STEM Careers and Technological Change

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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 tasks 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 changed especially quickly over the last decade, 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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1 Introduction

Science, Technology, Engineering, and Math (STEM) jobs are a key contributor to innovation and productivity growth in most advanced economies (e.g. Griliches 1992, Jones 1995, Carnevale et al. 2011, Peri et al. 2015). Despite the high labor market payoff for college students majoring in STEM fields, there is a widespread perception that STEM workers are in short supply (Arcidiacono 2004, Carnevale et al. 2012, Kinsler and Pavan 2015, Cappelli 2015, Arcidiacono et al. 2016). Yet STEM employment in the U.S. has grown slowly in the past two decades, and 58 percent of STEM graduates leave the field within 10 years after receiving their degree (Carnevale et al. 2011, Charette 2013, Deming 2017).

In this paper we argue that perceived skill shortages, high initial returns for STEM majors and exit from STEM careers over time have a common cause - technological change, which introduces new job tasks and makes old tasks obsolete (e.g. Rosen 1975). 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.

We document several new facts about labor market returns for STEM majors, which corroborate the argument above. 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. While some STEM majors move on to higher-paying occupations such as management, most do not. We show that the STEM premium holds primarily for STEM jobs – as opposed to STEM majors – and that STEM jobs are disproportionately held by younger workers. 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 provide direct evidence on the changing technological requirements of jobs using a near-universe of online job vacancy data collected by the employment analytics firm Burning Glass Technologies (BGT). We use the BGT data to calculate a detailed measure of job task change over the 2007-2017 period. This measure captures how much the skill and task mix of an occupation has changed over a decade, and in what ways. We show that STEM jobs indeed have the highest rates of task change, and that this change is driven by the rise and decline of specific software and business processes requested by employers.

We interpret these patterns with 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 on-the-job at different rates according to their ability. Over time, the productivity gains from on-the-job learning are lower in careers with higher rates of task change, because more of the tasks learned in past years become obsolete. The model predicts that jobs with high rates of task change will have flatter age-earnings profiles, and that they will disproportionately employ young workers. We find strong support for these predictions in the data, for both STEM and non-STEM occupations.

Our model also predicts that the highest ability workers will choose STEM careers initially, but exit them over time. This is because the return to ability is higher in careers with low rates of change, where knowledge can accumulate. Consistent with this prediction, we find that worker 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 find that the wage return to ability decreases strongly with age for STEM majors.

While the BGT 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 the returns to technology-specific human capital becoming less valuable as new tasks are introduced to the workplace.[1]

Second, our results provide an empirical foundation for a large body of work in economics on vintage capital and technology diffusion (e.g. qGriliches 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.[2] 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.

Third, 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

[1]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.

[2]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.

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.

This paper builds on a line of work studying skill obsolescence, beginning with Rosen (1975). 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. **?** 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. 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.[3] 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-

[3]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.

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 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 (Selingo 2018).

The remainder of the paper proceeds as follows. Section 2 describes the data and documents the main empirical patterns described above. 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 Data

2.1 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.[4] This definition is relatively restrictive and excludes majors such as psychology, economics and

[4] 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.

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.[5]

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 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. However, the NSCG occupation definitions are coarse and do not map cleanly to the ACS. Finally, for some analyses we 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 2016 dollars using the Consumer Price Index (CPI).

We restrict our 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.[6] We are interested in studying the life-cycle profile of returns to STEM degrees, and large changes across birth

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

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

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).[7] Finally, 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 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).[8] Our main outcome is the real log hourly wage (in constant 2016 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).

[7]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.

[8]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.

2.2 Declining Life-Cycle Returns to STEM

Table 1 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 1-4 present results that compare STEM majors to all other non-STEM majors, while Columns 5-6 and 7-8 show "Pure" and "Applied" Science majors respectively. While earnings increase substantially over the life-cycle for all college graduates regardless of major, STEM majors earn substantially more at labor market entry and experience relatively slower wage growth over the first decade of working life. Dividing Column 3 by Column 1 yields a STEM wage premium of 30 percent at age 24 but only 18 percent at age 35.

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 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.[9] 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 89 percent at age 24 to 71 percent at age 35, and continues to decline thereafter. The share of Pure Science majors in STEM jobs also declines, from 35 percent at age 24 to 27 percent at age 35. The share of non-STEM majors in STEM jobs stays constant at around 12 percent.

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

[9] 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).

$$\ln y_{it} = \alpha_{it} + \sum_{a}^{A} \beta_a A_{it} + \sum_{a}^{A} \gamma_a \left(A_{it} * AS_{it}\right) + \sum_{a}^{A} \delta_a \left(A_{it} * PS_{it}\right) + \zeta X_{it} + \theta_t + \epsilon_{it} \tag{1}$$

where a_{it} is an indicator function $I\left(Age = a\right)_{it}$ 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 indicator functions that are equal to one if a respondent has an Applied Science or Pure Science major 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 1 presents population-weighted estimates of equation (1) for full-time working men ages 23-50 with at least a bachelor's degree. Panel A presents results using the ACS, and Panel B presents results using the NSCG. Each point in Figure 1 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.[10]

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.[11]

[10]The results are very similar when we restrict the NSCG sample to years after or before 2008, covering the cases that do and do not overlap with the ACS respectively.

[11]Appendix Figure A5 shows that excluding workers with graduate degrees flattens the return to pure

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.

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. Appendix Figure A3 shows estimates of equation (1), but with an indicator for working in a STEM occupation as the outcome variable. Applied Science degree holders exit from STEM occupations rapidly in the first 10-15 years after college, and timing coincides closely with the earnings results in Figure 1. Appendix Figure A4 shows that the probability of full-time employment also declines over the life-cycle for Applied Science majors, while the opposite holds for Pure Science.

The results in Figure 1 are robust to a variety of alternative specifications and sample definitions.[12] Appendix Figures A5, A6 and A7 presents results that include part-time workers, that exclude workers with graduate degrees, and that add industry fixed effects respectively. These yield very similar results. Appendix Figures A8 and A9 show results that group all STEM degrees together and that separate out engineering and computer science respectively.

Figure 2 presents estimates of equation (1) 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

science degrees, suggesting that part of the growth in Figure 1 reflects selection into graduate school over time. Appendix Table A1 studies selection into graduate school using the NLSY. We find that while graduate school attendance is overall more common in later years (e.g. the NLSY97 vs. the NLSY79), 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.

[12] Hanson and Slaughter (2016) document the rising share of high-skilled immigrants in U.S. STEM fields. 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.

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 (1) 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.[13] 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 3. 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).[14]

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 earn the same amount in STEM and non-STEM occupations.

The patterns in Figure 3 yield 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

[13]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.

[14]Appendix Figure A10 adds industry fixed effects to the results in Figure 3, which produces generally similar results except that the return to Applied Science majors in non-STEM occupations drops by about 50 percent.

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.

2.3 Measuring Technological Change at the Job Task Level

Why do STEM careers have flatter age-earnings profiles? One possible reason is that the requirements of STEM jobs change over time, rendering previously learned job tasks obsolete. In order to study obsolescence directly, it is necessary to measure changing job task demands within narrowly defined job categories (e.g. Autor and Handel 2013).

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 very 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.[15]

Vacancy data are ideal for measuring the changing task requirements of jobs, for two reasons. First, vacancies directly measure employer demand. Second, vacancy data allow for a detailed study of changing task demands *within* occupations over time. Due to data

[15]See Hershbein and Kahn (2018) and Deming and Kahn (2018) for more detail on the coverage of BG data and comparisons to other sources such as the Job Openings and Labor Force Turnover (JOLTS) survey. BG data closely match JOLTS and other sources for professional, managerial and technical occupations - in general, jobs that require a bachelor's degree. The coverage is less comprehensive for lower-skilled occupations such as food service, construction, and personal care.

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.

We study how the mix of task demands *within* each occupation changes between 2007 and 2017.[16] For each year, we collect all the tasks that ever appear in a job vacancy for a particular occupation. We then calculate the share of job ads in which each task appears in each year. This includes tasks that never appear - either because they are new to 2017 or because they disappear over the decade. We calculate the absolute value of the difference in shares for each task, divide by the total in both years, and then sum these shares to obtain an overall measure of task change at the occupation level:[17]

$$TaskChange_o = \frac{\sum_{t=1}^{T}\left\{Abs\left[\left(\frac{Task_o^t}{JobAds_o}\right)_{2017} - \left(\frac{Task_o^t}{JobAds_o}\right)_{2007}\right]\right\}}{\sum_{t=1}^{T}\left[\left(\frac{Task_o^t}{JobAds_o}\right)_{2017} + \left(\frac{Task_o^t}{JobAds_o}\right)_{2007}\right]} \tag{2}$$

Conceptually, equation (2) measures the replacement rate of tasks for an occupation. A value of zero indicates a job that requires exactly the same tasks in 2007 and 2017, while a value of one indicates a job that requires a completely new set of tasks. Table 2 presents the 3 and 6 digit (SOC) occupation codes with the highest and lowest measures of $TaskChange_o$. We restrict the sample in Table 2 to professional occupations (SOC codes that begin with a 1 or a 2) with at least 25,000 total vacancies in the 3-digit case and 10,000 total vacancies

[16] Our results are similar when we calculate changing task demands at the occupation-by-industry level. However, the BG data lack industry designations in a relatively large number of cases, so calculate task change at the occupation level in our main analysis.

[17] Over the 2007-2017 period, some occupations experience large changes in the average number of tasks per vacancy. Conversations with BG staff suggest this may be partly due to differences over time in where job vacancies are posted and how specifically they are written. We account for this by calculating the number of tasks per job in each year and then multiplying the $TaskChange_o$ measure times the ratio of tasks per job ad in 2007 compared to 2017. This downweights instances where $TaskChange_o$ 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.

in the six-digit case. This is for ease of presentation only, and we include all of the SOC codes in our analysis. The vacancy-weighted mean value for $TaskChange_o$ is 0.127, and the standard deviation for 6 (3) digit occupations is 0.056 (0.040).

Overall, STEM jobs have a rate of task change that is about one standard deviation higher than all other occupations (0.165 vs. 0.120 for 3 digit SOCs). Column 1 of Panel A shows the 3 digit SOC codes with the highest values of $TaskChange_o$. STEM jobs comprise six of the ten professional occupations with the highest rate of task change over the 2007-2017 period.[18] These include Lawyers and Judges, Architects and Surveyors, Physical Scientists, Life Scientists, Engineers, Drafters and Engineering Techicians, and Mathematical Scientists (including Statisticians). Moving to 6 digit occupation codes in Panel B, the 6-digit SOC codes with the highest values of $TaskChange_o$ include Mechanical Drafters, Computer Programmers, Architectural and Civil Drafters, Software Developers, Advertising and Promotions Managers, Environmental Engineers, and Insurance Underwriters.

Panels C and D of Table 2 show the 3 and 6 digit professional occupations with the least task change between 2007 and 2017.[19] The professional occupations with the least amount of task change include social scientists, health practitioner jobs (including nurses, physicians and dentists), teachers, managers, health and life science technicians, and counselors and social workers.

At the 6 digit level, the occupations with the lowest values of $TaskChange_o$ include mostly health and education jobs such as Pediatricians, Nurses, Dentists, Veterinarians, Physicians and Surgeons, Psychiatrists and Teachers. Notably, many of these jobs require some form of occupational license. In jobs with formal barriers to entry such as licensing and

[18]The 3 digit non-professional occupations with the highest values of $TaskChange_o$ include Occupational and Physical Therapy Assistants, Office and Administrative Support Workers, Electrical and Electronic Equipment Mechanics, Metals and Plastics Workers, Financial Clerks, and Secretaries and Administrative Assistants.

[19]The 3 digit non-professional occupations with the lowest values of $TaskChange_o$ are (in order from lowest to highest) Motor Vehicle Operators, Other Food Preparation Workers, Cooks and Food Preparation, Food and Beverage Serving Workers, Food Processing Workers, Retail Sales Workers, Materials Moving Workers, Entertainment Attendants, Personal Appearance Workers, Supervisors of Food Prep Workers, Other Protective Service Workers, and Nursing and Home Health Aides.

degree requirements, task change might manifest through changes in training rather than changes in task 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 measure $TaskChange_o$ may understate job task change in cases such as these.

We see two broad trends when digging into the details of changing occupational requirements. First, following Deming (2017) and Deming and Kahn (2018), we see large overall increases in the share of job vacancies requiring teamwork, communication and "social skills". These increases are particularly large for STEM jobs. Second, 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 tasks are softwares such as Python and JavaScript as well as general terms related to data analysis (including machine learning) and data management.

Specific software and business process requirements are more frequently listed for STEM occupations overall, and they also change more rapidly. Some examples of tasks that became much less frequently required between 2007 and 2017 are specific softwares such as UNIX, SAP, Oracle Pro/Engineer and Adobe Flash. Overall, specific software requirements account for about 12 percent of the total change, and most of the fastest growing tasks between 2007 and 2017 are software-related. The occupation-level correlation between the baseline $TaskChange_o$ measure and one that only includes software is 0.72.[20]

Software is a particularly important measure of occupational change, for three reasons.

[20]Appendix Table A2 presents a version of Table 2 that ranks occupations by $TaskChange_o$ 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 2, such as Art and Design Workers, Media and Communications Workers, and Financial Specialists. Like Table 2, most of the slowest-changing 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.

First, business innovation is increasingly driven by improvements in software, in the information technology (IT) sector in particular but also in more traditional areas such as manufacturing (Arora et al. 2013, Branstetter et al. 2018). Second, because software requirements are specific and verifiable, they are most likely to signal substantive changes in job tasks. One concern is that some task 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. Third and related, new software requirements may capture broader shifts in job tasks that are not well measured in BG data.

3 Model

The results in Section 2 show that the returns to STEM careers decline over the life-cycle, and that the tasks required in STEM jobs also change relatively rapidly over time. In Section 3, we develop a stylized model of educational choice and learning (both in school and on-the-job) that can account for the empirical patterns described above. The key parameter in our model is the replacement rate of job tasks over time. As new tasks replace old tasks, workers’ skills become obsolete, pushing down earnings relative to careers in which technological progress is slower.

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:

$$Y_{jt} = \int_0^1 y_{jt}(i)di \tag{3}$$

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.

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 a taste parameter u, who graduate from college and enter the job market at time $t = 0$.[21] 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 dstributed 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 $t \geq 0$.[22] As described earlier, workers earn wages according to their productivity schedule over tasks α_{jt}. Thus we can write the worker's problem as:

$$\underset{s,j_t}{Max} \left\{ \left[\sum_{t=0}^{T} PDV\Big(W_{jt}(a, s, \alpha_{jt}) \Big) \right] - C(a, u, s) \right\} \tag{4}$$

[21] 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.

[22] 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.

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 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:

$$\alpha_{jt}(i) = f\left(a, s, F_j, \Delta_j\right) \tag{5}$$

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 realized schooling choice is more closely aligned with the technical complexity of their chosen career s_j. Specifically, let the worker's realized 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.[23]

Workers also learn on the job. Each year that an individual works in career j, her produc-

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

tivity in the tasks existing at time t increases by a, the worker's ability. 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). While ability does not directly affect $F_j S^*$, it affects it indirectly through the worker's chosen field of study.

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 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]

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

$$g_{jt}(v) = \Delta_j (1 - \Delta_j)^{(t-v)}; v > 0 \tag{7}$$

Equation (6) 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 (7) 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).

[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 $g_{jt}(v) = (1 - \Delta_j)^{(t-v)} - (1 - \Delta_j)^{(t-v+1)} = \Delta_j (1 - \Delta_j)^{(t-v)}$.

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

$$\alpha_{jt}(i) = \begin{cases} (F_j S^*) + [a(t+1)] = \alpha_{jt}^{PRE} & \text{if } v = 0 \\ a(t-v+1) = \alpha_{jt}^{POST(v)} & \text{if } v > 0. \end{cases} \tag{8}$$

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.

3.4 Equilibrium Task Prices and Individual Wages

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

$$p_{ijt} = \alpha_{ijt}(a, s). \tag{9}$$

Equation (9) shows that workers of the same (a, s) type are paid the same price for each task. However, since the production function in (3) is career- and time-specific, workers will be paid differently for the same tasks. 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 $g_{jt}(v)$:

$$\begin{aligned} W_{jt} &= \int_0^1 p_{ijt} di = \int_0^1 \alpha_{ijt}(a, s) di \\ &= \left\{ (1-\Delta_j)^t \alpha_{jt}^{PRE} \right\} + \left\{ \sum_{v=1}^{t;t>0} \Delta_j (1-\Delta_j)^{t-v} \alpha_{jt}^{POST(v)} \right\} \end{aligned} \tag{10}$$

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 $t = 0$, $W_{j,t=0} = F_j S^* + a$. In $t = 1$, the worker becomes more productive in these initial task vintages through on-the-job learning. However, these learning gains are counterbalanced by the share (Δj) 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 task 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 task obsolescence and equation (10) reduces to a simple expression where wages increase linearly with ability over time. As $\Delta_j \to 1$, both terms in equation (10) go to zero except in the entry year $t = 0$. As Δ_j gets closer to one, a larger share of tasks 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 are more likely to 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 task 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 study technical fields is decreasing in ability and that technical fields have higher values of the in-school productivity term $F_j S^*$. However, in the model, the high labor market returns to a STEM career for new college graduates arises from higher

in-school learning as well as ability sorting. We test the relative importance of these two explanations using data on ability on college major choice from the NLSY.

4. *Higher ability workers are more likely to 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. The Model Appendix develops a simple three-period model that allows for endogenous schooling choices and sorting across careers over time. We find that among workers who initially choose STEM careers, those with the highest ability are more likely to sort out of STEM over time. Intuitively, the return to ability is higher in careers where more of the gains from on-the-job learning accumulate over time, 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. 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 4 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 intersecting 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

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

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 seeking to maximize lifetime earnings might switch careers over time as their productivity declines. Panel B provides an illustration of the determinants of career switching. The solid blue line and the dotted green line are the same cases as Panel A, with $F_j S^* = 6, \Delta_j = 0.2$ and $F_j S^* = 3, \Delta_j = 0.15$ respectively. The dashed red line considers the second case, but 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 Technological Change and Life-Cycle Earnings

We test the first prediction of the model by studying life-cycle earnings patterns in careers with different values of Δ_j - which we measure empirically using the $TaskChange_o$ measure developed in Section 2.3:

[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 task obsolescence. Total wages increases as long as the gains outweigh the losses, i.e. when $\frac{a}{(F_j S^* + a)} > \Delta_j$.

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

This follows a similar format to equation (1) and Figure 1, except that instead of using indicators for STEM major we directly interact the technological change measure $TaskChange_o$ with two-year age bins. The results are in Figure 5. We present separate estimates of equation (11) for STEM and non-STEM occupations. As in Figure 1, the γ coefficients can be interpreted as the relative earnings return to jobs with higher rates of technological change, for each age group.

We find the same life-cycle patterns as in Figures 1, 2 and 3 - jobs with higher rates of task change have flatter age-earnings profiles. The estimates imply that occupations with a one standard deviation higher value of $TaskChange_o$ (0.056) pay 15 percent higher wages at ages 23-24 but only 4.5 percent higher wages at ages 39-40.

Importantly, this pattern holds equally for STEM and non-STEM occupations. While the scale is different because STEM jobs have higher average values of $TaskChange_o$, the pattern of declining returns over the first decade of working life is clear 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. Appendix Figure A11 shows that these results are robust to controlling for industry fixed effects. Appendix Figure A12 shows that we find a life-cycle pattern in wage returns when we calculate $TaskChange_o$ using only measures of software usage. Finally, Appendix Figure A13 shows similar results when separating the sample by STEM/non-STEM majors rather than STEM/non-STEM jobs.

Figure 6 tests the second prediction of the model by studying occupational sorting directly. We estimate:

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

Equation (12) asks whether young people are relatively more likely to be employed in occupations with high rates of technological change. One issue is that workers move up the occupational ladder as they age, and higher-paying professional occupations also tend to have higher values of $TaskChange_o$. To account for occupational upgrading, Figure 6 presents two different estimates of equation (12). The first restricts the sample to professional occupations, while the second restricts the sample to STEM majors.

The dashed line in Figure 6 shows that professional occupations with higher values of $TaskChange_o$ have younger workforces. The estimates imply that workers in jobs with a one standard deviation higher value of $TaskChange_o$ are about 1 percentage point more likely to be ages 25-26 than ages 39-40. Since each two-year age group comprises about 7 percent of our sample, a 1 percentage point difference is large relative to a baseline where all age groups are evenly distributed across occupations.

The solid line in Figure 6 restricts the sample to STEM majors, regardless of occupation. We find a very similar pattern. The difference between age 25-26 and age 39-40 implies that STEM majors in jobs with a one standard deviation higher value of $TaskChange_o$ are about 1.5 percentage points more likely to be ages 25-26 than ages 39-40. In results not reported, we also find that this pattern holds for all workers (not just STEM majors) when we control directly for the average wage of the occupation.

Overall, we find strong evidence of higher employment and relative wages for young workers in jobs with higher rates of task change, confirming the first two predictions of the model. Appendix Figure A14 shows that this pattern also holds when we measure $TaskChange_o$ using only software.

4.2 Accounting for Ability Differences by Major

We find that STEM majors are positively selected on ability, in both waves of the NLSY.[28] 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 3 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.[29] While each skill measure strongly and independently predicts wages, adding them as controls does not meaningfully change 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.

[28] Appendix Table A3 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.

[29] 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.

In our model, high ability workers are more likely to major in STEM because they have a lower cost of learning technical subjects. Yet higher earnings in STEM fields are driven by the specific human capital accumulated in school, not by ability directly. The pattern of results in Table 3 is consistent with our model, and inconsistent with a simpler story where ability alone determines both major choice and earnings. Our results are also consistent with 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 1-3 holds when controlling for worker skills. The results are in Figure 7. 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.

4.3 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 the returns to being a fast learner are greater in jobs with *lower* rates of task 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:

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

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 4. The outcome in Columns 1 and 2 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.

Column 2 studies sorting in more detail by adding $AGE_{it} * STEM_i$, $AGE_{it} * AFQT_i$ and $AGE_{it} * STEM_i * AFQT_i$ interactions to equation (14). This tests whether ability sorting in and out of STEM occupations is different for STEM majors. We find that it is not - the coefficient on the triple interaction $AGE_{it} * STEM_i * AFQT_i$ is almost exactly zero, suggesting that the pattern of ability sorting holds regardless of major.

Columns 3 and 4 of Table 4 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. 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 4 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 4B.

Thus the results in Table 4 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. In results not reported, we show very similar results when we substitute STEM majors for STEM occupations in Columns 3 and 4.[30]

5 Job Task Change in Earlier Periods

Our model predicts that increases in the rate of task change Δ_j should flatten the age-earnings profile of careers. The empirical application in Section 4 was a comparison of 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 computer/IT revolution of the 1980s should correspond to an increase in the rate of task change and a rising relative return for young workers in STEM careers.

The BG data only allow us to calculate detailed measure of job task changes for the 2007-2017 period. We study the impact of technological change in earlier years using a database of classified job ads assembled by Atalay et al. (2018). Atalay et al. (2018) assemble the

[30] All the interactions have the same sign, although the implied convergence rates are much slower, perhaps because of endogenous switching across STEM and non-STEM occupations based on expected returns.

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 task content and relate job title to SOC codes using a text processing algorithm.[31] Atalay et al. (2018) map words and phrases to widely-used existing task 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 $TaskChange_o$ from equation (2) using the Atalay et al. (2018) data and job task classifications.[32] 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 task measures computed by Atalay et al. (2018), although the results are not sensitive to other choices.[33] We calculate $TaskChange_o$ 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 $TaskChange_o$ for each time period and occupation (6 digit SOC code) in the Atalay et al. (2018) data, and then compute the vacancy-weighted average in each period for STEM and non-STEM occupations. The results - in Panel A of Figure 7 - show three main findings. First, the rate of task change for non-STEM occupations is relatively constant at around 0.4 in each period.

[31] Atalay et al. (2018)use a model called Continuous Bag of Words (CBOW), which finds synonyms for words and phrases based how often they each appear next to similar words and phrases. The example given in Atalay et al. (2018) is as follows: “For example, to the extent that ’iv nurse,’ ’icu nurse,’ and ’rn coordinator’ all tend to appear next to words like ’patient’,’care’, or ’blood’ one would conclude that ’rn’ and ’nurse’ have similar meanings to one another.” The exact CBOW model estimation details are in Appendix C.3 of Atalay et al. (2018).

[32] The data and programs can be found on the authors’ public data page - https://ssc.wisc.edu/~eatalay/occupation_data.html

[33] The BG data are much richer and more detailed than the classified ad data from Atalay et al. (2018). We use the largest number of skills to maximize comparability to later periods, while recognizing that only comparisons *within* datasets are trustworthy. Other approaches such as using only DOT and/or O*NET, or only the skill measures that we can find in both data sources, yield broadly similar results.

Second, the rate of task change in STEM occupations fluctuates markedly, with peaks that occur during the technological revolution of the 1980s. The $TaskChange_o$ 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 $TaskChange_o$ 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 task 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 7 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:

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

where c_{it} is an indicator function $I\left(year = c\right)_{it}$ 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 function 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 7. 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 task 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 $TaskChange_o$ 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.

Thus the results in Figure 7 confirm the predictions of the model that young STEM workers earn relatively higher wages during periods of rapid task change, when their skills are newer and relatively more valuable.[34] 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 period.

Similarly, we find no consistent evidence that wages for young non-STEM workers move in any systematic way with the rate of occupational task change. Finally, although we do not have the data to calculate $TaskChange_o$between 2000 and 2007, we find that a very high return for young STEM workers during the 1999-2003 period, which coincides with the

[34]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.

technology boom of the late 1990s (e.g. Beaudry et al. 2016).

6 Conclusion

This paper presents new evidence on the life-cycle returns to STEM education. We show that the economic payoff to majoring in applied STEM fields such as engineering and computer science is initially very high, but declines by more than 50 percent in the first decade after college. STEM majors have flatter age-earnings profiles than college graduates who major in other subjects, even after controlling for cognitive ability and other important determinants of earnings.

We argue that the lower return to experience in STEM fields is due to the changing nature of STEM jobs themselves. We calculate detailed measures of job task requirements using job vacancy postings over the 2007-2017 period, and show that STEM jobs have relatively high rates of job task change over the most recent decade. Both STEM and non-STEM occupations that rank higher on our new measure of job task change employ younger workforces, and have flatter age-earnings profiles.

We formalize the key mechanism of job task 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 by the introduction of new job tasks that make the old one obsolete. 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.

We use historical data on job vacancies assembled by Atalay et al. 2018 to test whether the predictions of our framework hold during earlier periods, such as the computer and IT revolution of the 1980s. We find large increases in the rate of task 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, a finding that is supported by the predictions of the model.

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 skill shortages by hastening skill obsolescence among older workers. Our approach of using vacancy data to measure job task change also makes a contribution to the study of technological change, to the extent that progress manifests itself in the changing nature of work.

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 (Selingo 2018). 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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Table 1: Life-Cycle Earnings and Employment for STEM Majors

Age	Non-STEM Major		STEM Major		"Pure" Science		"Applied" Science	
	Wages	Share in STEM Job	Wages	Share in STEM Job	Wages	Share in STEM Job	Wages	Share in STEM Job
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
23	32,236	0.122	42,277	0.699	32,840	0.337	47,007	0.880
24	36,632	0.123	47,608	0.727	35,909	0.353	52,727	0.891
25	43,354	0.125	54,149	0.715	44,849	0.334	58,188	0.881
26	46,918	0.123	57,971	0.725	49,472	0.360	61,558	0.880
27	51,722	0.125	62,324	0.716	53,181	0.309	66,286	0.893
28	54,856	0.124	65,621	0.676	57,243	0.297	69,590	0.856
29	58,389	0.120	69,961	0.658	62,651	0.304	73,765	0.843
30	62,787	0.124	73,772	0.651	69,109	0.293	76,309	0.845
31	67,567	0.122	80,097	0.613	79,274	0.275	80,546	0.798
32	71,933	0.123	82,266	0.617	79,894	0.271	83,536	0.802
33	74,608	0.121	89,800	0.598	91,085	0.268	89,109	0.776
34	79,971	0.117	94,009	0.578	98,442	0.265	91,542	0.753
35	85,897	0.116	101,143	0.546	105,914	0.267	98,291	0.712
36	89,875	0.119	103,950	0.546	111,807	0.261	99,114	0.722
37	93,259	0.125	108,221	0.531	114,927	0.286	103,804	0.693
38	94,453	0.123	112,042	0.510	117,943	0.260	108,081	0.678
39	99,481	0.111	114,797	0.508	121,372	0.253	110,477	0.675
40	99,952	0.116	116,127	0.485	123,224	0.256	111,678	0.629
41	103,447	0.112	117,203	0.474	123,281	0.253	113,388	0.613
42	104,068	0.116	116,886	0.500	122,578	0.270	113,511	0.637
43	106,122	0.116	124,672	0.478	132,626	0.267	120,005	0.603
44	108,777	0.108	124,720	0.487	129,115	0.267	122,278	0.609
45	111,802	0.104	126,337	0.502	136,001	0.273	121,420	0.619
46	111,235	0.103	128,250	0.458	141,341	0.232	121,746	0.571
47	112,430	0.100	129,106	0.485	136,539	0.274	125,350	0.591
48	112,002	0.096	129,968	0.481	136,772	0.283	126,601	0.579
49	112,347	0.096	130,408	0.469	139,118	0.278	126,111	0.564
50	111,754	0.098	130,289	0.461	137,439	0.273	126,606	0.557

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 2: 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
231	Lawyers, Judges and Related Workers	0.239
171	Architects and Surveyors	0.217
192	Physical Scientists	0.207
191	Life Scientists	0.203
172	Engineers	0.197
173	Drafters and Engineering Technicians	0.197
152	Mathematical Scientists	0.184
113	Operations Specialties Managers	0.173
254	Librarians, Curators and Archivists	0.172
232	Legal Support Workers	0.165

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

SOC code	Occupation Title	Rate of Task Change
173013	Mechanical Drafters	0.404
151131	Computer Programmers	0.355
173011	Architectural and Civil Drafters	0.344
151133	Software Developers, Systems Software	0.301
112011	Advertising and Promotions Managers	0.282
172081	Environmental Engineers	0.281
132053	Insurance Underwriters	0.281
291051	Pharmacists	0.281
173012	Electrical and Electronics Drafters	0.274
152011	Actuaries	0.244

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

SOC code	Occupation Title	Rate of Task Change
193	Social Scientists and Related Workers	0.099
291	Health Diagnosing and Treating Practitioners	0.101
252	Pre-K, Primary and Secondary School Teachers	0.104
259	Other Education, Training and Library Occupations	0.105
253	Other Teachers and Instructors	0.109
292	Health Technologists and Technicians	0.117
111	Managers and Executives	0.122
194	Life, Physical and Social Science Technicians	0.126
299	Other Healthcare Practitioners	0.128
211	Counselors and Social Workers	0.131

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

SOC code	Occupation Title	Rate of Task Change
291065	Pediatricians	0.030
291171	Nurse Practitioners	0.050
291021	Dentists	0.052
193031	Clinical Psychologists	0.054
291131	Veterinarians	0.054
292052	Pharmacy Technicians	0.056
252059	Special Education Teachers, All Other	0.056
291066	Psychiatrists	0.057
291069	Physicians and Surgeons, All Other	0.063
291151	Nurse Anesthetists	0.067

Notes: This table uses online job vacancy data from Burning Glass Technologies (BG) to calculate the rate of task change between 2007 and 2017 for each 3- and 6-digit Standard Occupational Classification (SOC) code. The task change measure ranges between 0 and 1, with zero indicating that the tasks demanded by employers in the occupation in 2007 were exactly the same as in 2017, and 1 indicating that the job has a completely different set of task demands. The average value of the task change measure is 0.13 - see the text for details. Professional Occupations are SOC codes where the first digit begins with a 1 or a 2.

Table 3: 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

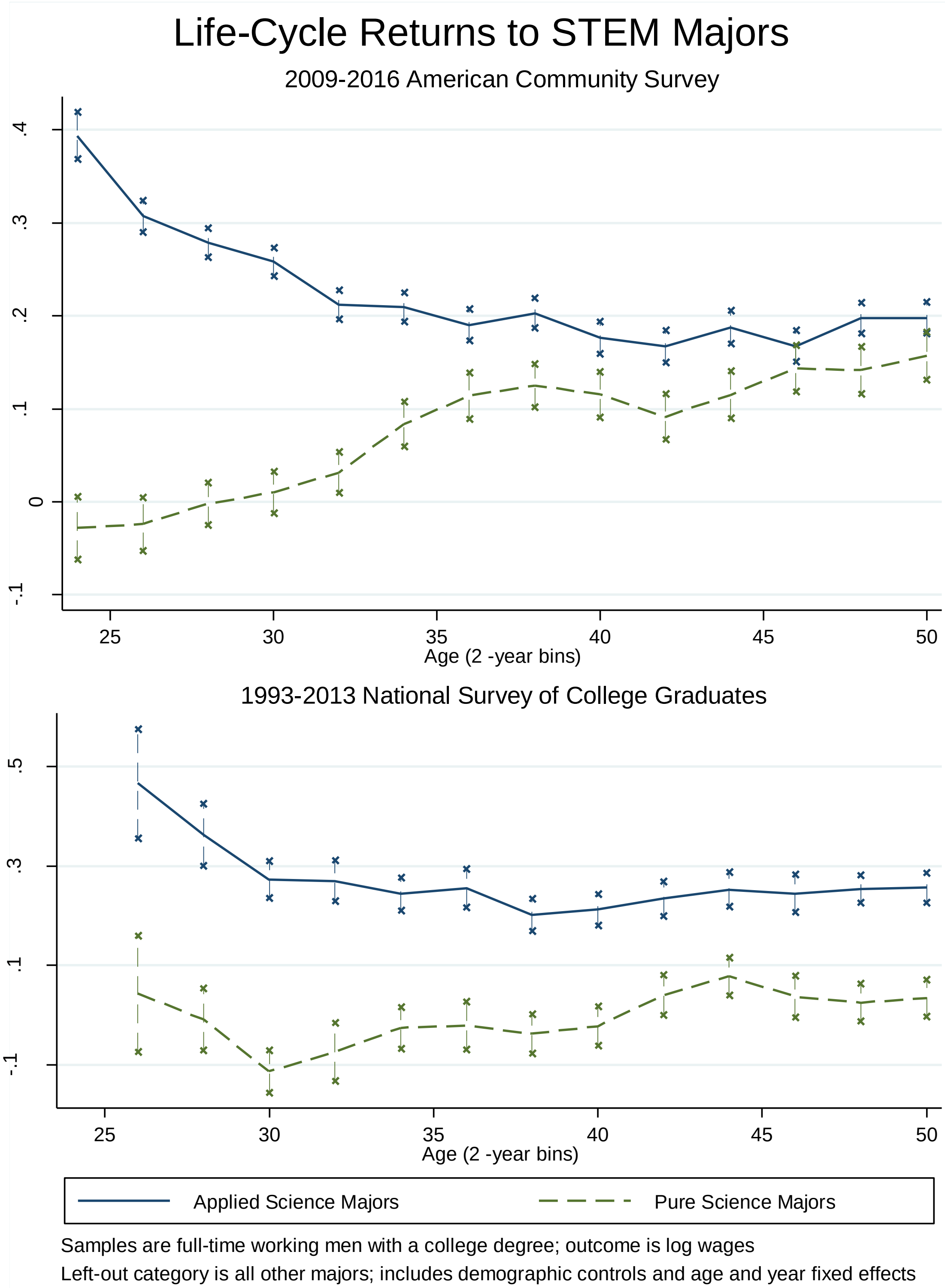
Notes: Each column reports results from a regression of real log hourly wages on indicators for college major, occupation and/or industry (in columns 3 through 5), individual skills, indicator variables for race and years of completed education, age and year fixed effects, and additional controls as 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 4: STEM Majors, Relative Wages and Ability Sorting in the NLSY

	In a STEM Job		Ln (Wages)	
	(1)	(2)	(3)	(4)
STEM Major	0.352***	0.170***	0.116***	0.005
	[0.035]	[0.055]	[0.034]	[0.120]
AFQT (Standardized)	0.084***	0.066***	0.063*	0.017
	[0.016]	[0.014]	[0.033]	[0.032]
Age (Linear)	0.002	-0.001	0.013	0.007
	[0.005]	[0.004]	[0.008]	[0.009]
Age * AFQT	-0.005**	-0.006***	0.013***	0.024***
	[0.002]	[0.002]	[0.005]	[0.005]
Age * STEM Major		0.015*		0.027*
		[0.008]		[0.014]
STEM Major * AFQT		0.095**		0.187*
		[0.048]		[0.097]
STEM Major * AFQT * Age		0.000		-0.041***
		[0.007]		[0.013]
R-squared	0.183	0.190	0.237	0.242
Number of Observations	11,214	11,214	8,685	8,685

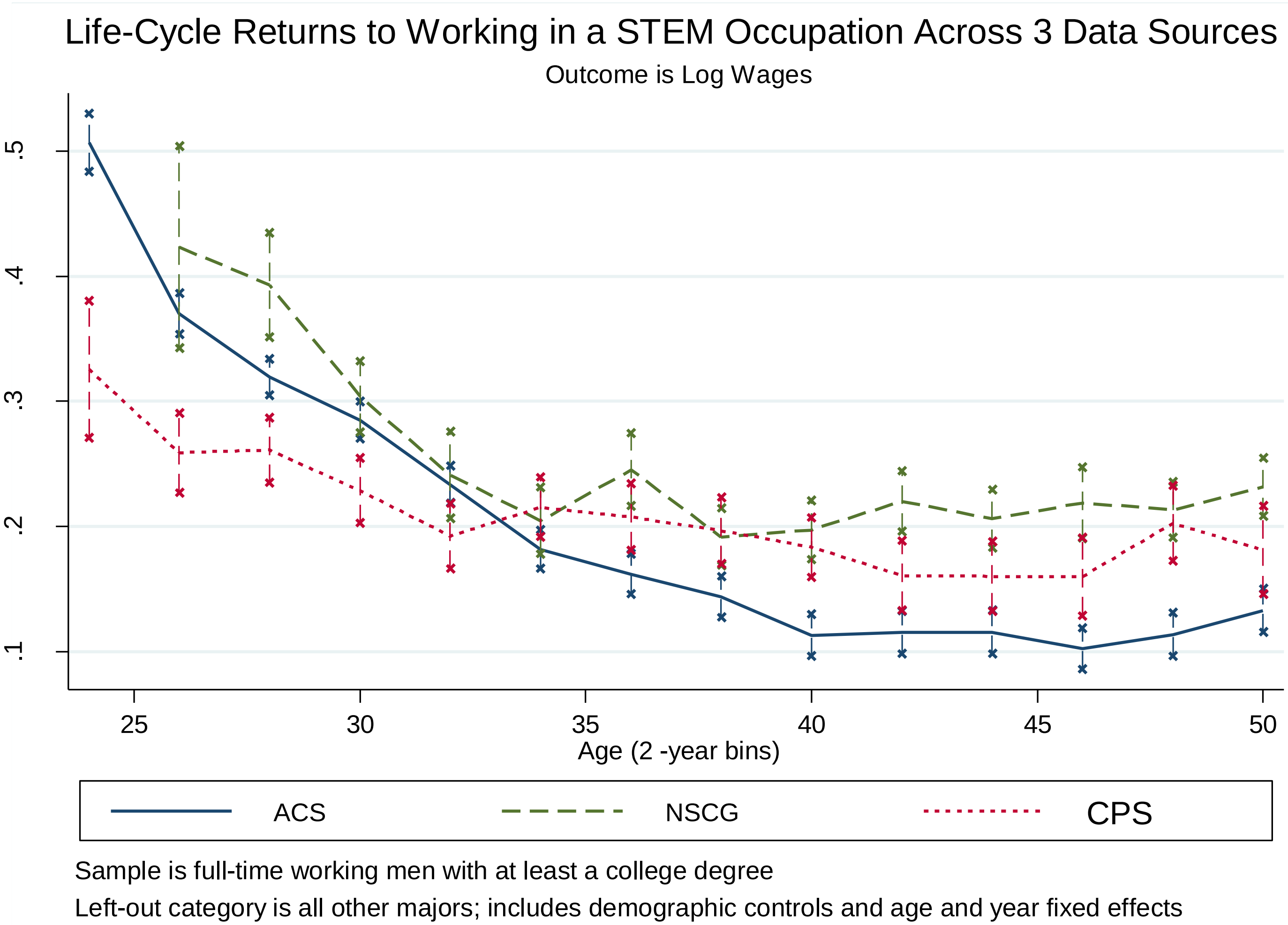
Notes: Each column reports results from a regression of indicators for working in a STEM occupation (Columns 1 and 2) or real log hourly wages (Columns 3 and 4) on indicators for majoring in a Science, Technology, Engineering and Mathematics (STEM) field, cognitive, social and noncognitive skills, indicator variables for 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.

Figure 1



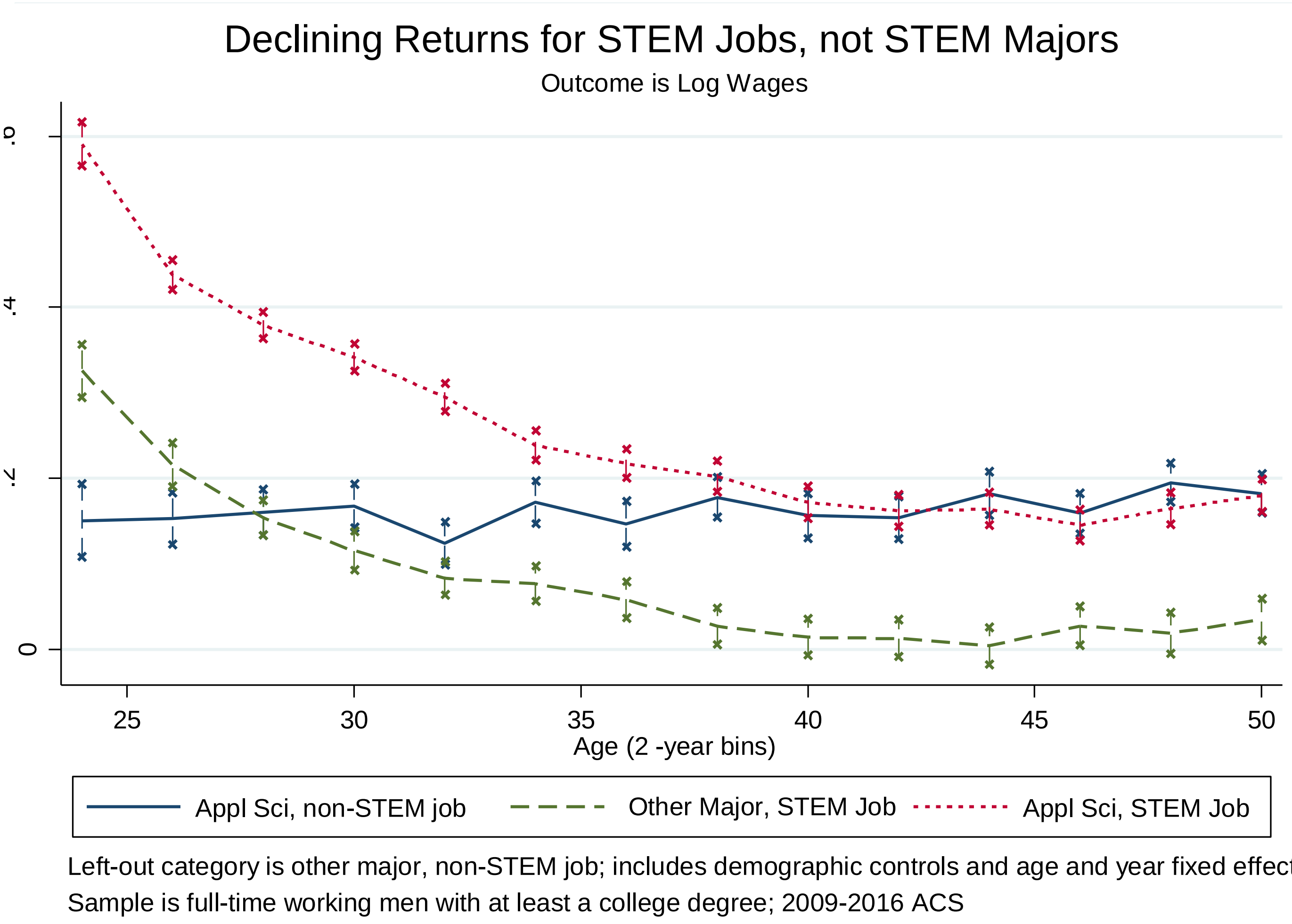
Notes: The figure plots coefficients and 95 percent confidence intervals from an estimate of the returns to majors over time, following equation (1) in the paper. "Pure" Science includes biology, chemistry, physics, mathematics and statistics, while "Applied" Science includes engineering and computer science.

Figure 2



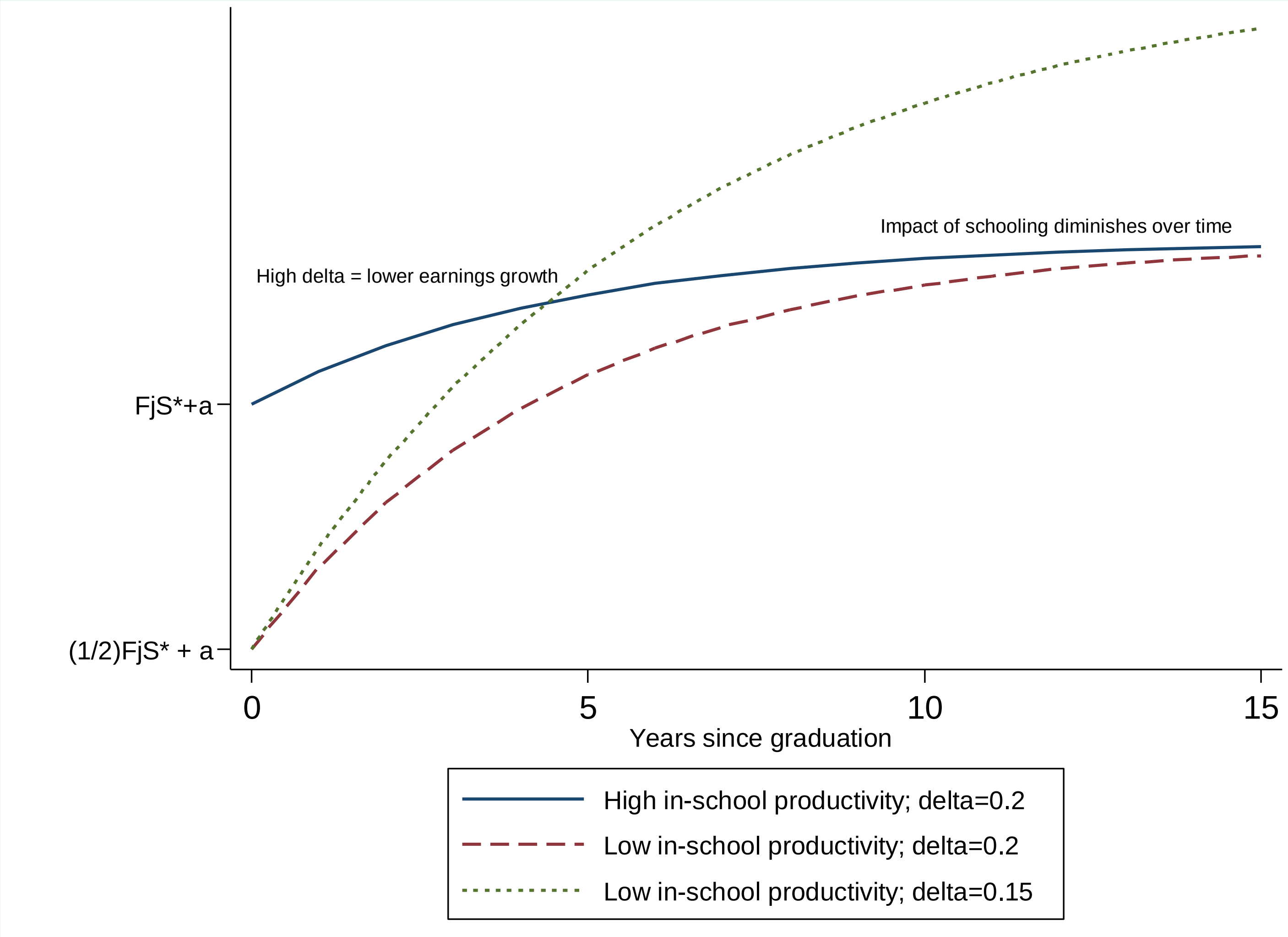
Notes: The figure plots coefficients and 95 percent confidence intervals from three separate estimates of equation (1) in the paper, except we interact age bins with indicators for working in a STEM occupation rather than earning a STEM degree. STEM occupations are defined using the 2010 Census Bureau 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 3



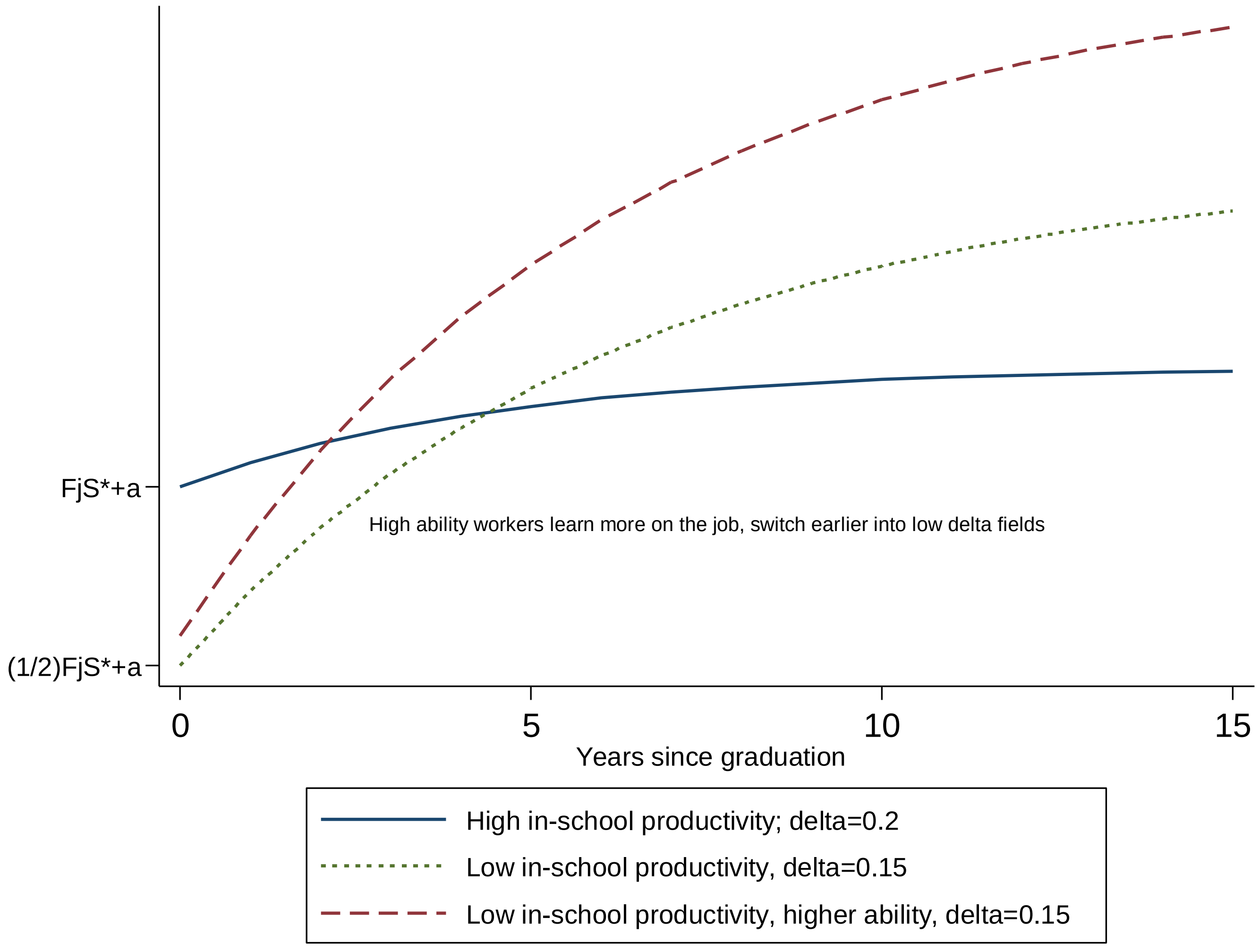
Notes: The figure plots coefficients and 95 percent confidence intervals from an estimate of the returns to majors over time, following equation (1) in the paper, but adding occupation and major interactions. "Applied" Science majors include engineering and computer science.

Figure 4A



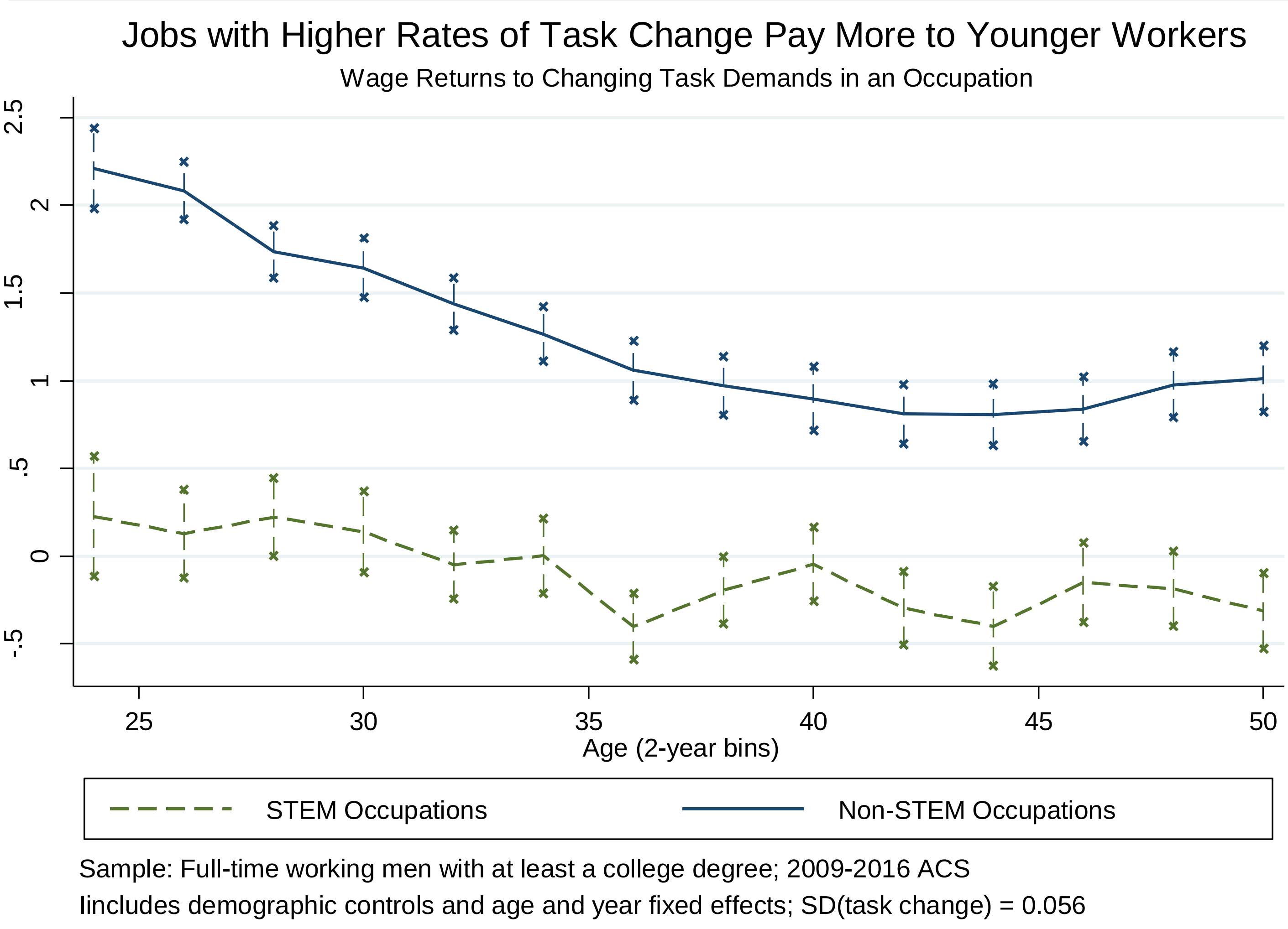
Notes: This Figure simulates earnings growth from the model in Section 3 of the paper when $F_j S^* = 6$ (high in-school productivity) or $F_j S^* = 3$ (low in-school productivity) and the rate of task change Δ_j is equal to 0.20 or 0.15. See the text for details.

Figure 4B



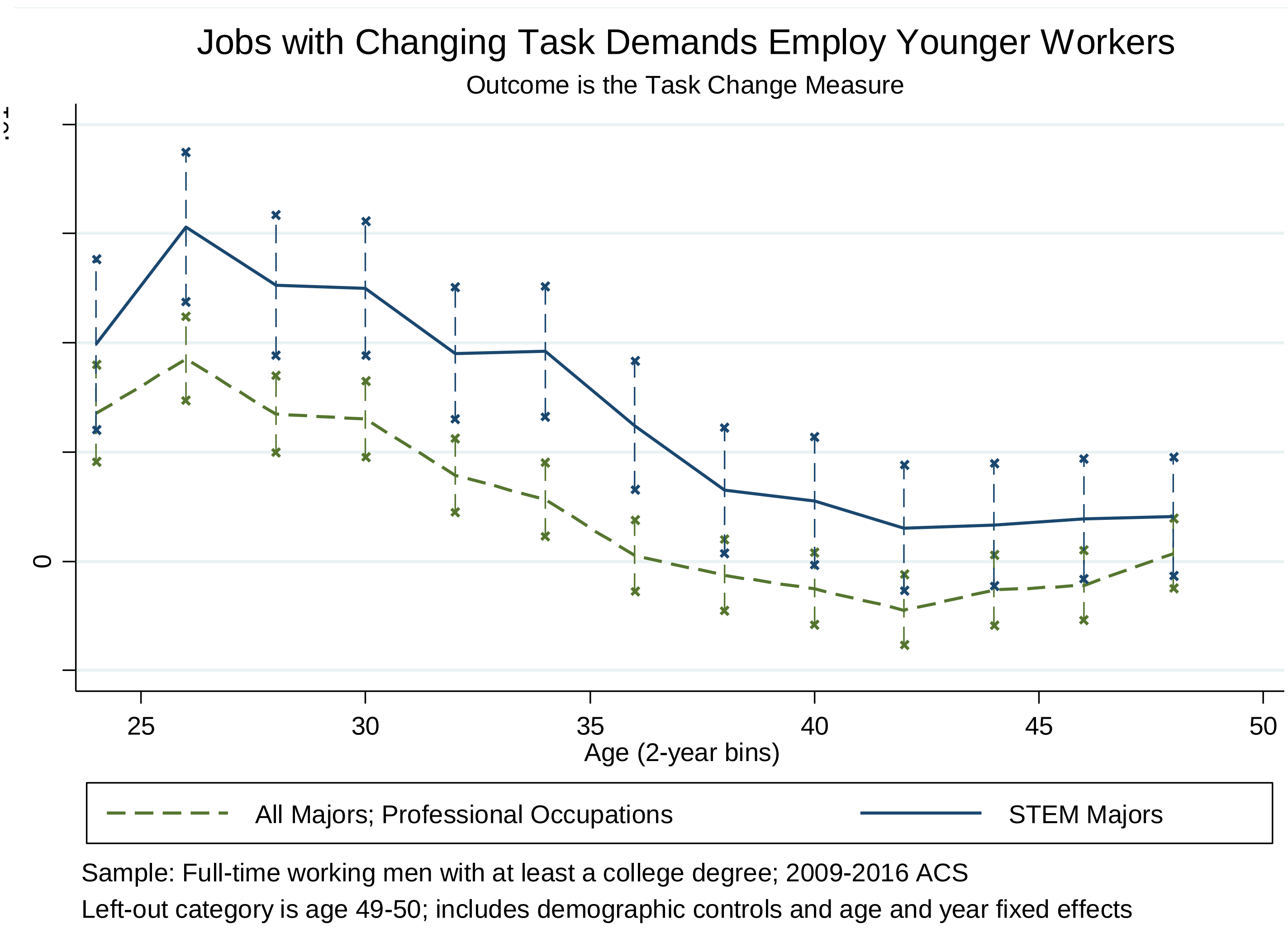
Notes: This Figure simulates earnings growth from the model in Section 3 of the paper when $F_j S^* = 6$ (high in-school productivity) or $F_j S^* = 3$ (low in-school productivity), the rate of task change Δ_j is equal to 0.20 or 0.15, and for a high vs. low ability worker. See the text for details.

Figure 5



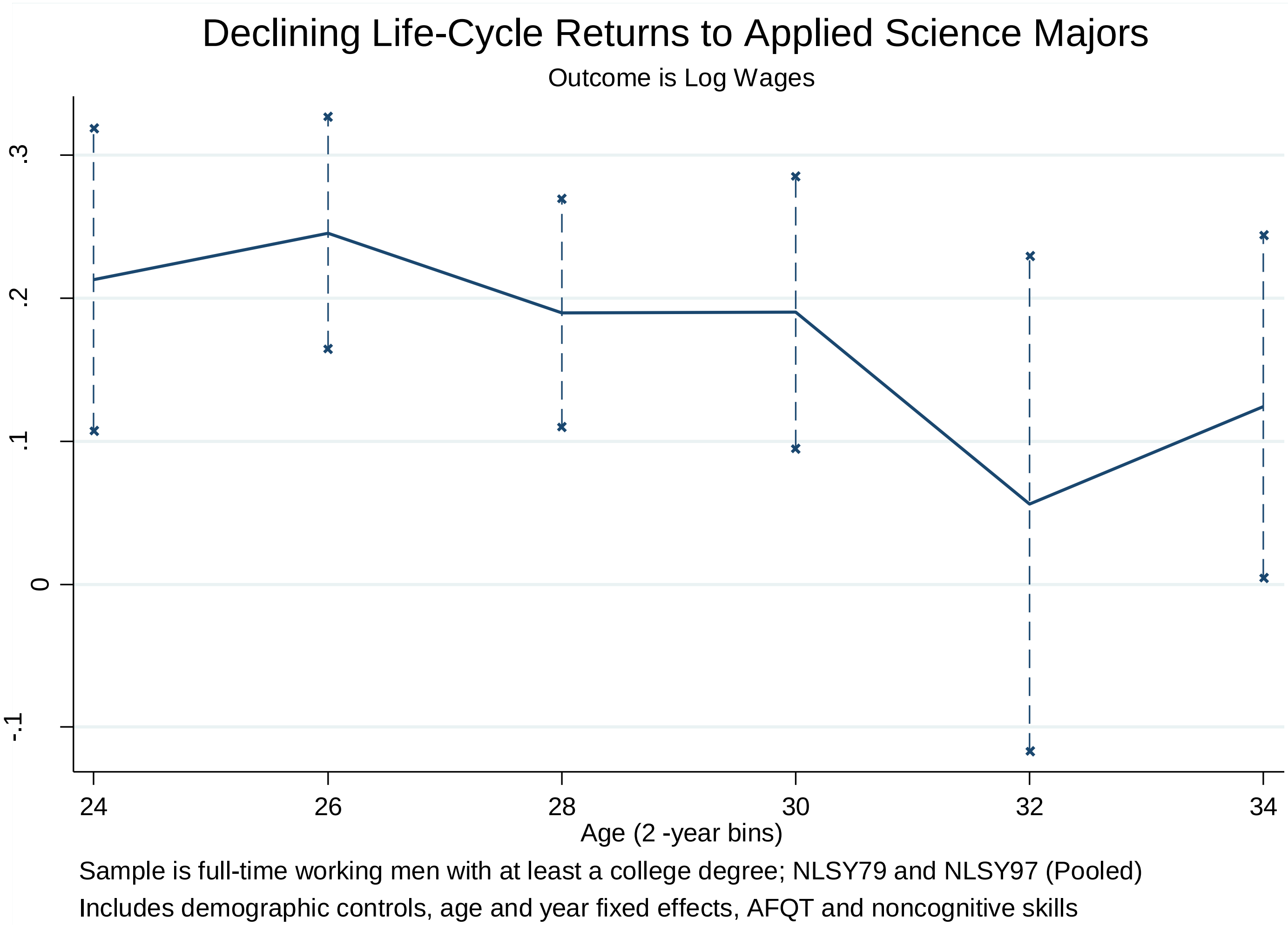
Notes: The figure plots coefficients and 95 percent confidence intervals from equation (10) in the paper, a regression of log wages on interactions between age and the task change measure Δ_j that is estimated using 2007-2017 online job vacancy data from Burning Glass Technologies. STEM occupations are defined using the 2010 Census Bureau classification. See the text for details.

Figure 6



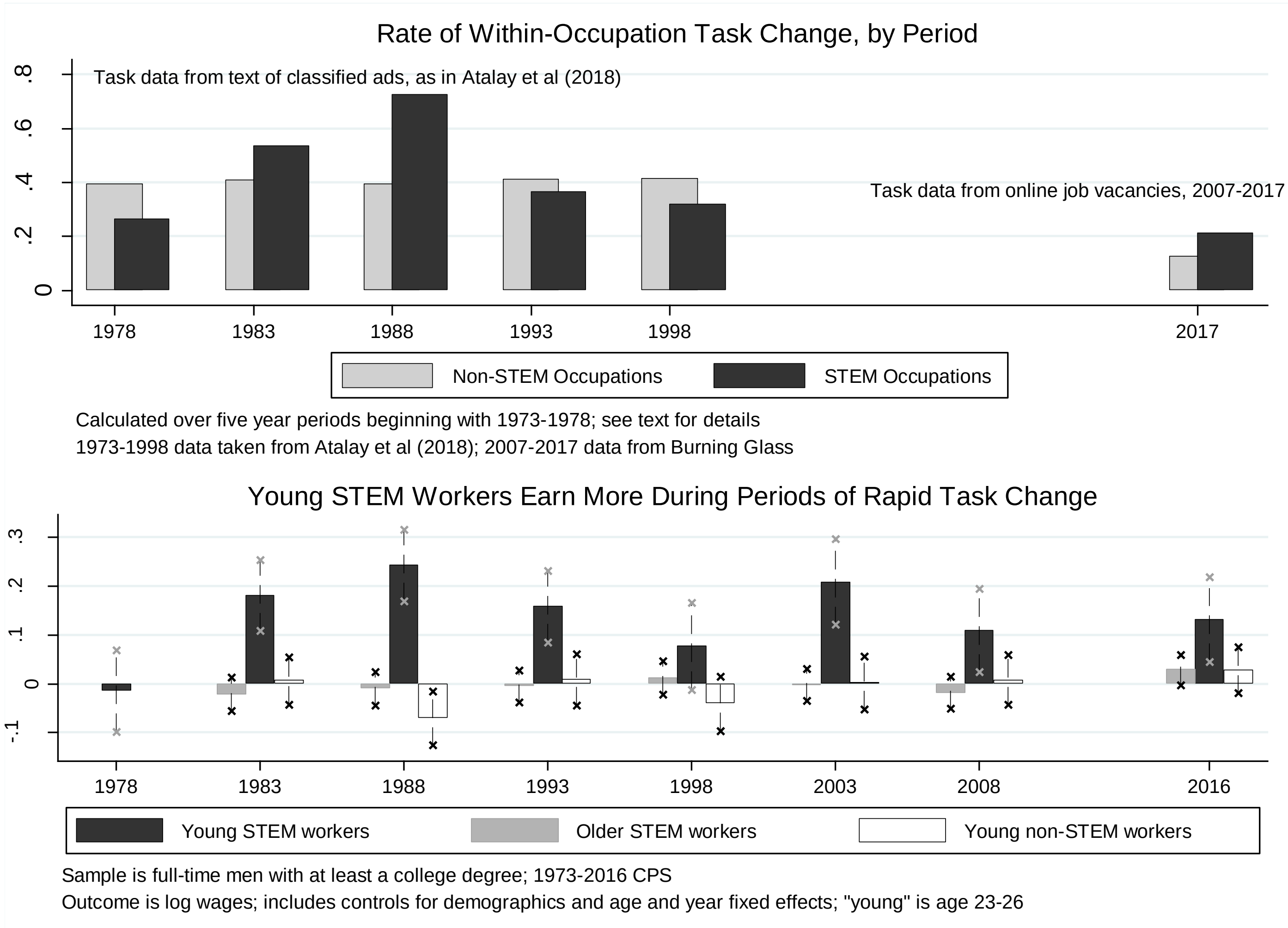
Notes: The figure plots coefficients and 95 percent confidence intervals from equation (11) in the paper, a regression of the task change measure Δ_j (which is estimated using 2007-2017 online job vacancy data from Burning Glass Technologies) on occupation by age group interactions. STEM occupations are defined using the 2010 Census Bureau classification. See the text for details.

Figure 7



Notes: The figure plots coefficients and 95 percent confidence intervals from an estimate of the returns to Applied Science majors over time, following equation (1) in the paper. "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 8



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.

Appendix Results

NOT FOR PUBLICATION

Table A1: Selection into Graduate School in the NLSY

Outcome is an indicator for graduate education	(1)	(2)	(3)
Cognitive Skill (AFQT, standardized)	0.099***	0.099***	0.131***
	[0.022]	[0.022]	[0.032]
STEM Major	-0.034	-0.110***	-0.013
	[0.032]	[0.041]	[0.073]
NLSY Wave	0.103***	0.063**	0.089*
	[0.027]	[0.031]	[0.051]
STEM Major * NLSY Wave		0.181***	0.162
		[0.064]	[0.121]
AFQT * NLSY Wave			-0.028
			[0.044]
STEM Major * AFQT			-0.100*
			[0.062]
STEM Major * AFQT * NLSY Wave			0.027
			[0.100]
R-squared	0.030	0.035	0.038
Number of Observations	1,360	1,360	1,360

Notes: Each column reports results from a regression of an indicator for graduate school attendance on the Armed Forces Qualifying Test (AFQT) score, indicators for college major, an indicator for whether the respondent is in the National Longitudinal Survey of Youth (NLSY) 1997 survey wave, and other variables as shown. The regression also includes controls for race. The sample pools the 1979 and 1997 NLSY waves together and is restricted to men with at least a college degree. STEM majors are defined following Peri, Shih and Sparber (2015). "Pure" Science majors include biology, chemistry, physics, mathematics and statistics, while "Applied" Science includes engineering and computer science. We normalize scores across NLSY waves using the crosswalk developed by Altonji, Bharadwaj and Lange (2012). The sample is restricted to ages 23-34 to maximize comparability across survey waves. *** p<0.01, ** p<0.05, * p<0.10.

Table A2: Occupations with the Highest and Lowest Rates of Software-Related Task Change

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

SOC code	Occupation Title	Software Task Change
171	Architects and Surveyors	0.062
151	Computer Occupations	0.058
173	Drafters and Engineering Technicians	0.030
172	Engineers	0.030
152	Mathematical Scientists	0.029
271	Art and Design Workers	0.028
273	Media and Communications Workers	0.025
274	Media and Communications Equipment Workers	0.024
131	Business Operations Specialists	0.022
132	Financial Specialists	0.019

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

SOC code	Occupation Title	Software Task Change
151131	Computer Programmers	0.140
151133	Software Developers, Systems Software	0.133
151134	Web Developers	0.098
173011	Architectural and Civil Drafters	0.094
173013	Mechanical Drafters	0.094
271014	Multimedia Artists and Animators	0.076
151142	Network and Computer Systems Administra	0.069
271024	Graphic Designers	0.067
151141	Database Administrators	0.065
151141	Software Developers, Applications	0.065

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

SOC code	Occupation Title	Software Task Change
291	Health Diagnosing and Treating Practitioners	0.002
252	Pre-K, Primary and Secondary School Teachers	0.004
253	Other Teachers and Instructors	0.004
292	Health Technologists and Technicians	0.004
211	Counselors and Social Workers	0.008
251	Postsecondary Teachers	0.009
259	Other Education, Training and Library Occupations	0.010
299	Other Healthcare Practitioners	0.010
191	Life Scientists	0.010
193	Social Scientists	0.010

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

SOC code	Occupation Title	Software Task Change
291065	Pediatricians	0.000
291151	Nurse Anesthetists	0.000
292021	Dental Hygienists	0.001
291131	Veterinarians	0.001
291171	Nurse Practitioners	0.001
291066	Psychiatrists	0.001
252011	Preschool Teachers	0.001
291021	Dentists	0.001
292055	Surgical Technologists	0.001
291062	Family and General Practitioners	0.001

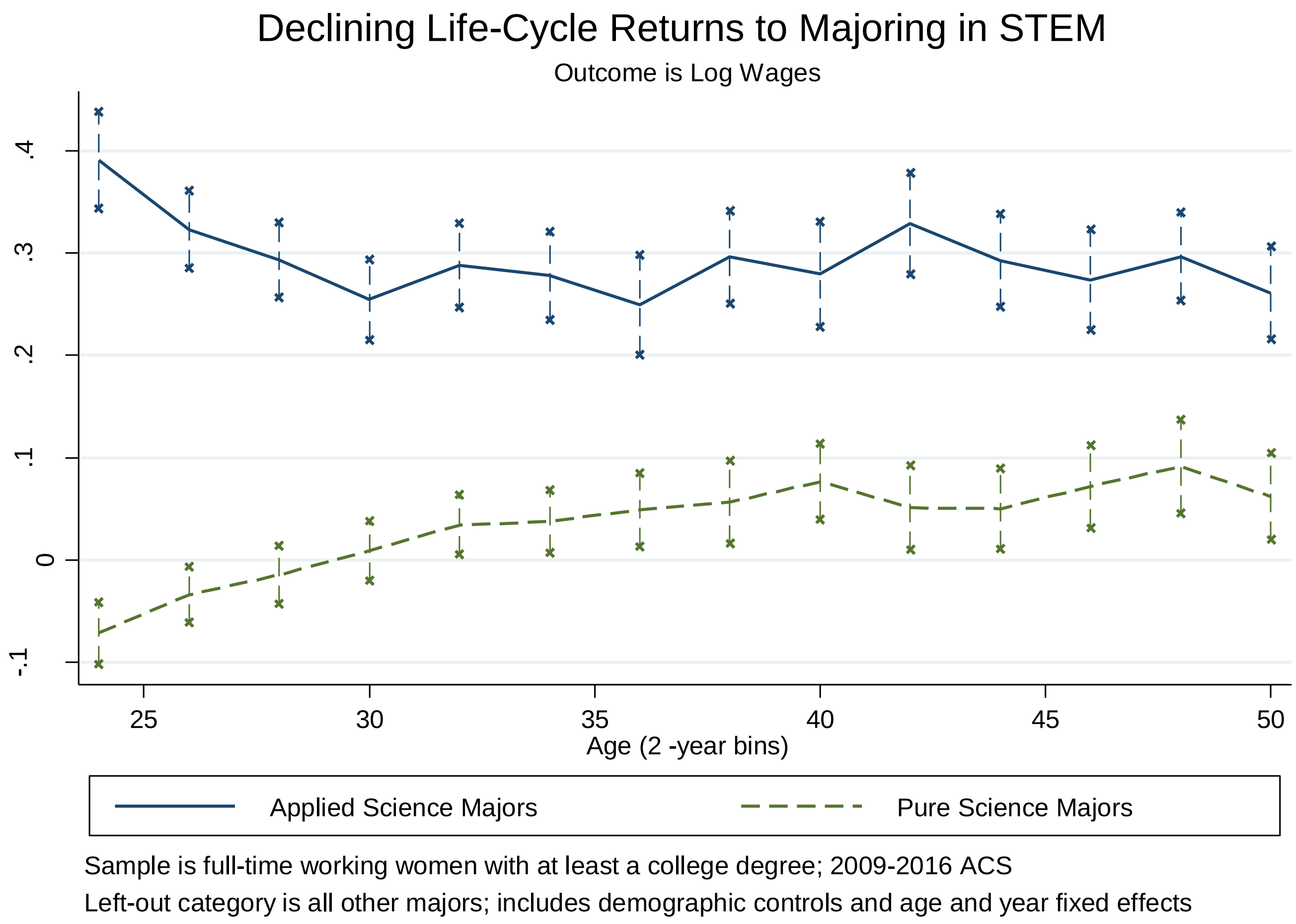
Notes: This table uses online job vacancy data from Burning Glass Technologies (BG) to calculate the rate of change for software-related tasks between 2007 and 2017 for each 3- and 6-digit Standard Occupational Classification (SOC) code. The task change measure ranges between 0 and 1, with zero indicating that the tasks demanded by employers in the occupation in 2007 were exactly the same as in 2017, and 1 indicating that the job has a completely different set of task demands. We restrict the set of occupations in the table to those with at least 10,000 total vacancies posted in both 2007 and 2017. The average value of the software task change measure is 0.016 - see the text for details. Professional Occupations are SOC codes where the first digit begins with a 1 or a 2.

Table A3: Ability Sorting into STEM Majors in the NLSY

Outcome is AFQT Score (standardized)	(1)	(2)	(3)
STEM Major	0.083**	0.076	
	[0.039]	[0.051]	
NLSY 97 Wave	0.048	0.044	0.051
	[0.053]	[0.056]	[0.055]
STEM Major * NLSY Wave		0.019	
		[0.079]	
Applied Science Major			0.083
			[0.056]
Applied Science Major * NLSY Wave			-0.021
			[0.089]
R-squared	0.217	0.217	0.217
Number of Observations	1,360	1,360	1,360

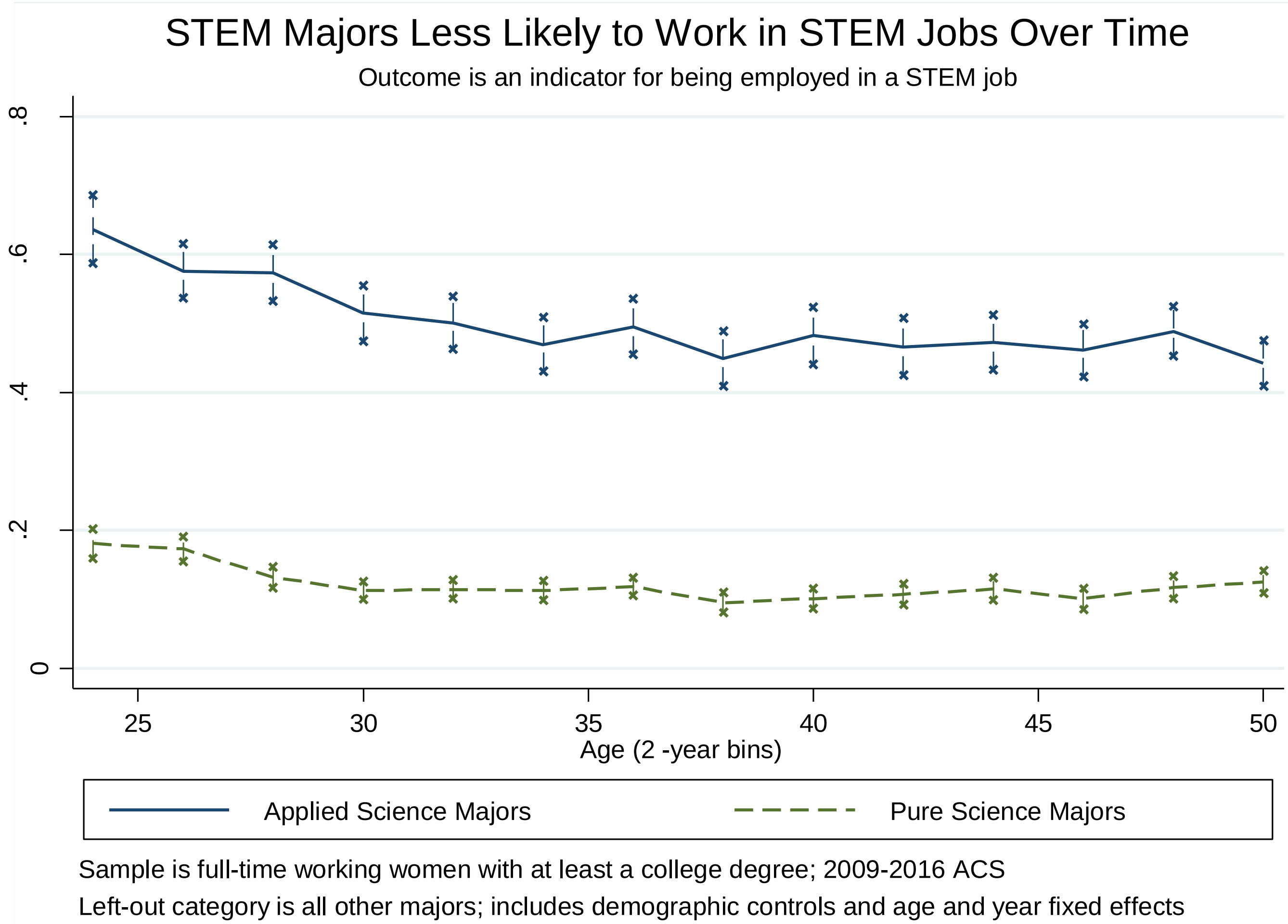
Notes: Each column reports results from a regression of the Armed Forces Qualifying Test (AFQT) score on indicators for college major and an indicator for whether the respondent is in the National Longitudinal Survey of Youth (NLSY) 1997 survey wave. The regression also includes controls for race and the age at which the test was taken. The sample pools the 1979 and 1997 NLSY waves together and is restricted to men with at least a college degree. STEM majors are defined following Peri, Shih and Sparber (2015). "Pure" Science majors include biology, chemistry, physics, mathematics and statistics, while "Applied" Science includes engineering and computer science. We normalize scores across NLSY waves using the crosswalk developed by Altonji, Bharadwaj and Lange (2012). The sample is restricted to ages 23-34 to maximize comparability across survey waves. *** p<0.01, ** p<0.05, * p<0.10.

Figure A1



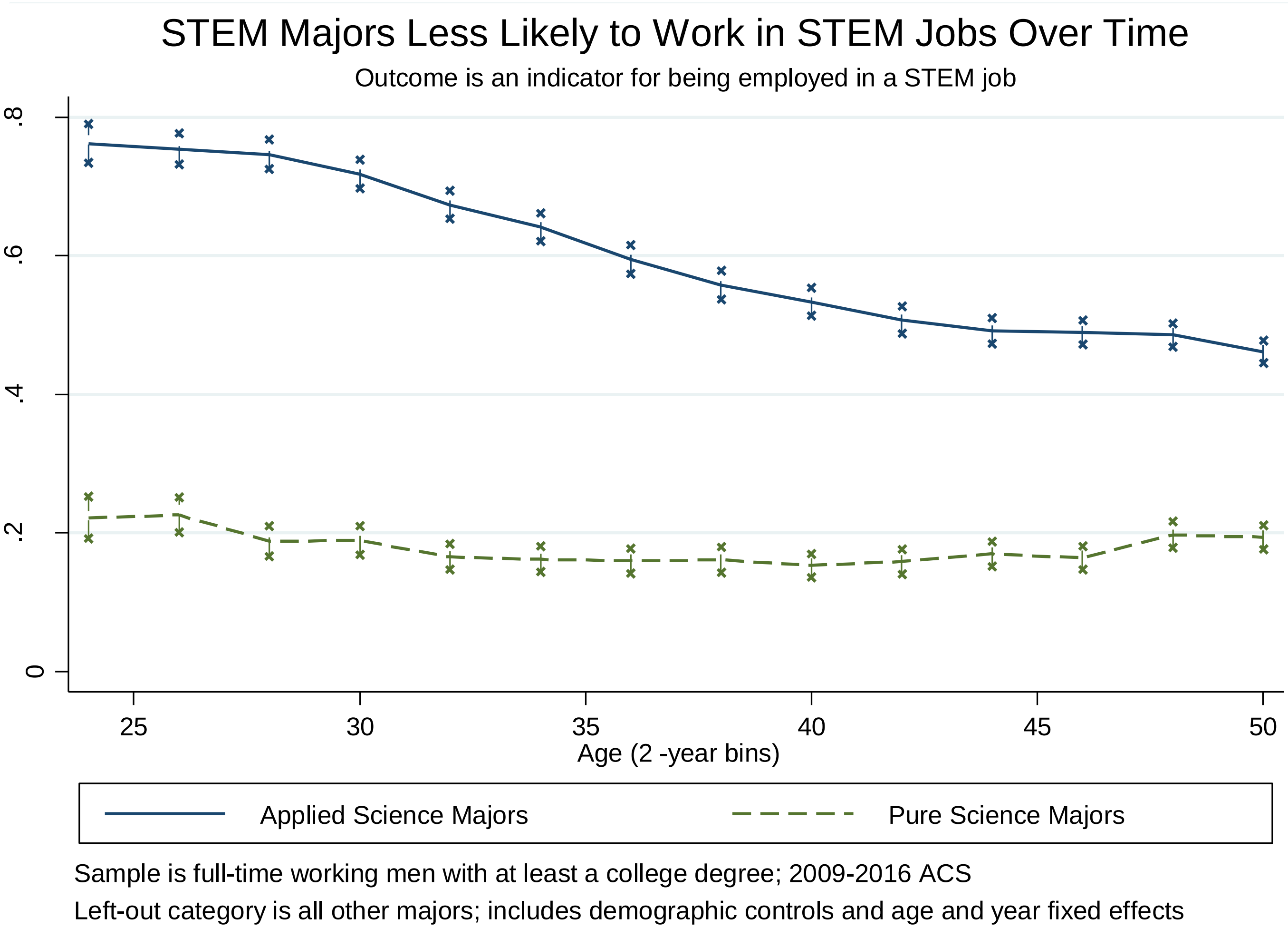
Notes: The figure plots coefficients and 95 percent confidence intervals from an estimate of the returns to majors over time for women, following equation (1) in the paper. "Pure" Science includes biology, chemistry, physics, mathematics and statistics, while "Applied" Science includes engineering and computer science.

Figure A2



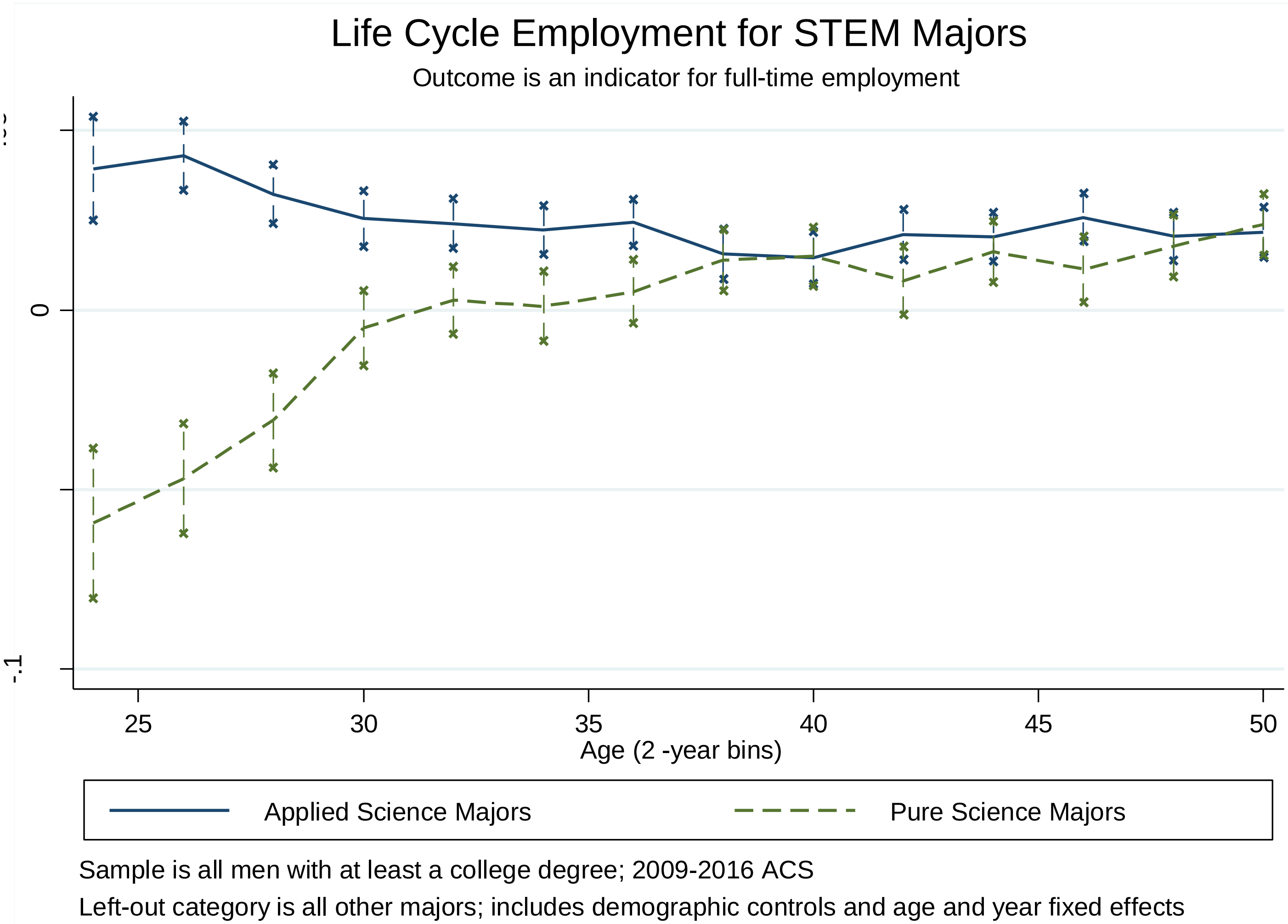
Notes: The figure plots coefficients and 95 percent confidence intervals from an estimate of equation (1) in the paper, except with an indicator for working in a STEM occupation as the outcome. "Pure" Science includes biology, chemistry, physics, mathematics and statistics, while "Applied" Science includes engineering and computer science. STEM occupations are defined using the 2010 Census Bureau classification.

Figure A3



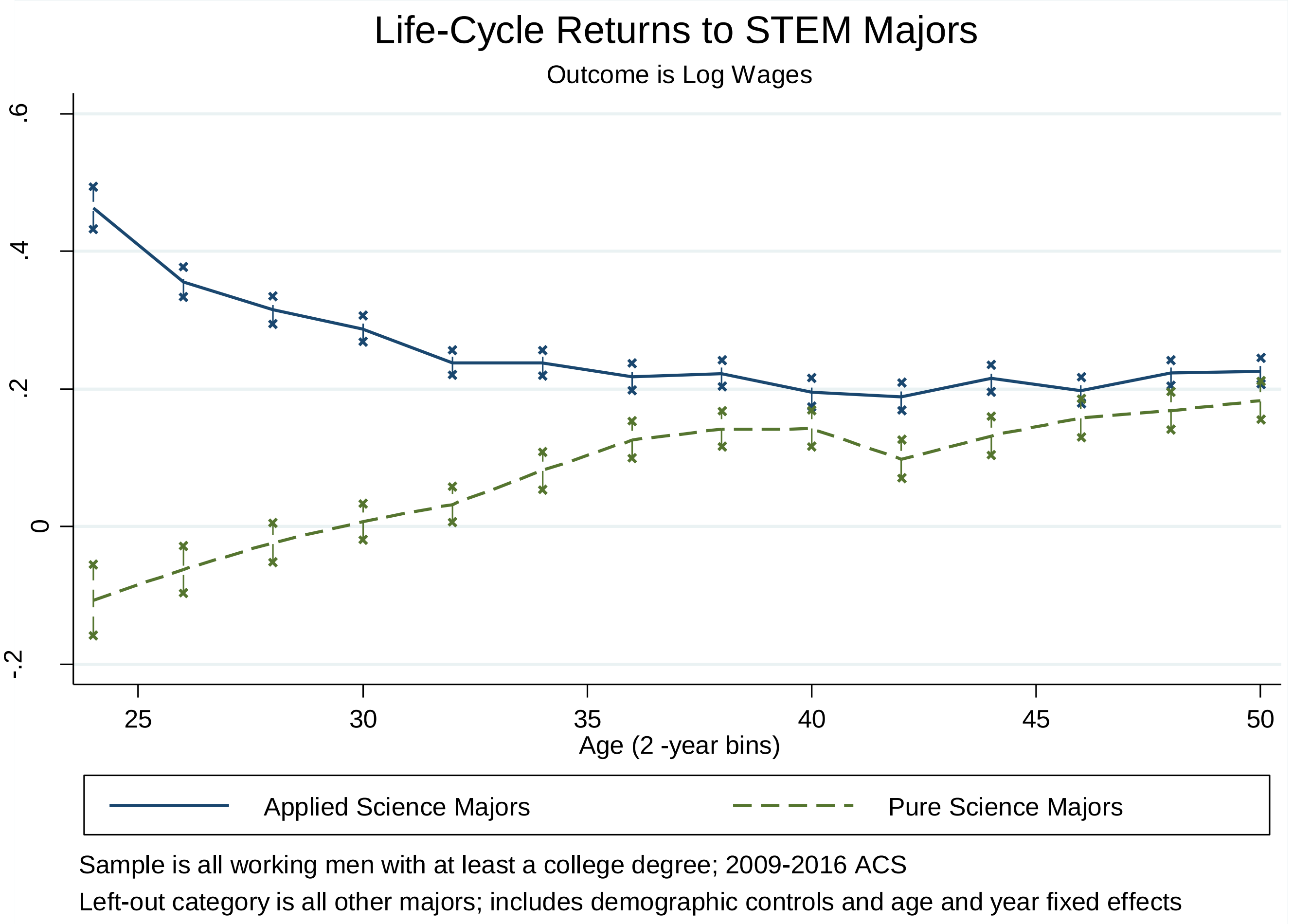
Notes: The figure plots coefficients and 95 percent confidence intervals from an estimate of equation (1) in the paper, except with an indicator for working in a STEM occupation as the outcome. "Pure" Science includes biology, chemistry, physics, mathematics and statistics, while "Applied" Science includes engineering and computer science. STEM occupations are defined using the 2010 Census Bureau classification.

Figure A4



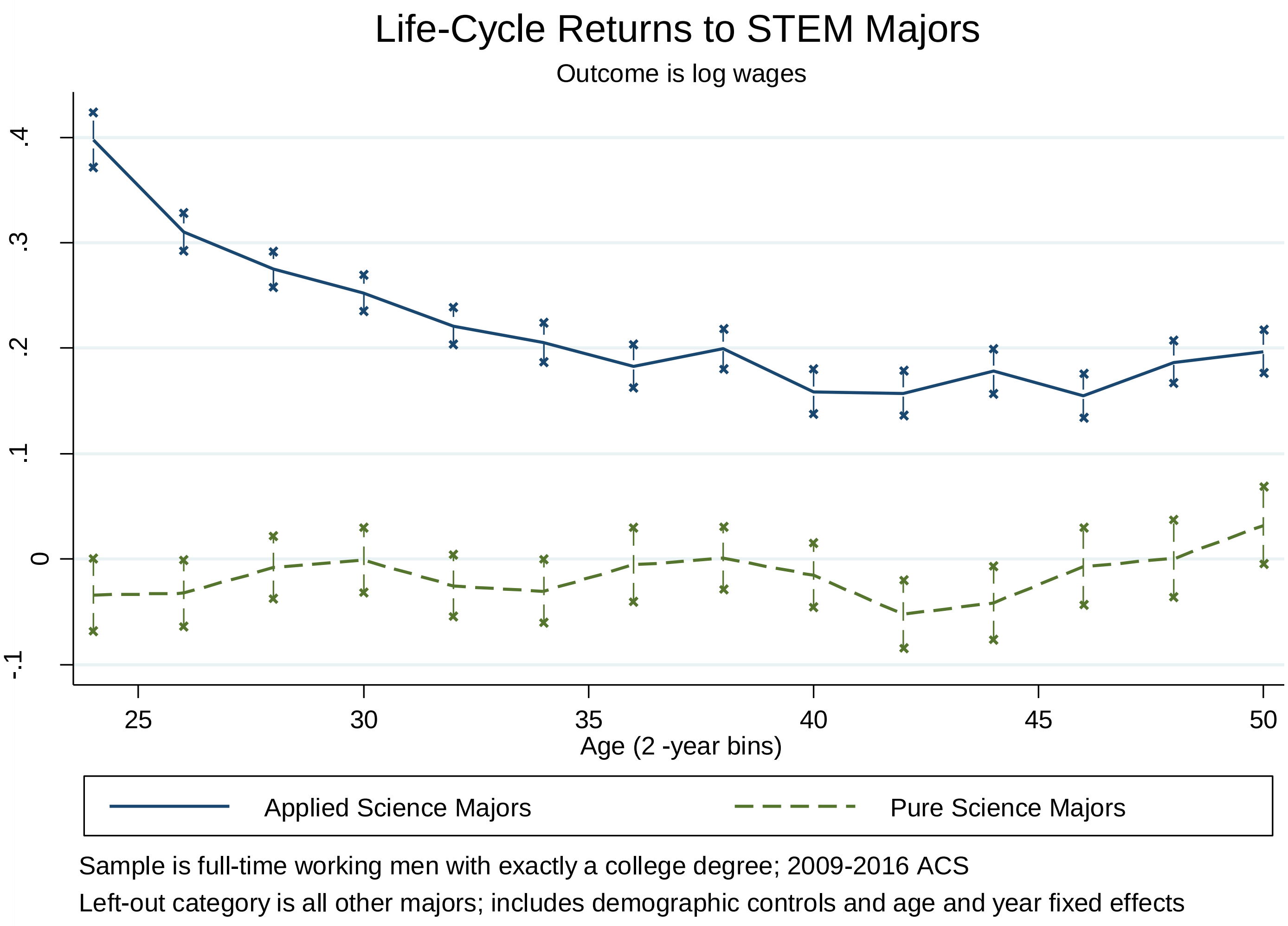
Notes: The figure plots coefficients and 95 percent confidence intervals from an estimate of equation (1) in the paper, except with an indicator for working full-time as the outcome. "Pure" Science includes biology, chemistry, physics, mathematics and statistics, while "Applied" Science includes engineering and computer science.

Figure A5



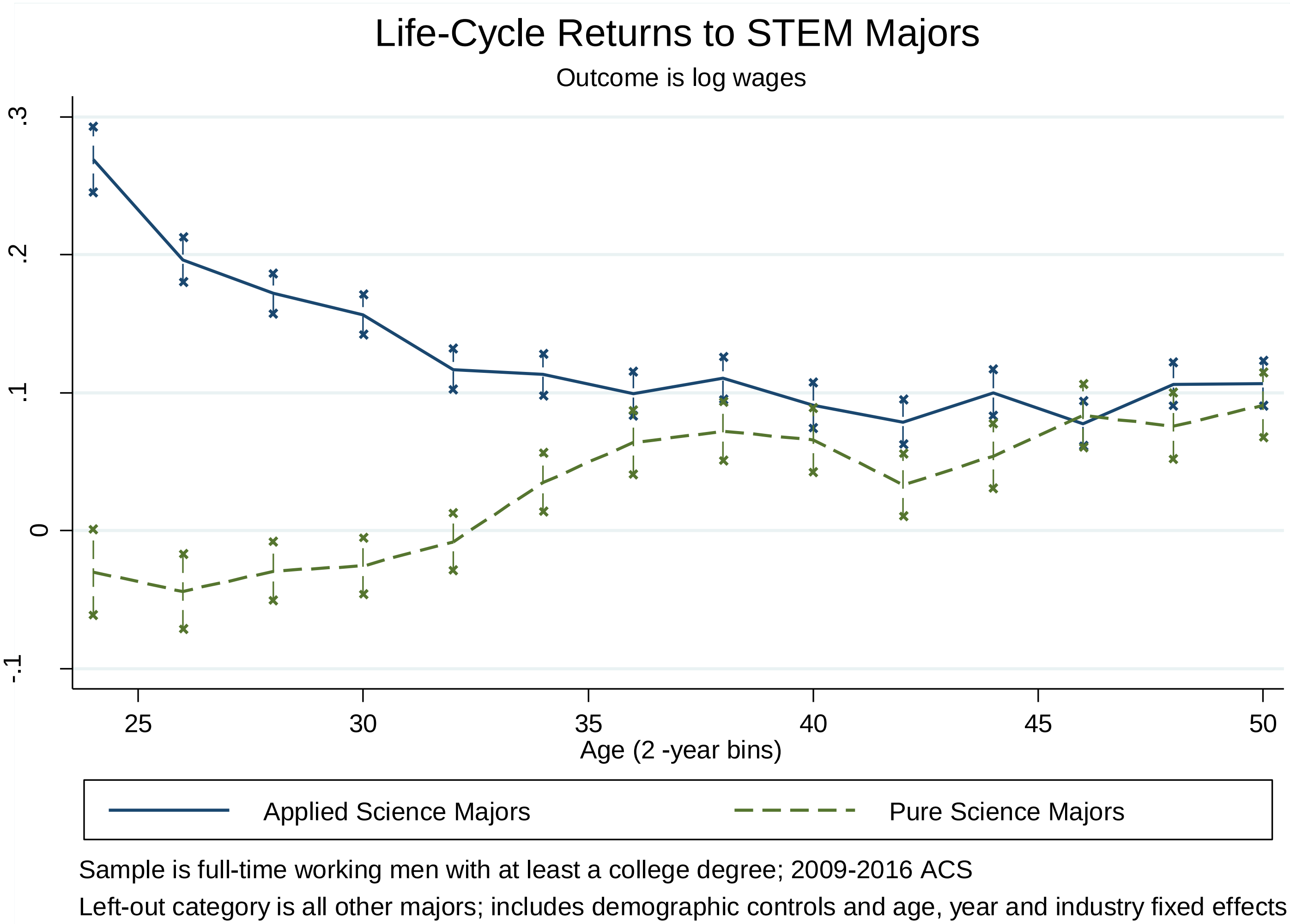
Notes: The figure plots coefficients and 95 percent confidence intervals from an estimate of equation (1) in the paper, except the sample includes all working men (not just full-time). "Pure" Science includes biology, chemistry, physics, mathematics and statistics, while "Applied" Science includes engineering and computer science.

Figure A6



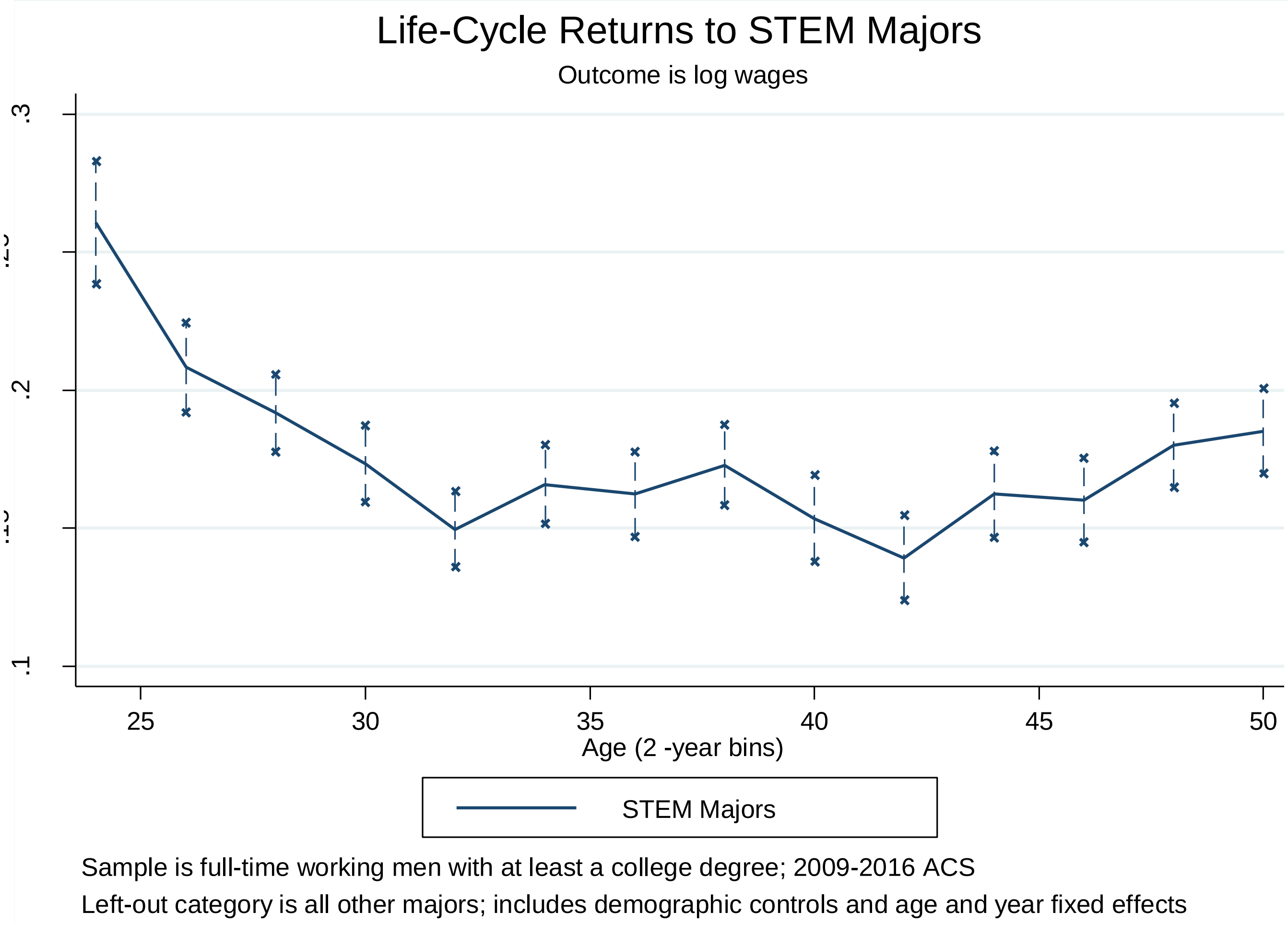
Notes: The figure plots coefficients and 95 percent confidence intervals from an estimate of equation (1) in the paper, except the sample is restricted to full-time working men with exactly a bachelor's degree. "Pure" Science includes biology, chemistry, physics, mathematics and statistics, while "Applied" Science includes engineering and computer science.

Figure A7



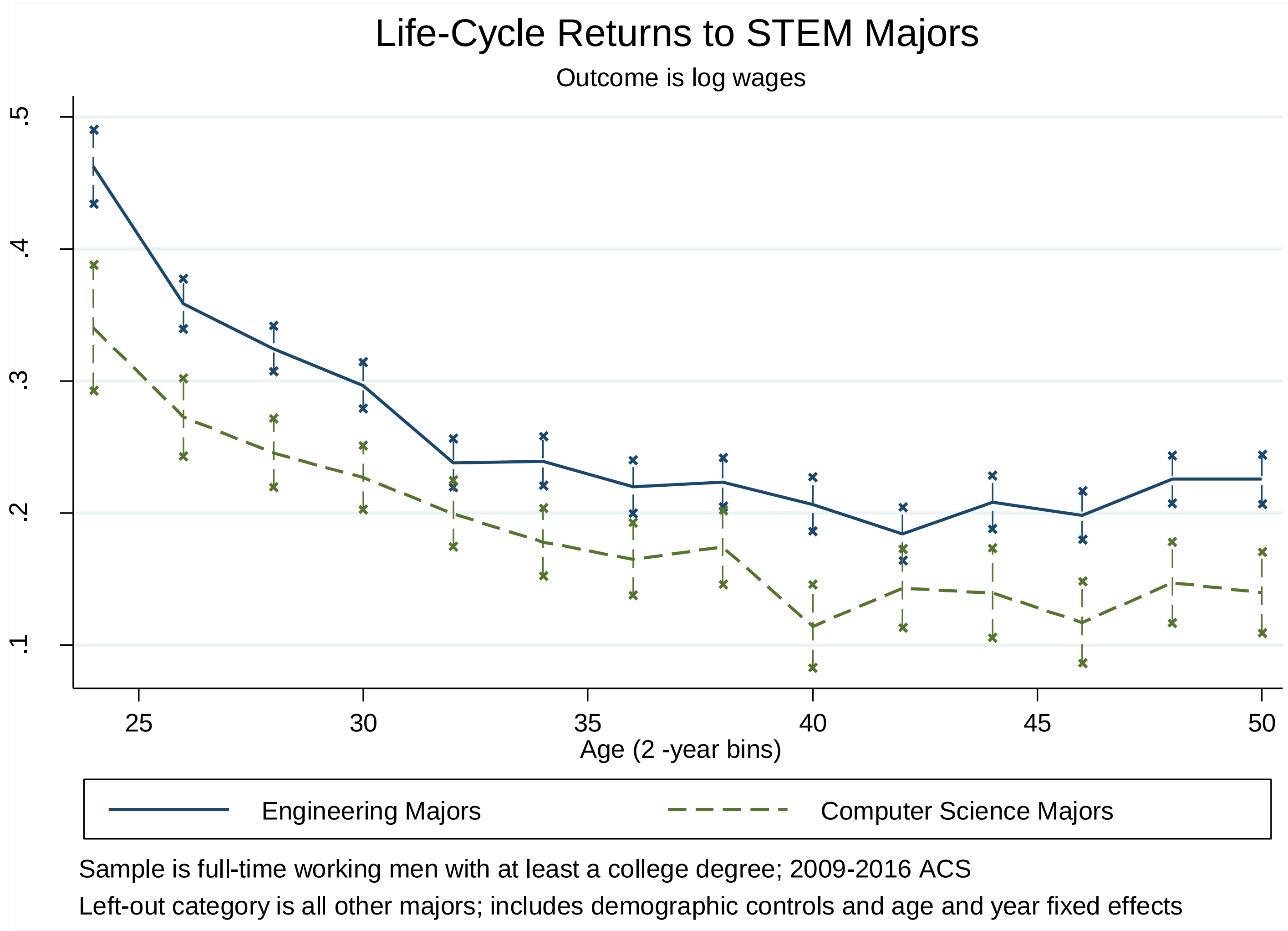
Notes: The figure plots coefficients and 95 percent confidence intervals from an estimate of equation (1) in the paper, except with industry fixed effects also included in the regression. "Pure" Science includes biology, chemistry, physics, mathematics and statistics, while "Applied" Science includes engineering and computer science.

Figure A8



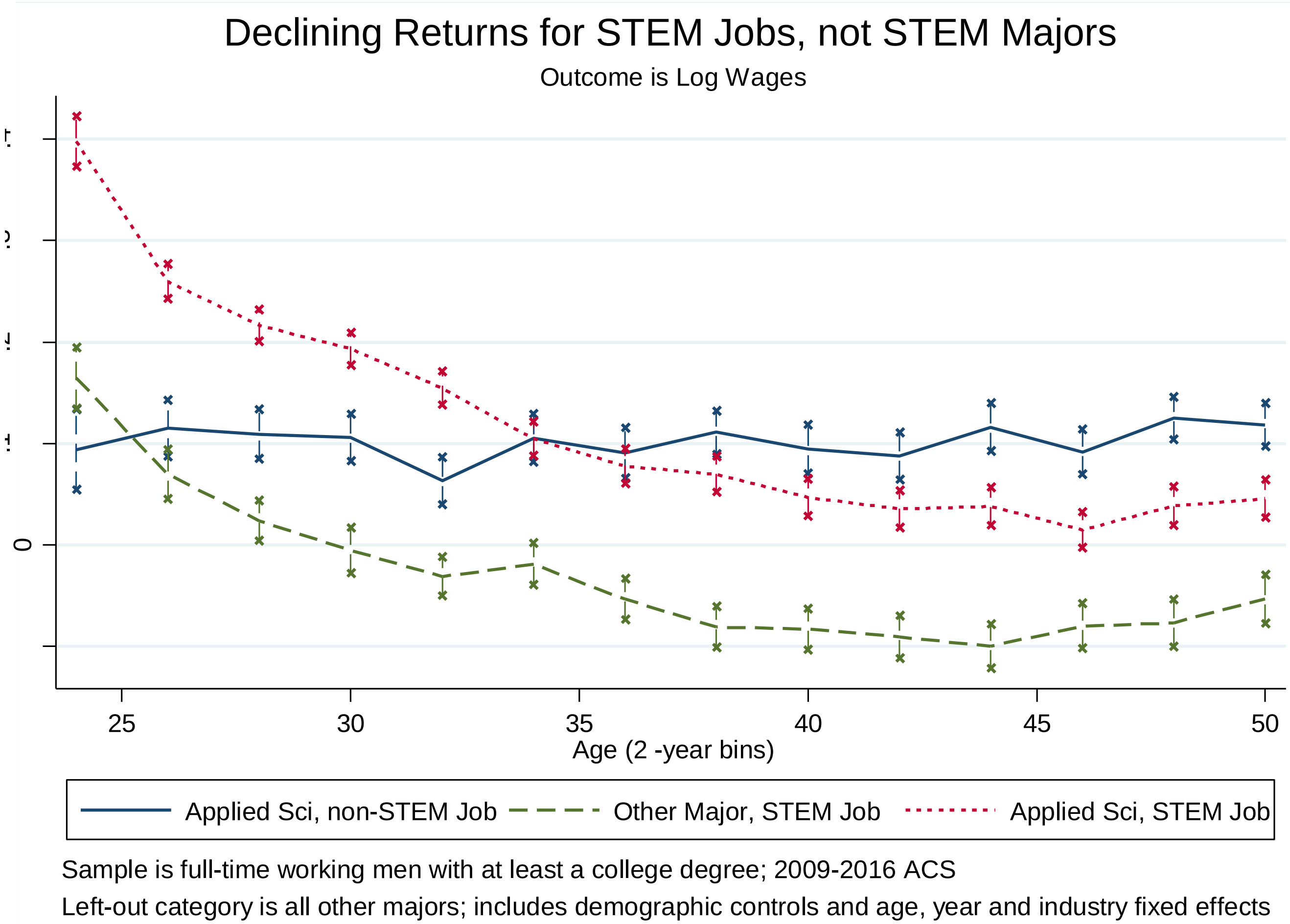
Notes: The figure plots coefficients and 95 percent confidence intervals from an estimate of equation (1) in the paper. The definition of STEM majors is taken from Peri, Shih and Sparber (2015).

Figure A9



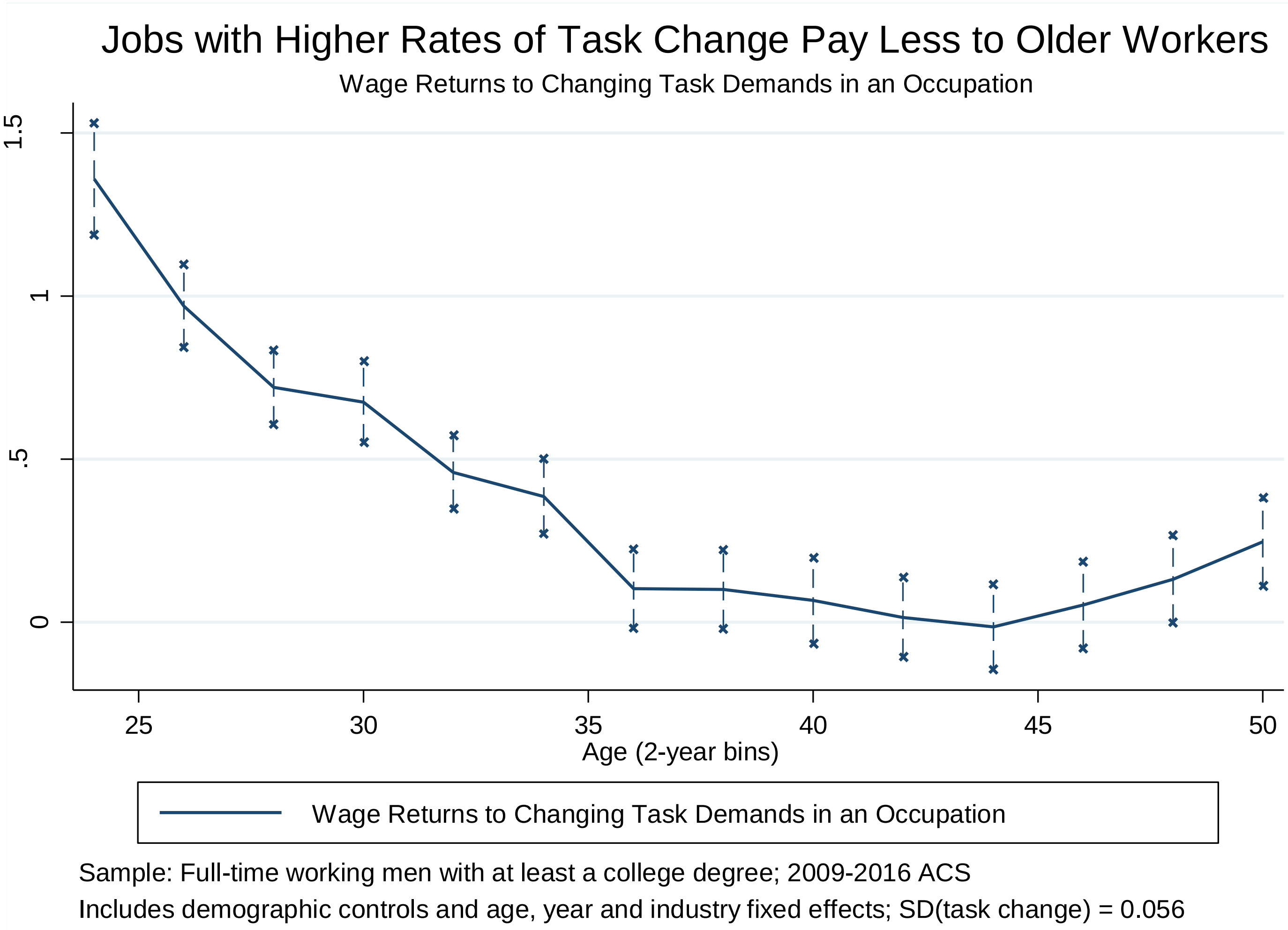
Notes: The figure plots coefficients and 95 percent confidence intervals from an estimate of equation (1) in the paper, except with Engineering and Computer Science majors estimated separately.

Figure A10



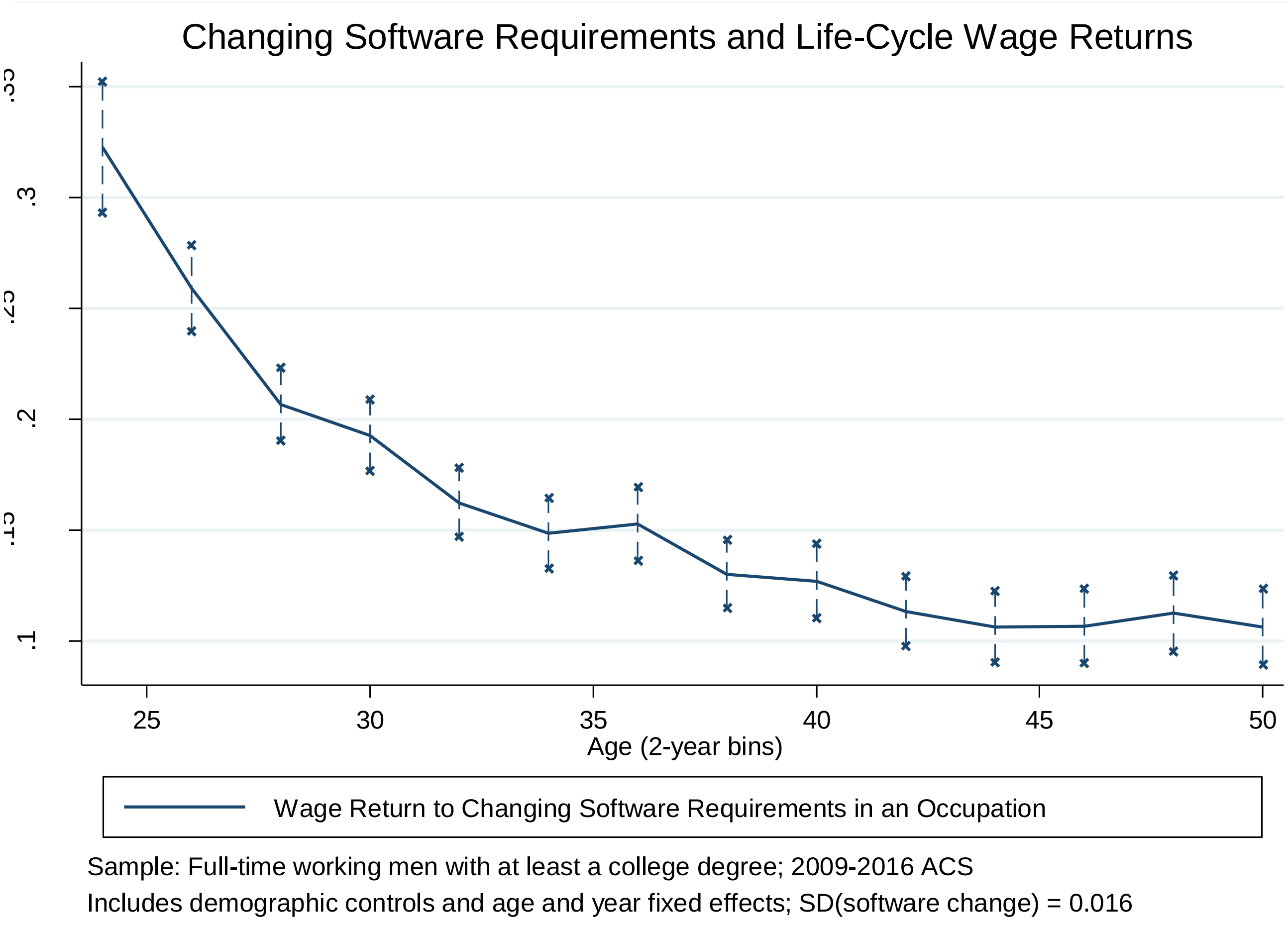
Notes: The figure plots coefficients and 95 percent confidence intervals from an estimate of the returns to majors over time, following equation (1) in the paper, but adding occupation and major interactions as well as industry fixed effects. "Applied" Science majors include engineering and computer science.

Figure A11



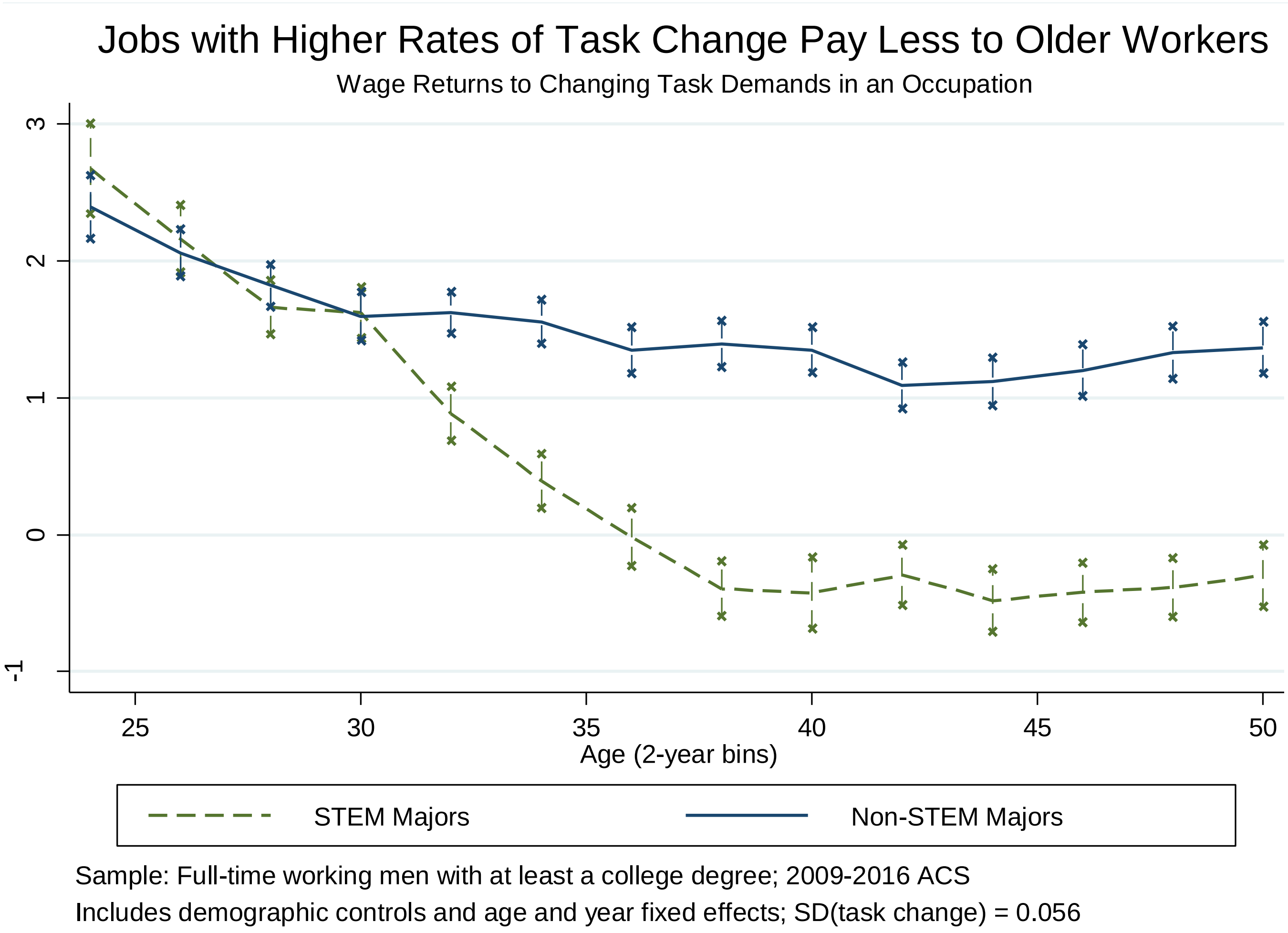
Notes: The figure plots coefficients and 95 percent confidence intervals from equation (10) in the paper, a regression of log wages on interactions between age and the task change measure Δ_j that is estimated using 2007-2017 online job vacancy data from Burning Glass Technologies. This figure also adds industry fixed effects. STEM occupations are defined using the 2010 Census Bureau classification. See the text for details.

Figure A12



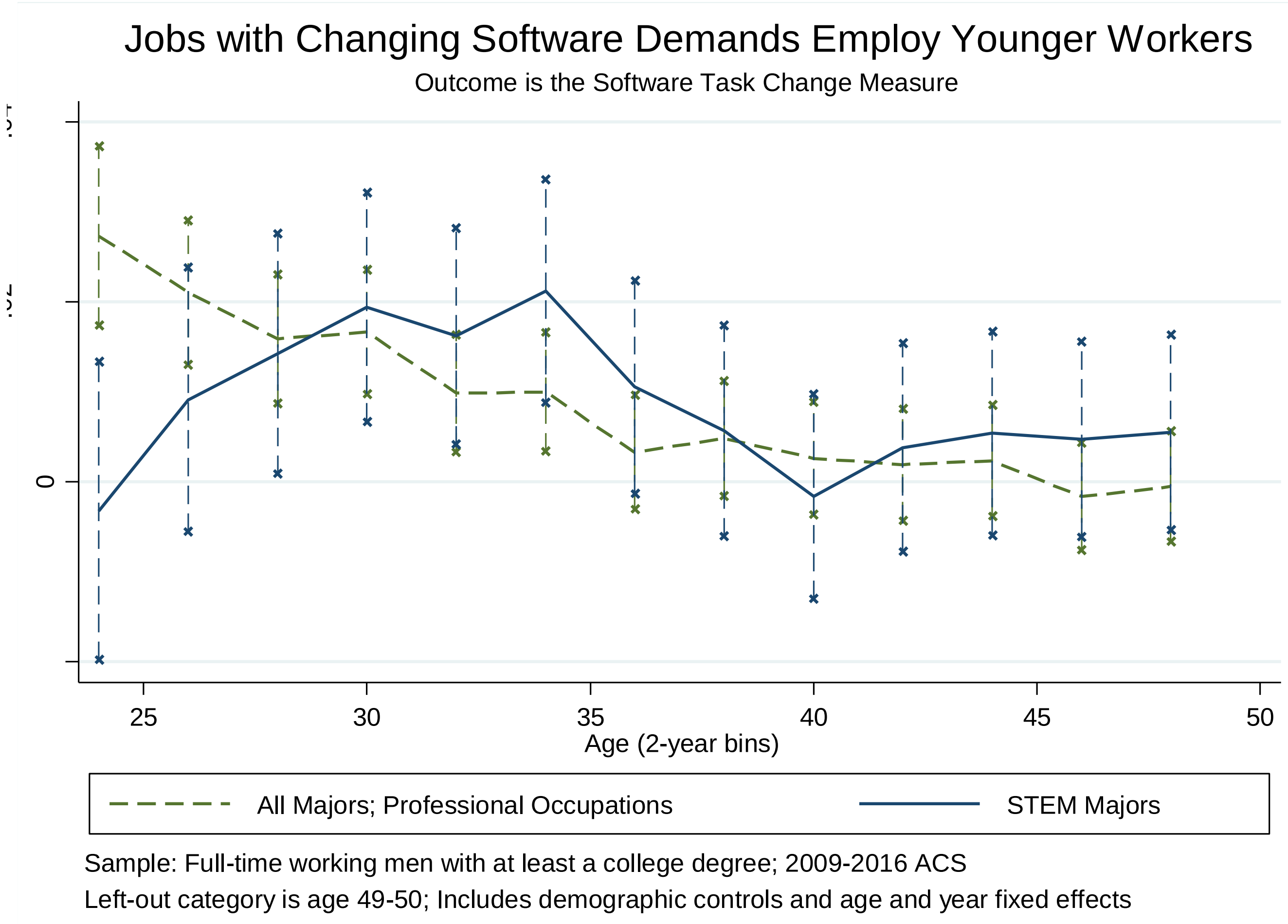
Notes: The figure plots coefficients and 95 percent confidence intervals from equation (10) in the paper, a regression of log wages on interactions between age and the task change measure Δ_j that is estimated using 2007-2017 online job vacancy data from Burning Glass Technologies. In this figure, the task change measure is restricted to software requirements. STEM occupations are defined using the 2010 Census Bureau classification. See the text for details.

Figure A13



Notes: The figure plots coefficients and 95 percent confidence intervals from equation (10) in the paper, a regression of log wages on interactions between age and the task change measure Δ_j that is estimated using 2007-2017 online job vacancy data from Burning Glass Technologies. In this figure, we interact age with indicators for STEM major rather than occupation. The STEM major definition comes from Peri, Shih and Sparber (2015). See the text for details.

Figure A14



Notes: The figure plots coefficients and 95 percent confidence intervals from equation (11) in the paper, a regression of the task change measure Δ_j (which is estimated using 2007-2017 online job vacancy data from Burning Glass Technologies) on occupation by age group interactions. In this figure, the task change measure is restricted to software requirements. STEM occupations are defined using the 2010 Census Bureau classification. The definition of STEM majors is from Peri, Shih and Sparber (2015). See the text for details.

Model Appendix

September 2018

1 Wage Growth across Careers as a function of Δ_j

The first prediction of the model is that wage growth over time is lower in careers with higher rates of task change Δ_j. This is equivalent to showing that the derivative of the difference in wages between year t and year zero with respect to Δ ($\frac{\partial(W_{j0}-W_{jt})}{\partial\Delta}$) is positive for $t \geq 1$.

Proposition 1. $\frac{\partial(W_{j0}-W_{jt})}{\partial(\Delta)} \geq 0 \ \forall t \geq 1$

Proof. Rearranging equation (10) - the expression for wages W_{jt} in section 3.4 - and taking the difference between year 0 and year t, we obtain:

$$\begin{aligned} W_{j0} - W_{jt} = FS(1-(1-\Delta)^t)) + a[1-(1-\Delta)^t(t+1) \\ - \sum_{v=1}^{t} \Delta(1-\Delta)^{t-v}(t-v+1). \end{aligned} \tag{1}$$

The derivative of this expression is

$$\frac{\partial(W_{j0}-W_{jt})}{\partial(\Delta)} = tFS(1-\Delta)^{t-1} + at(t+1)(1-\Delta)^{t-1} + \sum_{v=1}^{t}(t-v+1)(1-\Delta)^{t-v-1}[\Delta(t-v+1)-1], \tag{2}$$

$$\frac{\partial(W_{j0}-W_{jt})}{\partial(\Delta)} = tFS(1-\Delta)^{t-1} + at(t+1)(1-\Delta)^{t-1} + \sum_{x=0}^{t-1}(x+1)(1-\Delta)^{x-1}[\Delta(x+1)-1], \tag{3}$$

$$\frac{\partial(W_{j0}-W_{jt})}{\partial(\Delta)} = tFS(1-\Delta)^{t-1} + at(t+1)(1-\Delta)^{t-1} - \left(\frac{(\Delta^2x^2(1-\Delta)^{t-1}+\Delta^2(1-\Delta)^{t-1}+2\Delta^2x(1-\Delta)^{t-1}}{\Delta^2}\right) - \left(\frac{\Delta(t-1)(1-\Delta)^{t-1}+(1-\Delta)^{t-1}-1)}{\Delta^2}\right). \tag{4}$$

Where the final expression substitutes in the closed form solution for the summation component. We show that this derivative is positive in two steps. First, we demonstrate that it is monotonically increasing in t for all relevant values of the parameters. Then, we show that this derivative is positive for all values of Δ when $t = 1$. Thus we conclude that the derivative is always positive on the parameter space.

To begin, assume that $F = 0$. Because the first term is always positive, increasing F will only tend to make $\frac{\partial(W_{j0}-W_{jt})}{\partial(\Delta)}$ larger. So if the derivative is positive for $F = 0$, it is also positive for $F > 0$. Furthermore, set $a = 1$, the lowest possible value. Taking the derivative of the remaining expression with respect to t yields:

$$\frac{\partial^2(W_{j0}-W_{jt})}{\partial(\Delta)\partial(t-1)} = \frac{((\Delta-1)(1-\Delta)^{(t-1)}((\Delta(t-1)+\Delta+1)log(1-\Delta)+\Delta))}{\Delta^2}$$

Note that the first term in the numerator will be negative, so for this expression to be positive we need

$$(\Delta(t-1)+\Delta+1)log(1-\Delta)+\Delta < 0$$

or

$$t-1 > -\frac{1}{log(1-\Delta)} - \frac{1}{\Delta} - 1.$$

Because the right hand side of this inequality is always negative, we know that $t \geq 1 \implies$

$\frac{\partial^2(W_{j0}-W_{jt})}{\partial(\Delta)\partial(t-1)} > 0$. Thus, it suffices to demonstrate that $\frac{\partial(W_{j0}-W_{jt})}{\partial(\Delta)} > 0$ when $t = 1$. If we evaluate the derivative at $t = 1$ we get $2a - 1$ which is greater than zero for all $a > 1/2$. $\square$

2 Showing Career Choice and Selection on Ability in a Three Period Model

A clear way to see the predictions of this model are with a simple three-period and two-industry example. Let the only industries be STEM ($j = T$) and non-STEM ($j = N$). Assume STEM education is more technical than the non-STEM education. Specifically, assume that $S = 1$ in for STEM and $S = 0$ for non-STEM. Furthermore, assume that the rate of task change is higher in STEM than in non-STEM (i.e. $\Delta_T > \Delta_N$) and the initial productivity in STEM is higher than in non-STEM (i.e. $F_T > F_N$). Finally, assume that the cost function is $C(s, a, u) = s(c - a - u)$ where $c \in \mathbb{R}^+$ is a constant such that, $\forall a$ and u, $(c - a - u) > 0$.

We solve this problem in two parts. First, we find the optimal choice of schooling ($S = 0$ or $S = 1$ in this simplified case) given each chosen career path. Second, we solve for the payoffs of each career choice and characterize the conditions under which workers of a given (a, u) type will make each choice. There are eight possible career paths in the three-period case, so we begin by finding the optimal choice of S for each of them. We will refer to these eight cases in shorthand as $TTT, TTN, TNN, TNT, NTT, NTN, NNT$and NNN, with the order of letters representing the order of periods.

If we restrict industry choice to STEM in all periods, the optimization problem becomes

$$\begin{aligned}
&\max_s \, (F_T(1-|S-s|)+a) + \big((1-\Delta_T)(F_T(1-|S-s|)+2a)+\Delta_T a\big) \\
&\quad +(1-\Delta_T)^2[F_T(1-|S-s|)+3a] + \Delta_T(1-\Delta_T)2a + \Delta_T a - s(c-a-u) \qquad (5) \\
&\max_s \, (F_T(s)+a) + \big((1-\Delta_T)(F_T(s)+2a)+\Delta_T a\big) \\
&\quad +(1-\Delta_T)^2[F_T(s)+3a] + \Delta_T(1-\Delta_T)2a + \Delta_T a - s(c-a-u) \qquad (6)
\end{aligned}$$

Where equation (6) is equivalent to equation (5) because $S = 1$ and $0 \leq s \leq 1$.[1] Taking the derivative of equation (6) with respect to s and setting it equal to zero yields:

$$\underbrace{F_T + (1-\Delta_T)F_T + (1-\Delta_T)^2 F_T}_{\text{MB of Technical Education}} - \underbrace{(c-a-u)}_{\text{MC of Technical Education}} = 0.$$

[1] We suppress discount factors for simplicity - including them does not change any of the model's qualitative predictions.

This first order condition can be easily separated into two interpretable sections. The first section is the marginal benefit of an additional unit of technical education, the second section is the marginal cost of an additional unit of technical education. Satisfaction of this first order condition implies a solution where an individual is indifferent between all levels of technical education. Because the likelihood that this condition holds exactly is zero, we ignore this case.

Thus, individuals will always select completely technical coursework (STEM) or completely non-technical coursework (non-STEM). We have the following individual demand curve for technical education

$$s^* = \begin{cases} 1 & \text{if } F_T + (1-\Delta_T)F_T + (1-\Delta_T)^2 F_T - (c-a-u) > 0 \\ 0 & \text{if } F_T + (1-\Delta_T)F_T + (1-\Delta_T)^2 F_T - (c-a-u) < 0 \end{cases}$$

where s^* represents the optimal level of technical education. To avoid the trivial case where individuals never choose any technical education, assume that, for every type, the marginal benefit of technical education, conditional on choosing strictly a STEM career, is larger in magnitude than the marginal cost. From these assumptions we derive our first proposition.

Proposition 2. *Individuals that choose to work in STEM for all three periods* (TTT) *will allocate all education time to technical fields* ($s^* = 1$).

Using the analogous assumptions, we can derive the individual demand curve for technical education if we restrict industry choice to non-STEM in both periods. Specifically, we get

$$s^* = \begin{cases} 1 & \text{if } -F_N - (1-\Delta_N)F_N - (1-\Delta_N)^2 F_N - (c-a-u) > 0 \\ 0 & \text{if } -F_N - (1-\Delta_N)F_N - (1-\Delta_N)^2 F_N - (c-a-u) < 0. \end{cases}$$

As long as wages in non-STEM fields are greater than zero, case one (complete technical education) is never optimal. Thus, we arrive at our second proposition

Proposition 3. *Individuals that choose to work in non-STEM for all three periods* (NNN) *will allocate all education time to non-technical fields* ($s^* = 0$).

There are six ways individuals can choose to split their career between STEM and non-STEM occupations over their life cycle. As long as $\Delta_T > \Delta_N$ and $F_T > a$, the cases where workers switch from non-STEM to STEM (e.g. TNT, NTT, NTN, NNT) are never optimal. This is because switching into a career with a higher rate of task change will diminish both the value of what was learned in school and the value of future accumulated learning. Furthermore, it can be shown that it never makes sense to switch from STEM to non-STEM in the last period (TTN). This is because there is always an immediate loss from switching associated with losing the value previous learning.[2]

Because of this, the only relevant alternative to consider other than full specialization (TTT or NNN) is when a worker chooses STEM initially but switches to non-STEM in the final two periods (TNN). The maximization problem for the TNN career path is:

$$\begin{aligned}
&\underset{s}{max}\ (F_T(1-|S-s|)+a)+(1-\Delta_N)(F_N(1-|S-s|))+a \\
&\qquad +(1-\Delta_N)^2(F_N(1-|S-s|))+(1-\Delta_N)2a+\Delta_N a+-s(c-a-u) \\
&\underset{s}{max}\ (F_T(s)+a)+(1-\Delta_N)(F_N(1-s))+a \\
&\qquad +(1-\Delta_N)^2(F_N(1-s))+(1-\Delta_N)2a+\Delta_N a+-s(c-a-u)
\end{aligned}$$

Proposition 4. *Workers on the TNN career path will allocate all education time to technical fields ($s^*=1$).*

Proof. The proof above shows that individuals will always choose either $s^*=0$ or $s^*=1$. Any individual who chooses $s^*=0$ will earn more by choosing NNN rather than working in STEM in the first period (TNN), because $F_N(1)+a > F_t(0)+a = a$ and $(1-\Delta_N)(F_N(1)+2a)+\Delta_N a+(1-\Delta_N)^2[F_N(1)+3a]+\Delta_N(1-\Delta_N)2a+\Delta_N a > (1-\Delta_N)(F_N(1))+a+(1-\Delta_N)^2(F_N(1)+(1-\Delta_N)2a+\Delta_N a$. Thus, any worker who chooses the TNN career path must have chosen $s^*=1$. □

Now that we have determined the optimal education choice conditional on each career path, we can move to the second part of the problem: given the total utility of each option, which individuals should select which career path? This is equivalent to a discrete choice problem where each relevant career path is the choice variable. Mathematically, individuals solve the following maximization problem

$$Max(W^{TTT}-C(1,u,a), W^{NNN}-C(0,u,a), W^{TNN}-C(1,u,a))$$

[2] We exclude these proofs but can reproduce them upon request.

where

$$
\begin{aligned}
W^{TTT} - C(1,u,a) =& F_T + a + (1-\Delta_T)(F_T+2a) + \Delta_T a \\
& + (1-\Delta_T)^2(F_T+3a) + \Delta_T(1-\Delta_T)2a + \Delta_t a - (c-a-u) \qquad (7) \\
W^{NNN} - C(0,u,a) =& F_N + a + (1-\Delta_N)(F_N+2a) + \Delta_N a \\
& + (1-\Delta_N)^2(F_N+3a) + \Delta_N(1-\Delta_N)2a + \Delta_N a \qquad (8) \\
W^{TNN} - C(1,u,a) =& F_T + a + (1-\Delta_N)(a) + \Delta_N a \\
& + (1-\Delta_N)^2(2a) + \Delta_N(1-\Delta_N)2a + \Delta_N a - (c-a-u). \qquad (9)
\end{aligned}
$$

To figure out exactly which types of individuals will select into each career track, we can compare the payoffs for each track and derive indifference conditions that allow us to split the type space by preference orderings over the three options. First, we compare the TNN career path to the TTT career path.

To figure out exactly who will choose the TNN career path, we derive the conditions under which an individual would choose TNN over TTT. The gains from switching can be obtained by subtracting the payoff for TNN (equation 9) from the payoff for TTT (equation 7):

$$
\begin{aligned}
W^{TNN} - W^{TTT} \equiv& (1-\Delta_N)a + \Delta_N a + (1-\Delta_N)^2 2a + (1-\Delta_N)\Delta_N(2a) \\
& - (1-\Delta_T)(F_T+2a) - \Delta_T a - (1-\Delta_T)^2(F_T+3a) - \Delta_T(1-\Delta_T)2a - \Delta_T a
\end{aligned} \tag{10}
$$

Workers will major in STEM, work in STEM initially and then switch in the second period (e.g. choose $s^* = 1$ and then the TNNcareer path) when the expression above is greater than zero. This results in a clear prediction for ability sorting:

Proposition 5. *For every $\Delta_N \in [0,1]$, there exists a minimum difference in rates of change across sectors $\Delta_T - \Delta_N > k_{\Delta_N}$ such that workers who choose TNN will have higher ability that workers who choose TTT. Furthermore, $\Delta_T - \Delta_N > k_{\Delta_N}$ is a necessary condition for $W^{TNN} - W^{TTT} > 0$.*

Proof. Differentiating the expression above with respect to ability yields:

$$
\frac{\partial\left(W^{TNN} - W^{TTT}\right)}{\partial a} = (3-\Delta_N) - (5 - 4\Delta_T + \Delta_T^2). \tag{11}
$$

This is greater than zero if $\Delta_T > 2 - \sqrt{2-\Delta_N}$. Thus, as long as Δ_T is sufficiently large relative to Δ_N, workers who choose TNNwill have higher ability than workers who choose

TTT.[3] For $\Delta_T, \Delta_N \in [0,1]$, $k_{\Delta_N} \in (0, .59]$ and is monotonically decreasing in Δ_N.

To prove the second part of proposition 5, we need to show that $W^{TNN} - W^{TTT} > 0$ only if $\Delta_T - \Delta_N > k_{\Delta_N}$. We can use equation (10) to represent the the switching returns inequality as follows.

$$W^{TNN} - W^{TTT} = (3 - \Delta_N)a - (5 - 4\Delta_T + \Delta_T^2)a - \Delta_T(1 - \Delta_T)F_T > 0. \tag{12}$$

If the inequality in equation (11) does not hold, then $(3-\Delta_N)a-(5-4\Delta_T+\Delta_T^2)a$ is negative, and because $\Delta_T(1 - \Delta_T)F_T$ is positive, it is impossible for the inequality in equation (12) to hold. Thus if the gap between Δ_T and Δ_N is not large enough, workers simply won't switch at all and the only career paths will be TTT and NNN. This means that any career switching we observe from T to N over time will always be among higher-ability workers. $\square$

We can also solve for the ability threshold $a_{TTT,TNN}$ at which workers would choose TNN over TTT by setting the expressions for the gains from switching equal to zero. With some simplification, we obtain the indifference condition:

$$a_{TTT,TNN} = \frac{F_T(2 - 3\Delta_T + \Delta_T^2)}{-2 - \Delta_N + 4\Delta_T - \Delta_T^2}.$$

By a similar logic, we can generate indifference conditions for other career trajectories assuming that workers make optimal education choices. Specifically, we solve for u as a function of a, which yields indifference curves along the (a, u) type space:

$$u_{TTT,NNN}(a) = \underbrace{Y_N(3 - \Delta_N + \Delta_N^2) - Y_T(3 - \Delta_T + \Delta_T^2) + C}_{k_1} + a\underbrace{[4(\Delta_S - \Delta_N) - 1 - (\Delta_T^2 - \Delta_N^2)]}_{k_2} \tag{13}$$

$$u_{NNN,TNN}(a) = \underbrace{Y_N(3 - 3\Delta_N + \Delta_N^2) - Y_T + C}_{k_3} + a\underbrace{[-1 - 5\Delta_N + \Delta_N^2]}_{k_4} \tag{14}$$

where $u_{TTT,NNN}(a)$ defines the indifference threshold between TTT and NNN - a fully STEM vs. non-STEM career - and $u_{TTT,TNN}(a)$ defines the indifference threshold between TTT and TNN. To reduce notational clutter, we abbreviate the subscripts for each indiference condition such that $u_{TTT,NNN}(a) = u_{T,N}(a)$, $u_{NNN,TNN}(a) = u_{N,TNN}(a)$, and $a_{TTT,TNN} = a_{switch}$.

[3] We have also analyzed this result for models with four or more periods. While the exact values that satisfy the $\Delta_T >> \Delta_N$ condition vary somewhat depending on the number of periods, the basic structure remains unchanged.

These indifference curves allow us to divide the two-dimensional type-space into six sections that represent all of the possible preference combinations over TTT,NNN and TNN.

Figure M.A1 shows a visual example of the optimal career choice for individuals of each (a, u) type, under the assumption that $\Delta_T - \Delta_N > k_{\Delta_N}$, so there will be career switching.

Sections 1 and 2 represent types who choose NNN, sections 3 and 4 represent types who choose TTT, and sections 5 and 6 represent types who choose TNN (we call these types "switchers" as shorthand).

Since we have assumed u and a are joint uniformly distributed, we can solve analytically for the average ability in each career path by using the indifference conditions as a weighting function:

$$\overline{a}_{TTT} = \frac{\int_1^{a_{T,TNN}} (u_{max} - u_{T,N}(a)) * a \; da}{\int_1^{a_{T,TNN}} (u_{max} - u_{T,N}(a)) \; da} \tag{15}$$

$$\overline{a}_{NNN} = \frac{\int_1^{a_{T,TNN}} u_{T,N}(a) * a \; da + \int_{a_{T,TNN}}^{u_{T,N}^{-1}(0)} u_{N,TNN}(a) * a \; da}{\int_{1,}^{a_{T,TNN}} u_{TN}(a) \; da + \int_{a_{T,TNN}}^{u^{-1}(0)} u_{N,TNN}(a) \; da} \tag{16}$$

$$\overline{a}_{TNN} = \frac{\int_{a_{T,TNN}}^{u_{T,N}^{-1}(0)} (u_{max} - u_{N,TNN}(a)) * a \; da + \int_{u_{T,N}^{-1}(0)}^{a_{max}} u_{max} * a \; da}{\int_{a_{T,TNN}}^{u_{T,N}^{-1}(0)} (u_{max} - u_{N,TNN}(a)) \; da + \int_{u_{T,N}^{-1}(0)}^{a_{max}} u_{max} \; da} \tag{17}$$

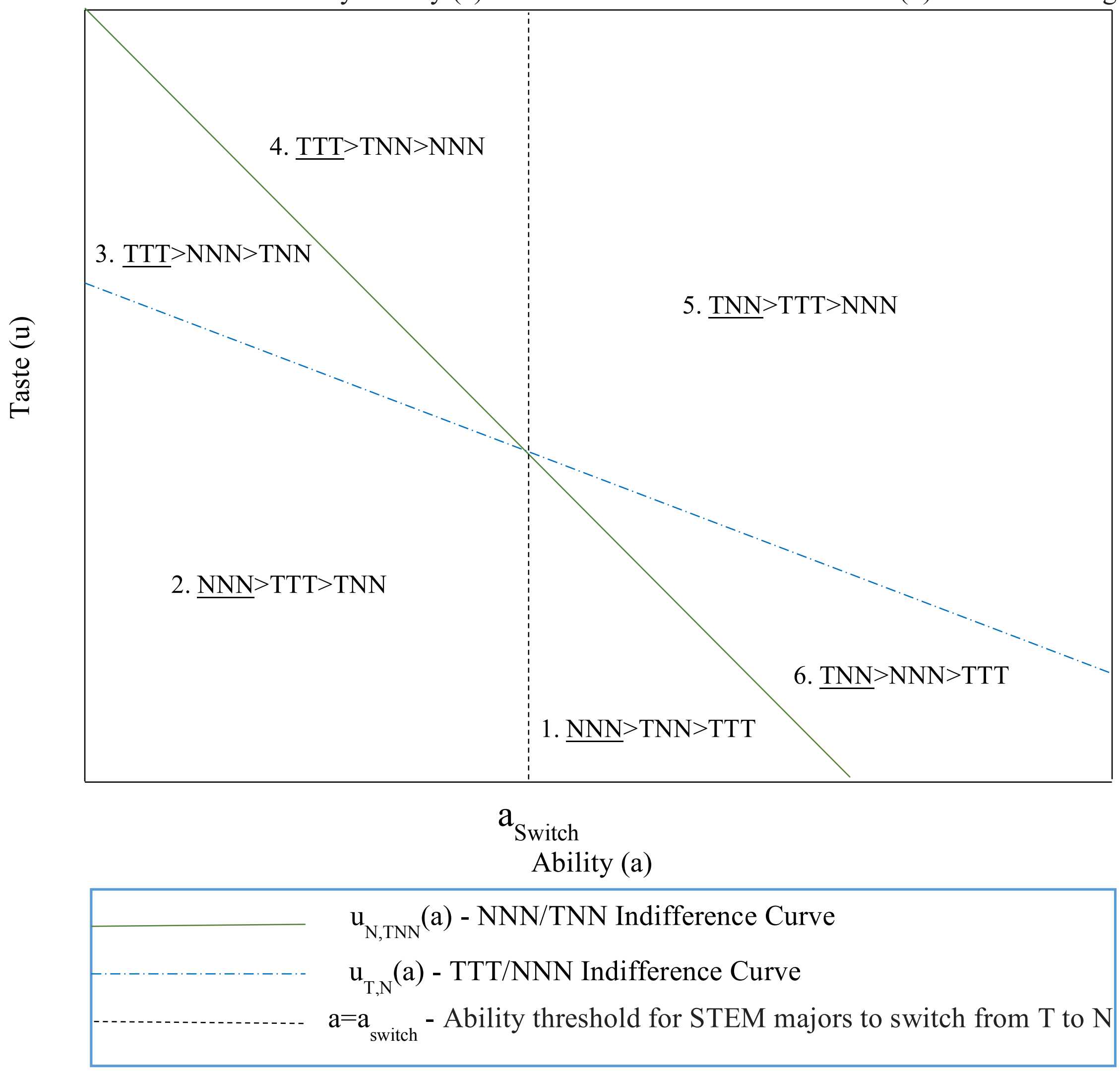
where $\overline{a}_{TTT}$ is the average ability of those who select into a STEM career, $\overline{a}_{NNN}$ is the average ability for those who select into a non-STEM career, and $\overline{a}_{TNN}$ is the average ability of those who select into a STEM occupation the first period and switch into non-STEM afterward.

As long as $\Delta_T - \Delta_N$ is large enough to cause ability selection out of STEM, then $\overline{a}_{TNN} > \overline{a}_{TTT}$ because $min(a_{TNN}) > max(a_{TTT})$. Furthermore, as long as $u_{N,TNN}(a)$ slopes downward, $\overline{a}_W > \overline{a}_N$. This is because if $u_{N,TNN}(a)$ slopes downward, the weighting function in equation 17 is monotonically increasing in a over $[a_{T,TNN}, a_{max}]$, meaning that $\overline{a}_{TNN} > \frac{a_{max}+a_{T,TNN}}{2}$. Furthermore, if we overestimate $\overline{a}_{NNN}$ by limiting our calculation those whose abilities are greater than $a_{T,TNN}$, we know that this overestimate is less than $\frac{a_{max}+a_{T,TNN}}{2}$ because the weighting function $u_{N,TNN}(a)$ is monotonically decreasing in a.

Thus $\overline{a}_{NNN} < \frac{a_{max}+a_{T,TNN}}{2} < \overline{a}_{TNN} \implies \overline{a}_{NNN} < \overline{a}_{TNN}$. Also, in this case, we can verify from equation 14 that $u_{N,TNN}(a)$ always slopes downward because $k_4 < 0$ for $\Delta_N \in [0, 1]$. Thus, under fairly general conditions, non-STEM occupations will attract higher ability workers over time.

Figure M.A1

Career Path Choices by Ability (a) and Taste for Technical Education (u) with Switching



Notes: This figure shows how different types would select into career paths in our model. There are six sections of the type space. Types in each section have strict preferences over the three career paths: STEM (TTT), non-STEM (NNN), or STEM to non-STEM switching (TNN). The optimal career path for individuals of each (a,u) type is underlined.