers	373	1.792	
Other Transportation Workers	536	1.824	
Textile, Apparel, and Furnishings Workers	516	1.859	
Other Personal Care and Service Workers	399	1.946	
Postsecondary Teachers	251	2.046	
Metal Workers and Plastic Workers	514	2.146	

Notes: This table uses online job vacancy data from Burning Glass Technologies (BG) to calculate the rate of skill change between 2007 and 2019 for each 3-digit Standard Occupational Classification (SOC) code. The average value of the skill change measure is 3.01 - see the text for details.

Table 2: Major Categories in Order of Skill Change

Major Category	Rate of Skill Change
Computer and Information Sciences	4.06
Engineering	3.52
Military Technologies	3.33
Engineering Technologies	3.31
Business	3.30
Construction Services	3.27
Communications	3.13
Communication Technologies	3.11
Architecture	3.06
Social Sciences	2.98
Environment and Natural Resources	2.89
Law	2.88
Transportation Sciences and Technologies	2.86
Mathematics and Statistics	2.85
Fine Arts	2.84
Physical Sciences	2.84
Electrical and Mechanic Repairs and Technologies	2.83
Agriculture	2.82
Area, Ethnic, and Civilization Studies	2.80
Biology and Life Sciences	2.76
English Language, Literature, and Composition	2.72
Interdisciplinary and Multi-Disciplinary Studies (General)	2.72
Philosophy and Religious Studies	2.71
Public Affairs, Policy, and Social Work	2.71
History	2.69
Linguistics and Foreign Languages	2.67
Psychology	2.65
Liberal Arts and Humanities	2.62
Nuclear, Industrial Radiology, and Biological Technologies	2.62
Criminal Justice and Fire Protection	2.59
Physical Fitness, Parks, Recreation, and Leisure	2.58
Precision Production and Industrial Arts	2.55
Library Science	2.55
Medical and Health Sciences and Services	2.52
Family and Consumer Sciences	2.49
Theology and Religious Vocations	2.37
Cosmetology Services and Culinary Arts	2.28
Education Administration and Teaching	1.84

Notes: This table uses online job vacancy data from Burning Glass Technologies (BG) to calculate the rate of skill change between 2007 and 2019 for each 3-digit Standard Occupational Classification (SOC) code. The average value of the skill change measure is 3.01. See the text for details on the construction of the skill change measure.

Table 3: STEM Majors, Relative Wages and Ability Sorting in the NLSY

	In a STEM Job		Ln(Wages)	
	(1)	(2)	(3)	(4)
STEM Major	0.331*** (0.019)	0.169*** (0.033)	0.129*** (0.024)	0.083 (0.070)
Cognitive Skills (AFQT, Standardized)	0.049*** (0.007)	0.038*** (0.006)	0.084*** (0.018)	0.070*** (0.018)
Age (Linear)	0.003 (0.003)	0.000 (0.003)	0.021*** (0.006)	0.021*** (0.006)
Age * AFQT	-0.003** (0.001)	-0.003*** (0.001)	0.010*** (0.002)	0.012*** (0.003)
Age * STEM Major		0.014** (0.005)		0.009 (0.008)
STEM Major * AFQT		0.099** (0.030)		0.087 (0.060)
STEM Major * AFQT * Age		-0.000 (0.004)		-0.017* (0.008)
Demographics and Age/Year FE	Yes	Yes	Yes	Yes
Noncognitive and Social Skills	Yes	Yes	Yes	Yes
Observations	25199	25199	19449	19449
R^2	0.193	0.201	0.283	0.284

Notes: Each column reports results from a regression of indicators for working in a STEM occupation (Columns 1 and 2) or real log hourly wages (Columns 3 and 4) on indicators for majoring in a Science, Technology, Engineering and Mathematics (STEM) field, cognitive, social and noncognitive skills, indicator variables for sex-by-age, 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 respondents 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 all college graduates ages 23-34 to maximize comparability across survey waves. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.