College Majors and Earnings Growth*

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Abstract

In this paper we estimate major specific earnings profiles using matched American Community Survey (ACS) and Longitudinal Employer-Household Dynamics (LEHD) data. The advantage of the matched data relative to the ACS alone is that it provides a long panel of worker earnings, thus avoiding estimating life cycle profiles using cross-cohort variation. Once we allow the returns to major to vary by cohort, we find that engineering, computer science, and business majors experience faster earnings growth relative to humanities majors. For example, the gap in earnings between technical majors like engineering and computer science and humanities grows by 5-6% between ages 23 and 50. Our estimates also indicate that more recent graduates in these fields earn a larger premium relative to humanities than earlier cohorts.

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1 Introduction

Estimating the labor market returns associated with college major is as common, if not more common, than estimating the returns to schooling quantity. In just the past decade, three lengthy reviews describe researchers rapid advances in this area (Altonji, Blom, and Meghir, 2012; Altonji, Arcidiacono, and Maurel, 2016; Patnaik, Wiswall, and Zafar, 2020). Two empirical facts lie behind the widespread interest in the returns to major. First, the number of high school graduates who matriculate to two- and four-year colleges has expanded considerably, making this a salient choice for a wider portion of the population.[1] Second, variation in earnings across different college majors can be as large as the earnings gap between college and high-school graduates (Altonji, Blom, and Meghir, 2012). Thus, it is important to accurately estimate the returns to major to inform student, school, and policy-maker choices.

While much progress has been made, the existing literature on the returns to major is primarily focused on estimating average returns across the life cycle. However, average returns can mask important heterogeneity in earnings growth. In an economy with credit constraints, variation in age-earnings profiles can have meaningful welfare consequences holding fixed average lifetime returns.[2] Additionally, heterogeneity in earnings profiles across the life cycle can complicate efforts to estimate average returns when the age distribution of a sample is skewed.

In this paper, we estimate major specific earnings profiles using matched American Community Survey (ACS) and Longitudinal Employer-Household Dynamics (LEHD) data. ACS data provide information on college major, while the LEHD data provide a long panel of worker earnings. The advantage of this data relative to working only with the ACS is that labor outcomes are observed over a significantly longer period, from 1985 to 2014, and that the same workers can be followed over time. We find substantially smaller variability

[1] Data from the *Digest of Education Statistics* shows that the percentage of 18- to 24-year-olds enrolled in four-year colleges and universities in 2020 was 31%, representing an increase of 5 percentage points since 2000. https://nces.ed.gov/programs/digest/d21/tables/dt21_302.60.asp

[2] Hampole (2022) provides evidence that students who rely on borrowing to finance college are more likely to select majors with high initial earnings, but relatively low lifetime earnings.

in earnings profiles by major when using the matched LEHD-ACS earnings data relative to estimates based only on ACS data. Importantly, we show that technical majors like computer science and engineering do not grow more slowly relative to other fields.

Our paper contributes to recent work that estimates heterogeneity in labor market returns to college major across the life cycle. Andrews et al. (2022), Martin (2022), and Deming and Noray (2020) use different data and empirical approaches to show that the returns to major vary with age. The findings in Deming and Noray (2020) have been particularly influential. Using data from the 2009-2017 American Community Survey (ACS), they document that computer science, engineering, and business majors earn significantly more than most other fields upon labor market entry, but that earnings gaps close considerably over the life cycle. The authors provide supporting evidence that this pattern may be driven by human capital depreciation, as computer science and engineering graduates tend to work in occupations that experience frequent changes in skill requirements over time.

We begin by first replicating the key result from Deming and Noray (2020) using only ACS earnings and major data from 2009 to 2019. Our findings are identical to Deming and Noray (2020) and indicate slower earnings growth for business and technical degrees like computer science and engineering. One potential concern with using the ACS to estimate major-specific earnings profiles is the relatively short time dimension of the panel. In particular, older cohorts are not observed when young, and younger cohorts are not observed when old. As a result, the model may conflate major-specific life cycle patterns in earnings with underlying changes in the returns to major by cohort.

To address this concern, we match ACS and LEHD data to generate a long panel of worker earnings that also contains major. We then re-estimate age-earnings profiles by major. The simplest specification mimics our cross-sectional approach with the ACS data, except the regression includes earnings prior to 2009. This alone greatly reduces heterogeneity in age-earnings profiles by major relative to the ACS, and already yields the result that technical majors have earnings growth on par with humanities majors. Our preferred model, which includes worker fixed effects, indicates that computer science, engineering, and business majors actually have steeper age-earnings profiles than humanities majors. So despite evidence that these fields experience relatively more frequent changes in skill requirements over time (Deming and Noray, 2020), any initial earnings advantages remain and even expand over the life cycle.

The remainder of the paper focuses on the factors driving the differences in age-earnings profiles estimated using the LEHD and the ACS. After ruling out some basic measurement and sample differences, we focus on three key ideas. The first is that the earnings premium associated with obtaining a technical or business degree may have increased for recent college graduates. This will tend to attenuate age-earnings profiles estimated using the ACS since identification relies primarily on cross-cohort earnings variation. If more recent business and technical graduates earn higher initial premiums, then wage growth will look slower for these fields since older cohorts have always earned a smaller premium. Second, the returns to a technical or business degree may have increased over time for workers of all ages. If true, then the LEHD sample will tend to exaggerate age-earnings profiles for these fields relative to the ACS since it includes many young workers from earlier periods with low earnings. Finally, age-earnings profiles may simply have changed over time and when we expand the panel backwards the estimates will reflect a weighted average of different profiles. We find that the differences in results between the LEHD and ACS are most consistent with the first explanation, that major-specific premia have changed across different cohorts, with recent cohorts of computer science and engineering majors seeing large gains in initial returns relative to humanities majors. In a final exercise, we explore whether selection into major according to ability or sorting into sub-fields within a major have changed across cohorts.

Our finding that the returns to technical and business degrees are relatively higher for more recent cohorts helps reconcile the differences in findings between Deming and Noray (2020) and Andrews et al. (2022). Using a sample of Texas high school graduates between 1996 and 2002, Andrews et al. (2022) find that engineering and business majors experience faster wage growth relative to liberal arts graduates. By focusing on a few cohorts as they age, Andrews et al. (2022) are not as reliant on cross-cohort comparisons to identify age-earnings profiles by major. However, their estimates are based on only one state and for a relatively young cohort. As a result they cannot speak to wage growth in the later stages of the working life.

The remainder of the paper proceeds as follows. We discuss the ACS and LEHD samples and matching process in Section 2. Section 3 details our empirical model and presents the main findings. We investigate heterogeneity and the robustness of our key results in Section 4 and conclude in Section 5.

2 Data

There are two primary data sources used in this paper, the ACS and LEHD. The sections below outline the key details for each sample.

2.1 ACS

We collect ACS data from the Integrated Public Use Microdata Series (IPUMS) 1% samples (Ruggles et al., 2021) covering the period from 2009-2019. Our analysis sample is similar to Deming and Noray (2020), focusing on respondents between the ages of 23 and 50 who have at least a four-year college degree and a valid major. We initially follow Deming and Noray (2020) and aggregate majors into five categories: engineering and computer science, business, life and physical science, social science, and other (humanities, education, vocational, etc.).[3] We also explore alternate degree field aggregations, one where we split humanities from other and a second where we allow for ten different major groups. We further depart from Deming and Noray (2020) in our preferred specifications by constraining the sample to individuals who are not currently enrolled, hold only a bachelor's degree, are in the labor force for at least 27 weeks, and have earnings above the first percentile of the earnings distribution by educational level.

Table 1 displays basic summary statistics for our ACS analysis samples. The first

[3]Information about the mapping from detailed degree fields to major categories is provided in Appendix Table A1.

column mimics the sample in Deming and Noray (2020), while the second and third columns sequentially limit the sample by education status and labor market engagement. The purpose of these restrictions is to more closely focus on individuals who are applying the human capital they accrued as undergraduates. Moving from left to right, the analysis sample contains fewer women and fewer minorities. The distribution of undergraduate majors also changes as we limit the sample. In particular, excluding graduate degree holders and those currently enrolled leads to a larger share of business majors and fewer life and physical science and other majors.

2.2 LEHD

The LEHD is a quarterly database of linked employer-employee data covering over 95% of employment in the United States (Abowd et al., 2009). We obtained access to data from 27 states that account for approximately 65% of the US workforce.[4] Earnings data are available from 1985 to 2015, though the initial year varies by state. The primary benefit of working with the LEHD is that earnings are observed for the same workers over many periods. The drawback of the LEHD is a lack of information on degree field. However, we use unique individual identifiers to link individuals present in any wave of the ACS to the LEHD. As a result, we can merge information about an individual's degree field with a long history of earnings.[5]

Table 2 provides summary statistics for the LEHD sample at person and person-year levels. To be consistent with our primary analysis using the ACS, we limit the LEHD sample to include only those individuals whose maximum educational attainment reported in the ACS was a bachelor's degree.[6] Annual earnings for the LEHD are constructed as the sum of earnings across quarters, jobs, and states in a given year.

Also included in Table 2 are statistics for individuals who appear concurrently in both

[4]The covered states include: AZ, CA, CO, CT, DE, IN, IO, ME, MD, MA, MS, NV, NJ, NM, NY, ND, OH, OK, PA, SD, TN, TX, UT, VA, WA, WI, WY.

[5]See Appendix section A.1 for details about the construction of the matched database.

[6]It is possible that some ACS respondents whose maximum educational attainment at the time of the survey is a bachelor's degree subsequently obtain a graduate degree. These individuals will be incorrectly classified as BA degree holders in the LEHD analysis. The earliest year of the ACS is 2009 and the final year of the LEHD earnings data is 2015. As a result, the degree of misclassification is likely small.

the ACS and LEHD samples between 2009 and 2015. This "Matched ACS sample" is thus cross-sectional in nature and focuses on BA degree holders who are between the ages of 23 and 50 and are attached to the labor force.[7] We use this sub-sample to illustrate that differences in age-earnings profiles across the ACS and LEHD are not driven by differences in geographical composition or earnings measures.

The top panel of Table 2 illustrates that the LEHD sample is composed of individuals from a wide range of birth cohorts, including some born in the 1950s and others born in the 1980s. The Matched ACS sample is composed of more recent birth cohorts since individuals who are above the age of 50 when interviewed for the ACS are excluded from the estimation sample when using the ACS or Matched ACS, but are still eligible for matching to the LEHD. In addition, individuals from more recent birth cohorts will be linked to just a few years of earnings in the LEHD, while individuals ages 40 and above in the ACS will be linked to 15 or more years of earnings records in the LEHD. The distribution of majors is fairly steady across the ACS (excluding graduate students and enrollees), Matched ACS, and LEHD.

The bottom panel of Table 2 instead highlights the key differences between the LEHD and either the Matched ACS sample or the full ACS sample. The LEHD data include earnings observations all the way back to 1985, while the ACS (and Matched ACS) only includes earnings observations from 2008 onwards. On average, each individual in the LEHD is observed for 9 years, while each individual is observed only once in the ACS. As a result, our primary ACS sample contains approximately 1.9 million observations (column 3 of Table 1), while our LEHD sample includes over 33 million observations.

[7]Note that when constructing the LEHD sample, we also use individuals from the ACS between 2016 to 2019 to match backwards. Because the LEHD earnings data only extends through 2015, these individuals are not part of the Matched ACS sample. As a result, the total number of unique individuals is actually larger in the LEHD than the Matched ACS.

3 Estimating Age-Earnings Profiles by Major

3.1 Empirical Model

We estimate age-earnings profiles by major using variations of the following regression model:

$$\ln \text{Earnings}_{imcat} = \beta_{m,a} + \gamma X_{it} + \theta_t + \delta_a + \pi_{m,c} + \alpha_i + \epsilon_{it} \tag{1}$$

where Earnings_{imcat} reflects annual earnings for individual i, with major m, born in cohort c, at age a, during period t. X_{it} includes gender, race, and age interacted with gender and race. It also includes indicators for veteran and citizenship status. θ_t and δ_a correspond to year and age-group fixed effects, respectively. The key parameters in the above equation are $\beta_{m,a}$, the earnings premium for individuals with major m at age a relative to humanities majors at age a. We typically report estimates of $\beta_{m,a} - \beta_{m,23}$, reflecting the excess wage growth relative to humanities for individuals with major m at age a. In practice, we generate two-year age bins and interact these with major.

Following Deming and Noray (2020), our initial regressions estimate $\beta_{m,a}$, γ, δ_a, and θ_t, subsuming the remaining terms into a composite error. We apply this model to the ACS, matched ACS, and LEHD samples. The richness of the LEHD data allows us to go further and estimate directly $\pi_{m,c}$, capturing changes in log earnings levels by major across 5-year birth cohorts. We also consider a version that replaces $\pi_{m,c}$ with $\pi_{m,t}$, allowing the level of log earnings by major to vary in five-year increments. Finally, we incorporate worker-fixed effects into the model, allowing α_i to be freely correlated with major and other individual characteristics. In this version, the $\pi_{m,c}$ terms are subsumed into the worker effects since major and birth cohort are time invariant within worker.

3.2 Results

3.2.1 ACS

In an effort to link our work with the previous literature, we begin by replicating the age-earnings profiles reported in Deming and Noray (2020) based on ACS data from 2009 to 2017. For this analysis, we keep all workers aged 23-50 who report a valid major. We estimate equation (1) by OLS where $\pi_{m,c}$ and α_i are part of the error term. Standard errors are clustered at the major-by-age level. Figure 1 displays the point estimates and confidence intervals for $\beta_{m,a}$. The reference major group is humanities and other degree fields. Our figure exactly matches Figure V in Deming and Noray (2020). The picture reveals that engineering, computer science, and business majors see their earnings advantage relative to humanities shrink as they age. It is also true that life and physical science majors and social science majors see their earnings rise both relative to the excluded group, and technical and business majors.

We investigate the robustness of these results to a variety of sample changes applied to the ACS. Our primary aim is to focus on a set of workers who are actively using the skills they obtained as undergraduates in the labor market. Table 3 displays estimates of earnings growth at ages 30, 40, and 50 relative to age 23 as the sample changes. The estimates in column (1) differ from Deming and Noray (2020) as the sample is expanded to include 2018 and 2019. In column (2) we exclude respondents who are currently enrolled, and in column (3) we further exclude graduate degree holders. In column (4) we eliminate individuals working less than 27 weeks, and in column (5) we also exclude individuals earning below the first percentile. Finally, the model in column (6) splits humanities majors from other majors and uses humanities as the reference category. Across each of the specifications, relative earnings growth in technical fields and business is negative and statistically significant. For engineering and science, the biggest change occurs when moving from column (1) to column (2). When we exclude current enrollees, the earnings premium for 23-year-old technical degree holders becomes larger, making earnings growth in technical majors even more negative. Earnings growth for life and physical science majors also declines dramatically in column (3). This is primarily driven by the exclusion of graduate degree holders. Going forward we continue to use humanities majors alone as the reference category as it allows for a more straightforward comparison between modern technically oriented degrees and a classical curriculum.

Despite the apparent robustness of the wage growth penalty experienced by science and business degree holders, a key empirical concern remains. Estimating life cycle earnings patterns using a relatively short panel of repeated cross-sections relies primarily on cross-cohort comparisons for identification. If cohorts are changing over time in unobserved dimensions, then earnings profile estimates may be biased. We address this concern in the next section using the panel dimension of the LEHD.

3.2.2 LEHD

In this section we present age-earnings profile estimates by major using the merged LEHD and ACS data. The primary advantage of the LEHD is the ability to observe individual-level earnings trajectories. As a result, the identification of age-earning profiles is not as reliant on cross-cohort comparisons.

However, the panel nature of the LEHD is not the only difference between the two samples. As discussed in Section 2.2, the geographical coverage of the LEHD is different than the ACS, and the source of earnings data also differs across the two samples. LEHD earnings data is based on unemployment insurance records collected by states, while the ACS surveys individuals directly about their earnings. The first two columns of Table 4 indicate that these sample differences have little impact on age-earning profile estimates by major. In the first column of results, we estimate equation (1) (subsuming cohort and worker effects into the error term) using our matched ACS sample. The geographical representation of these respondents is reflective of the geographical distribution of individuals we observe in the LEHD. The basic pattern of results is replicated. Technical and business degree holders have statistically significant slower earnings growth over the life cycle relative to humanities majors. Note that the sample restrictions and model specification match column (4) in Table 3. We exclude individuals who are currently enrolled, hold a graduate degree, work less than 27 weeks, or earn below the first percentile. Humanities majors are the excluded group.

The second column of Table 4 uses the same model and similar sample as column (1), but uses LEHD earnings data as the outcome instead of ACS earnings data.[8] Although we

[8]Note that the sample sizes differ between columns (1) and (2). The primary reason is that over their

are using the LEHD earnings data, we are still treating the sample as if it were a repeated cross-section. The estimated age-earnings profiles are mostly unchanged when we change the earnings measure. Technical and business majors continue to have slower earnings growth relative to humanities majors.

We now turn to estimating age-earnings profiles by major using the full LEHD sample. To start, we estimate equation (1), but continue to leave π_{mc} and α_i in the composite error term. The results are displayed in column (3) of Table 4. As a reminder, the sample excludes workers who are currently enrolled or obtained a graduate degree at the time they were interviewed in the ACS. We also exclude individuals who worked for less than 3 quarters or earned below the first percentile based on the LEHD data. The sample size in column (3) is now over 30 million observations as compared to about 1 million observations in columns (1) and (2).

The estimated age-earnings profiles change considerably when we use the full LEHD sample, especially for technical degree holders. While engineering and computer science majors still see slower earnings growth over the life cycle, the magnitude of the gap is much smaller. For example, instead of a relative decline of approximately 17 log-points for individuals aged 29-30, column (3) shows that the gap is now just 5 log-points for this group. Similarly, at the age of 49-50 the gap is smaller than 1 log-point and not statistically significant at the 10% level. Simply expanding the sample backwards, and thus adding earnings observations earlier in the life cycle for many workers, leads to a significant change in the age-earnings profiles. There are at least three potential explanations: (1) returns to major have shifted across cohorts, (2) returns to major have shifted over time, and (3) age-earnings profiles by major have changed over time.[9]

working life, individuals can move between states covered and not covered by the LEHD. If they happen to be in an uncovered state in the year of the ACS survey, they will appear in column (1) and not column (2).

[9] An additional explanation could be a change in sample composition when moving from column (2) to column (3). In particular, when we match the ACS backward to the LEHD, we include individuals who are above the age of 50 when participating in the ACS. While not included in columns (1) or (2), these individuals will enter the full LEHD sample in earlier years when they were 50 years old or younger. If the correlation between survival rates and labor market success vary across fields, we could be positively selecting from some fields and negatively selecting from other fields. While we think this is unlikely, in future versions we plan to exclude individuals in the ACS above the age of 60.

Consider first the cohort explanation. If recent cohorts of engineering and computer science majors earn a premium relative to humanities majors that is significantly higher than the premium earned by earlier cohorts (across all ages), then the age-earnings profile estimates using the ACS will be biased downwards. The apparent shrinking of the wage gap between technical majors and humanities majors across the life cycle is not indicative of slower wage growth, it instead reflects changes across cohorts in the premium associated with a technical degree. This type of bias is exacerbated when few years of repeated cross-sections are available. To understand the role that changes in the returns to cohort might play, we estimate a version of equation (1) that explicitly allows the returns to major to vary across birth cohorts. This entails estimating $\pi_{m,c}$, where we allow for 11 different birth cohorts split into five year increments between 1940 and 1990.[10] The results are displayed in column (4) of Table 4 and indicate that technical degree holders experience the same or even faster earnings growth over the life cycle as compared to humanities major. These patterns suggest that cross-cohort changes in returns are an important phenomena, which we investigate further in the next section.

However, an alternative explanation for the difference in age-earnings profile estimates across the ACS and LEHD is changes in returns to major over time. This is conceptually distinct from changes in returns across cohorts since changes in returns over time would influence all cohorts equally.[11] By linking earnings backwards through the LEHD, we are incorporating many observations from young workers in an earlier period. If the relative return to a technical degree is lower in earlier periods across all ages, then age-earnings profiles will be artificially steeper in the LEHD relative to the ACS. To investigate how important this phenomena might be, we replicate the model used in column (4) but replace $\pi_{m,c}$ with $\pi_{m,t}$. This allows the returns to major to vary over time in five-year increments from 1996 to 2014.[12] If changes over time in returns are responsible for the differences between the LEHD estimates and the ACS, we would expect the age-earnings profiles

[10]We leave 1950-54 as the reference category.

[11]In the extreme, if a single cohort were followed across the entire life cycle, it would not be possible to separate earnings growth across majors from changes in relative returns over time.

[12]Years before 1995 correspond to the reference category.

to revert back to the patterns observed in the ACS when $\pi_{m,t}$ is excluded. Column (5) shows the age-earnings profile estimates with time-varying returns to major and there is no difference relative to the LEHD model in column (3) that excludes either $\pi_{m,t}$ (or $\pi_{m,c}$). In other words, it does not appear that the difference between the baseline ACS and LEHD estimates is driven entirely by variation in the returns to major over time.

Before turning to the possibility that age-earnings profiles themselves have changed over time, we estimate a version of equation (1) with worker fixed effects. This is our preferred specification as it absorbs any unobserved heterogeneity across workers affecting the level of log-earnings that is correlated with major, including birth-cohort differences.[13] The estimated age-earnings profiles accounting for worker fixed effects are displayed in column (6) of Table 4. The results indicate that engineering and computer science majors see similar or even faster earnings growth over the life cycle relative to humanities majors. Moreover, the point estimates are very similar to the estimates based on the model that allows for changes in the returns to major by cohort (column (4)). The top panel of Figure 2 displays the point estimates for all age and major categories relative to humanities when worker fixed effects are included. The bottom panel of Figure 2 contrasts the age-earning profile estimates for technical and business majors using the ACS and the LEHD with worker fixed effects. The differences in earnings growth profiles across the two samples are quite stark, with the LEHD estimates painting a much more positive picture for graduates in technical and business majors.

As previously discussed, differences in the estimated age-earnings profiles between the ACS and LEHD samples could also reflect heterogeneity in the profiles themselves over time. When we use the longer LEHD panel, the estimates will tend to reflect a weighted average of the major specific earnings profiles across periods. Appendix Table A2 presents estimates of equation (1) (including worker fixed effects) separately for individuals born

[13]Typically, researchers avoid including worker fixed effects since it is not possible to identify level differences in the returns to major. Instead, they control for selection into major using a variety of approaches (see Patnaik, Wiswall, and Zafar (2020) for a review of these studies). Alternatively, other authors have used admission cutoffs rules to study major-specific returns using regression discontinuity designs (Hastings, Neilson, and Zimmerman, 2013; Kirkeben, Leuven, and Mogstad, 2016; Andrews, Imberman, and Lovenheim, 2017; Bleemer and Mehta, 2022).

before and after 1968. The results for the birth cohorts born prior to 1968 suggest mildly slower earnings growth for technical degree holders relative to humanities. Most of the slower growth comes from the first few years in the labor market. However, similar to the ACS sample, we do not observe the same workers across the full life cycle. As a result, young workers may differ from the older workers in ways not fully captured by individual fixed effects, complicating inference for this cohort. For the cohorts born after 1968, the results again suggest that technical majors have earnings growth on par or faster than humanities. The differences in age-earnings profiles between those born before and after 1968 are fairly mild, suggesting that the more important feature is to allow the major-specific earnings levels to vary by cohort. It is important to point out that if anything, more recent cohorts of technical majors have higher relative wage growth. Therefore, cohort heterogeneity in age-earnings profiles alone cannot be the primary cause for the differences between our findings and the findings in Deming and Noray (2020).

3.2.3 Changes in Returns by Cohort

Using the lengthy panel of worker earnings in the LEHD refutes the findings from the ACS that technical and business majors experience slower earnings growth over the life cycle relative to humanities majors. A key driver of the difference in results is related to changes in the returns to major by cohort. Panel A in Table 5 displays estimates of the major-by-cohort ($\pi_{m,c}$) coefficients when estimating equation (1) using the LEHD. Note that the age-earnings profiles from this specification are displayed in column (4) of Table 4.

The cohort-by-major estimates indicate that engineering and computer science majors have seen a significant increase in earnings levels relative to humanities majors across cohorts. The gap in the level of earnings between technical and humanities majors has grown by approximately 20 log-points between individuals born in the 1940s and the 1986-1990 birth cohorts. Business, social science, and other majors have also seen increases in earning levels relative to humanities in more recent cohorts, though smaller in magnitude.

For completeness, Panel B of Table 5 lists the estimates of the major-by-year effects

(π_{mt}) when estimating equation (1) using the LEHD. The age-earnings profiles from this specification are displayed in column (5) of Table 4. While there is mild growth in the relative returns to a technical degree over time, it is considerably smaller than the changes across birth cohorts. The recent surge in returns to majoring in a technical field is primarily experienced by recent graduates and has not permeated to older workers.

Computer science and engineering degree fields have seen the greatest cross-cohort increases in earnings levels relative to humanities, yet it unclear what is driving this change. There are two natural explanations. First, sorting into degree fields may have changed across cohorts such that technical majors are more positively selected relative to humanities than ever before. Alternatively, recent cohorts of computer science and engineering majors are learning a vintage of technical expertise that is especially valuable, expanding the earnings premium relative to humanities. Separating these mechanisms is challenging, though below we provide some suggestive evidence that both channels are likely relevant.

To examine how relative selectivity into technical fields has changed across time, we use survey data from the 1992 and 2019 Integrated Postsecondary Education Data System (IPEDS). We limit the sample to four-year degree granting institutions and calculate the total number of bachelors degrees awarded for each school-year by field of study.[14] Additionally, we use the sum of the 75th percentile math and verbal SAT scores from 2019 to rank schools according to enrollee test scores.[15] Two patterns suggest that technical majors have become more positively selected relative to humanities majors over time. First, among graduates from the top 100 four year post-secondary schools, the share of students pursuing an engineering or computer science major increased from 12.6% to 20.2% between 1992 and 2019. Second, the number of graduates outside of the top 100 schools has grown faster than among the top 100 schools, and these graduates are increasingly likely to select humanities or other majors. As a result, the share of humanities and other majors graduating from a top 100 school has declined from 12.2% in 1992 to 8.3%. These patterns are

[14] See Appendix Table A3 for the precise mapping between CIP major codes and degree field.

[15] We impute SAT scores for those schools only reporting ACT percentiles. Many schools report both SAT and ACT percentiles and we use these schools to predict the 75th percentile math and verbal SAT scores using a quadratic function of the 75th percentile of math and English ACT scores. Note also that rank is based only on the 2019 data, and is thus fixed across the 1992 and 2019 data.

consistent with recent cohorts of technical degree holders being relatively more selected than humanities majors.

There is also evidence that the type of skills being developed within technical and humanities majors has changed across cohorts. Using detailed degree data available in the ACS, we examine how the distribution of majors within the the broader technical and humanities majors has shifted.[16] Among technical degree holders, there has a been a sizeable shift towards computer related fields. Technical degree holders born in 1968 or later are considerably more likely to obtain degrees in computer and information systems, computer science, and computer engineering relative to technical degree holders born prior to 1968. The detailed technical majors that have shrunk the most across birth cohorts are general engineering, electrical engineering, and mechanical engineering. Among humanities majors, there has been shift towards communications and graphic design and away from fine arts, literature and history across birth cohorts born before and after 1968. It is also likely that the academic content of these detailed majors has changed over time as the associated technologies have evolved. As a result, part of the increase in the relative return to a technical major across birth cohorts likely reflects changes in skills accumulated during college and changes in skill prices. Further disentangling the sorting and skill mechanisms behind the changes in returns to major across birth cohorts is left for future work.

4 Robustness and Heterogeneity

In the following sections we investigate the sensitivity of our main findings to different sample and data choices, explore variation in age-earnings profiles by gender and race, and estimate age-earning profiles using a more dis-aggregated field of study definition.

[16] Appendix Tables A4 and A5 show the share of each detailed major within technical and humanities majors by birth cohort respectively.

4.1 Sample Selection

This section discusses whether our main results are robust to alternative sample selection criteria. Appendix Table A6 shows our preferred estimates of field-specific, age-earnings profiles alongside additional specifications. Column (1) displays the estimates from our preferred specification, based on a worker fixed effects model using the LEHD data (column 6 of Table 4). The estimation sample includes workers ages 23-50 earning above the 1st percentile who do not have graduate degree. Below we briefly discuss the sensitivity of our results to these restrictions.

First, we exclude workers below the age of 25 and re-estimate age-earnings profiles using the worker fixed effects model. The motivation for this sample alteration is a concern that the transition to the labor market has become relatively harder for more recent cohorts of humanities majors. In particular, recent humanities majors may take longer to find productive matches. By focusing on a slightly older set of individuals, we examine whether changes in early labor market frictions may be affecting our estimates of age-earning profiles. Column (2) of Appendix Table A6 show that the basic patterns are unchanged when we exclude workers ages 23-24 from our model. Individuals with a technical degree continue to experience mildly faster earnings growth between 25 and 50 as compared to humanities majors.

In our preferred model we exclude workers with very low earnings, in part to keep the focus on individuals who are attached to the labor force and likely utilizing the skills they obtained in college. In columns (3) and (4) of Appendix Table A6, we demonstrate that our key findings are not sensitive to different sample trimming choices. The results in column (3) are based on a sample that does not exclude any workers based on earnings, while the results in column (4) exclude workers with earnings below the two and a half percentile.

Finally, we consider how the inclusion of graduate degree holders impacts our estimates. In column (5) of Appendix Table A6 we display estimates of age-earnings profiles by major when graduate degree holders are included. Earnings growth in technical fields relative to humanities flattens, but there continues to be no evidence for slower earnings growth. The largest change occurs for life and physical sciences. The inclusion of graduate degree holders, many of which are likely doctors, results in significantly faster wage growth over the life cycle relative to humanities. By ages 49-50, life and physical science degree holders experience wage growth that is 21 log-points faster than humanities. When graduate degree holders are excluded, this gap is only 11 log-points.

We greatly prefer our baseline estimates that exclude graduate degree holders. It is often the case that graduate degree holders work before obtaining a degree and we cannot capture this with our sampling criteria. As a result, wage growth for graduate degree holders could reflect the change in earnings from earlier periods without the degree to later periods with the degree, thus conflating the effect of getting the degree.

4.2 NSCG

As we have already demonstrated, estimating age-earnings profiles by field of study using the relatively short panel of repeated cross-sections in the ACS can yield misleading results. We improve upon these estimates by linking the ACS to a long panel of individual earnings in the LEHD. An alternative approach is to use the National Survey of College Graduates (NSCG), a publicly available data set providing information on college major and earnings. The NSCG is a survey of college graduates in the US running intermittently from 1993 to 2017. The advantage of the NSCG relative to the ACS is that it provides a window into what young workers were earning during a much earlier period. However, the NSCG is not a panel and does not go back as far as the LEHD, and thus we prefer our estimates based on the LEHD.

Yet, we can use the NSCG to provide additional support for our main findings. In Appendix A.3, we replicate the key patterns we observe in age-earnings profiles using the NSCG. In particular, business and technical degree holders are estimated to experience slower earnings growth over the life cycle relative to humanities majors when we don't account for changes in returns to major by cohort. Once we incorporate cohort-by-major effects, engineering, computer science, and business majors exhibit faster earnings growth over the life cycle. Full details are provided in Appendix A.3.

4.3 Age-Earnings Profiles by Gender and Race

The estimated age-earnings profiles in column (6) of Table 4 and Figure 2 reflect averages across the population of workers with a bachelor's degree. In this section we explore whether age-earnings profiles by major vary with gender and race. Figure 3 plots estimates of $\beta_{m,a} - \beta_{m,23}$ by gender after estimating equation (1) separately for women and men. Each sub-plot corresponds to a different field of study. We find that men experience larger earnings growth in business and social sciences relative to humanities. The gap in earnings growth between men and women by age 49-50 in these fields is 5 and 7.8 log-points, respectively. By contrast, women holding Life and Physical Science majors experience higher earnings growth relative to men. Finally, gender differences in computer science and engineering degree holders are relatively small. The last sub-plot shows differences in other majors. In this case, we find that men tend to have higher earnings at the start of their careers but this difference decreases progressively and is no longer observed by age 45.

Similarly, Figure 4 shows how our estimates of $\beta_{m,a} - \beta_{m,23}$ vary by race. In this case, we observe that some groups experience larger earnings growth in specific majors. Whites obtain significantly slower growth in computer science and engineering relative to other-race individuals. A similar pattern is observed for life and physical sciences and other majors. By contrast, whites holding a degree in social sciences experience faster growth across all age categories. For business majors, Asians obtain the largest returns while Hispanic and Asian individuals experience the largest growth in life and physical Sciences. These differences across race are substantially smaller for social science degree holders. Finally, Blacks obtain larger earnings growth in engineering and computer science but relatively lower in business.

Overall, heterogeneity in age-earnings profiles by gender is fairly small, though we are restricting ourselves to individuals that are attached to the labor force. By contrast, racial heterogeneity in age-earning profiles is more salient, particularly for engineering and computer science degrees. In future work we plan to analyze more thoroughly how labor supply varies over the life cycle by major for women and why earnings grow especially quickly for non-white workers in technical fields.

4.4 Alternative Major Classification

Our previous results employ an aggregation of major categories into five and six groups for ease of comparison with Deming and Noray (2020). As Andrews et al. (2022) discuss, the use of a different or more detailed classification of fields of study might potentially change our results if there exists variation in returns to specific majors within each group (for example, in our baseline model, social science includes economics, anthropology, criminology, geography, international relations, political science, and sociology). For this reason, we consider an alternative, more disaggregated classification, based on the characterization of college majors used by Altonji, Kahn, and Speer (2016).[17] Specifically, we define the following groups: applied science, business and economics, computer science, education, engineering, humanities, medical services, natural science, services, and social science. Appendix Table A7 shows the sub-categories included in each group.

Using this alternative classification, we re-estimate (1), including worker fixed effects, leaving humanities as the reference category. Figure 5 shows our estimates of age-earnings profiles for each group, where we present two separate plots to enhance interpretability. We do not find large changes for technical majors relative to our main results. Engineering and applied science exhibit larger earnings growth relative to humanities. We also find a steeper profile after integrating economics into the business category. By contrast, we find a flatter profile for social science and computer science. In addition, graduates from computer science and medical services experience relatively slower growth than humanities in the first decade after graduation and then start progressively to catch up, with medical services graduates obtaining a significative positive premium by age 50. Finally, education majors see a rapid decline in earnings growth relative to humanities. Only around fifteen years after graduation does this gap start to reduce and close by age 50.

[17] They classify college majors into a set of 51 categories used by the Department of Education.

5 Conclusion

There is a vast literature in economics studying the impact of college major on labor market outcomes. Most of this literature is focused on estimating the effect of major on average earnings among all workers as opposed to how earnings across the life cycle vary with major. This paper contributes to a small, but growing literature that explores the latter question.

Recent works by Deming and Noray (2020) and Andrews et al. (2022) come to different conclusions regarding relative wage growth across college majors. Deming and Noray (2020) use broad cross-sections of workers over a relatively short time horizon and find that technical and business majors have slower earnings growth over the life cycle relative to humanities. Andrews et al. (2022) instead use panel data on a few cohorts of Texas college graduates and show that at least early in the life cycle, technical and business majors experience faster wage growth relative to humanities. Our paper reconciles these findings by exploiting many cohorts of workers over a long time period using matched ACS and LEHD data. Similar to Andrews et al. (2022), we find that technical and business majors experience faster wage growth relative to humanities over the full life cycle and across the US. The discrepancy in results between Deming and Noray (2020) and Andrews et al. (2022) is driven by our finding that recent cohorts of engineering, computer science, and business majors earn a higher premium relative to humanities majors when compared with earlier cohorts.

A next natural question to ask is why the relative earnings premium has risen for these majors. In our paper we consider two mechanisms, a change in the relative quality of graduates in these fields and a change in the type of skills being accumulated. However, our analysis is only suggestive and significant additional work needs to be done to more fully disentangle supply-side and demand-side mechanisms consistent with rising major premiums.

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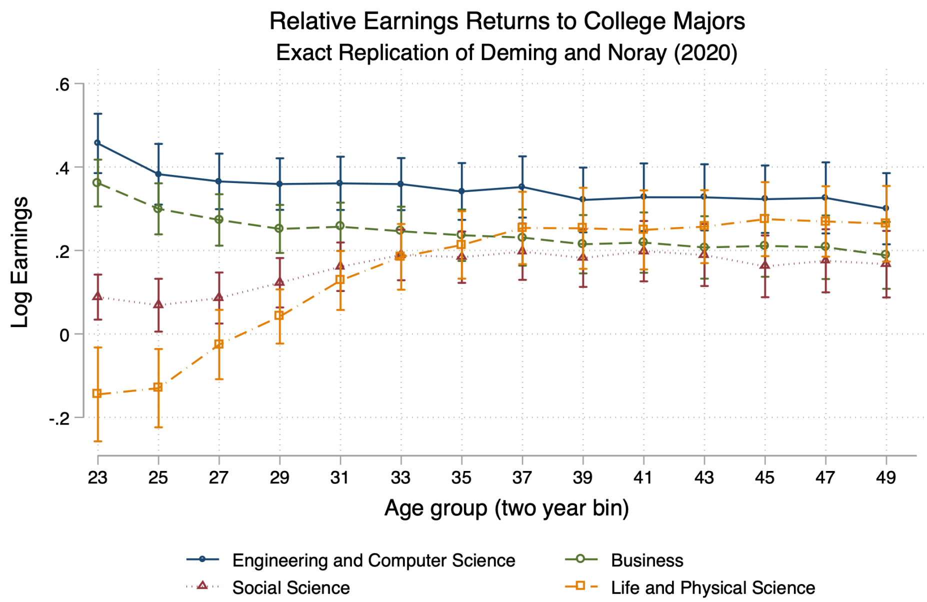
Figures and Tables

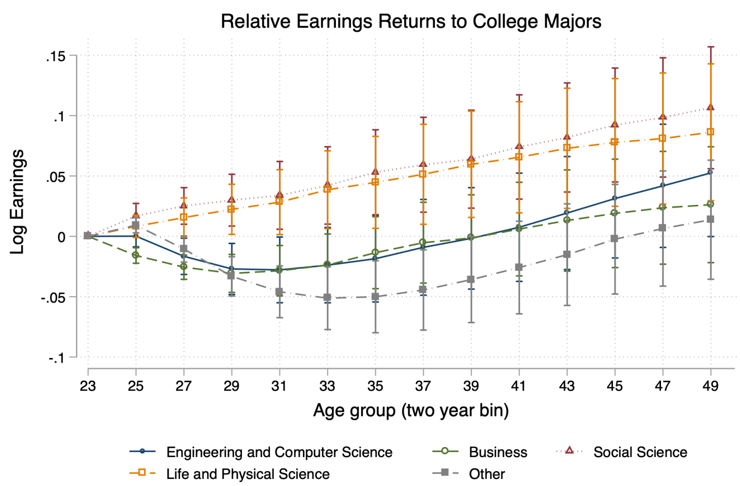
Figure 1: Replication of Deming and Noray (2020), Figure V



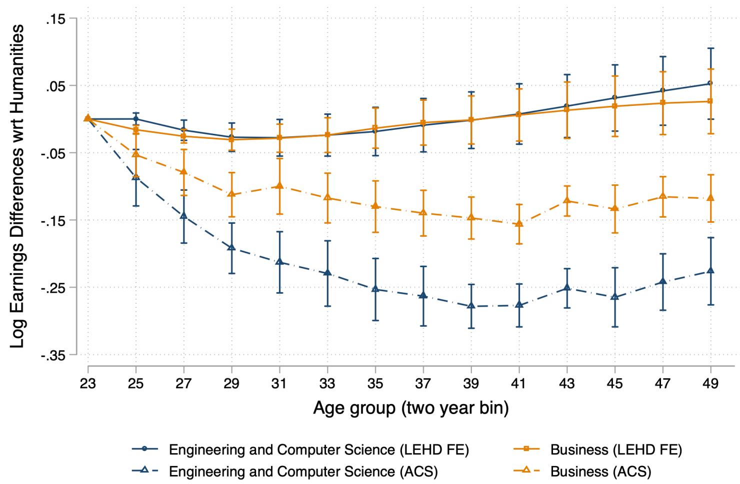
Notes: This plot replicates Figure V in Deming and Noray (2020). Each coefficient and 95% confidence interval corresponds to estimates of $\beta_{m,a}$ in equation (1) using annual log earnings as the dependent variable, excluding birth-cohort effects ($\pi_{m,c}$) and individual fixed effects (α_i). The sample is all four-year graduates observed in the 2009-2017 American Community Survey. We follow their categorization of majors to construct each group. The regression includes controls for sex-by-age indicators, age and year fixed effects, race and ethnicity, citizenship, veteran status and an indicator for having any graduate school education. Standard errors are clustered at the major-by-age level.

Figure 2: Earnings Growth Estimates

(a) Estimates Using Worker FE

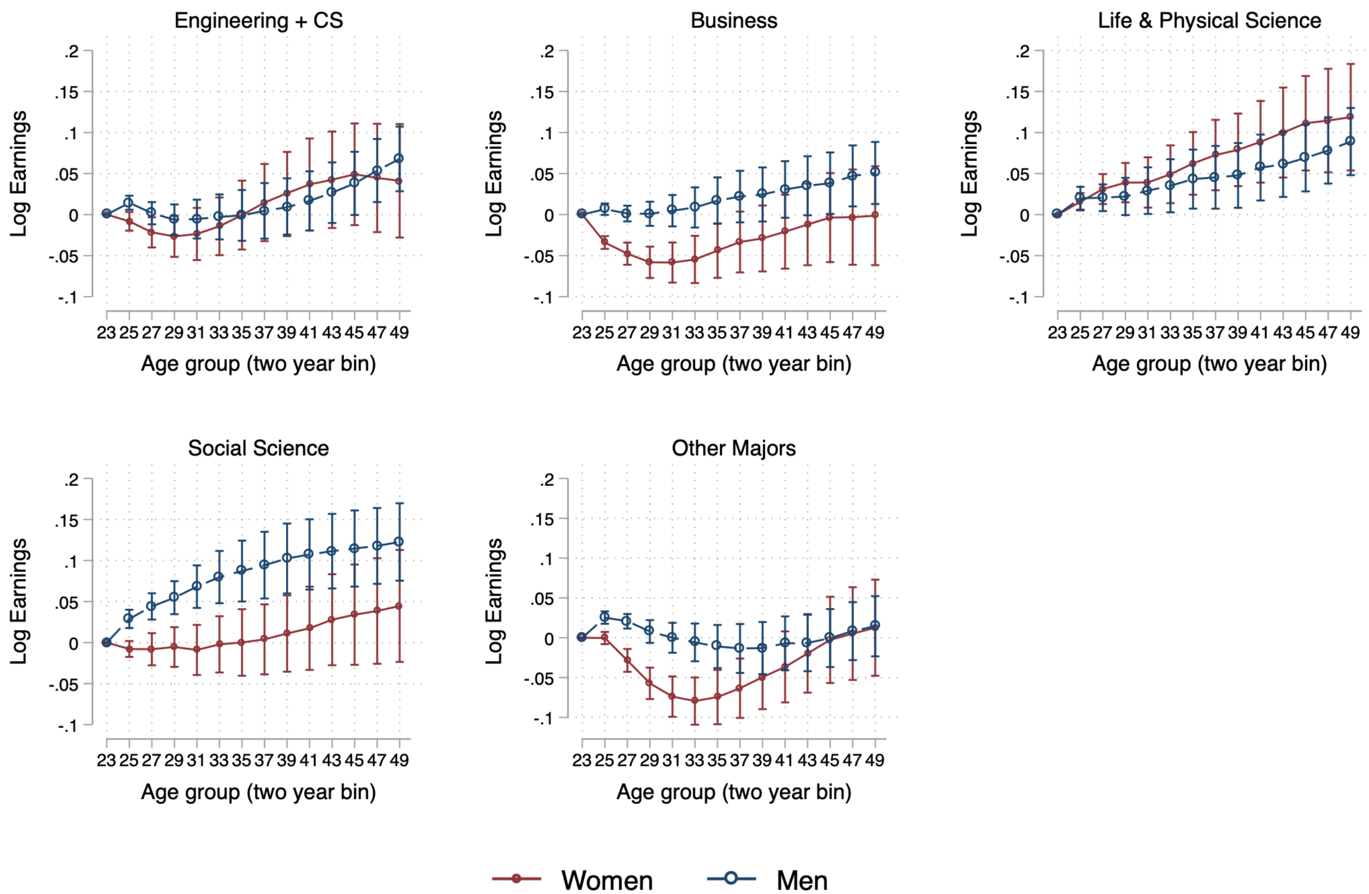


(b) Differences with ACS



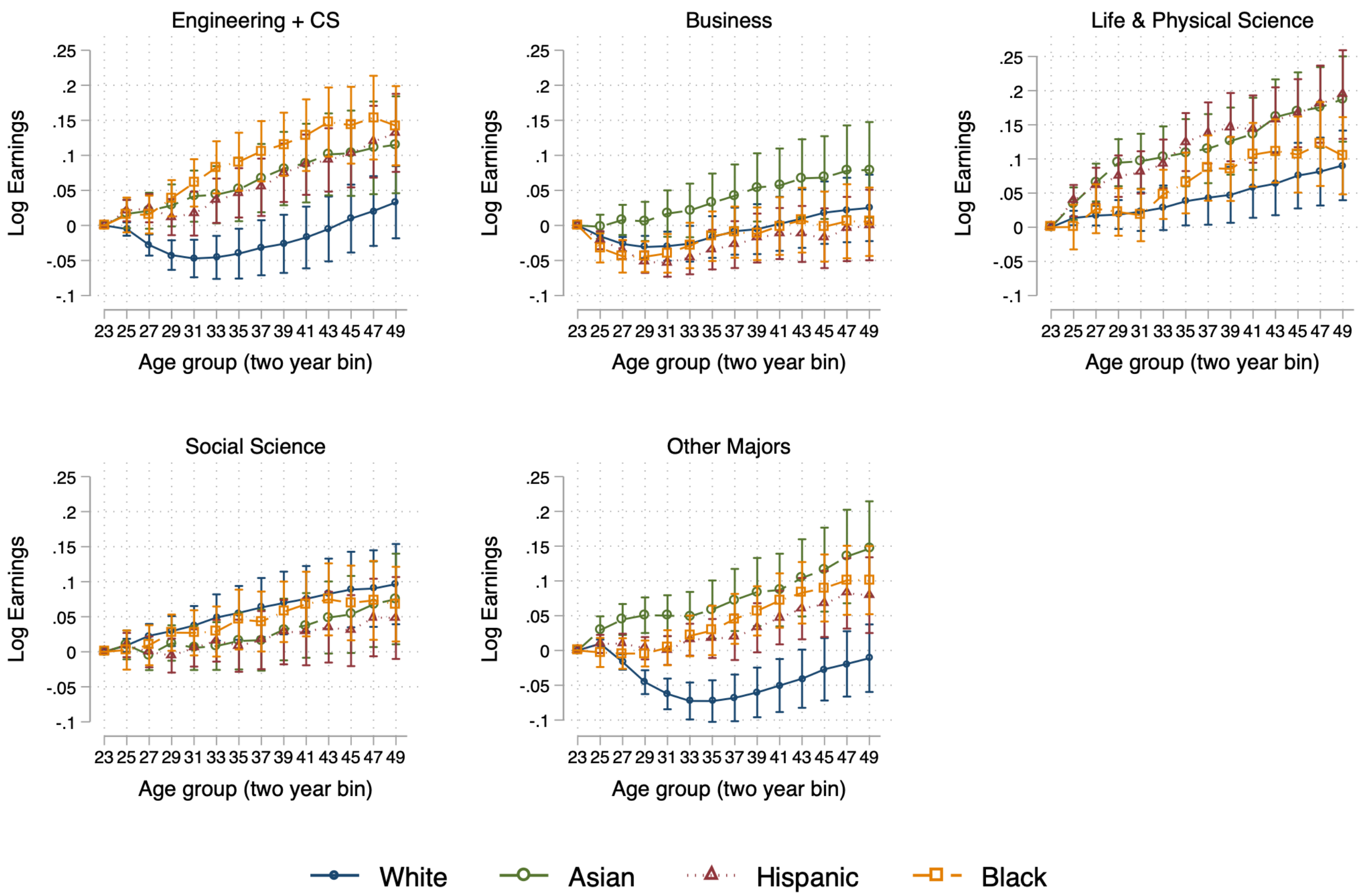
Notes: Panel (a) plots estimates and 95% confidence intervals of $\beta_{m,a} - \beta_{m,23}$ in equation (1) using LEHD annual earnings as the dependent variable. The sample consists of college graduates with a valid major who are not enrolled and do not have a graduate degree observed in the ACS between 2009 and 2019 linked to annual earnings in the LEHD 2014 snapshot. The LEHD earnings data is limited to workers: ages 23-50, ≥ 3 quarters of earnings, and above the 1st percentile of earnings. Classification of majors follows Deming and Noray (2020). The regression includes worker, year, and age-group fixed effects, plus indicators of age interacted with gender and race. Observations are weighted using the ACS person weights. Standard errors are clustered at the major-by-age level. Panel (b) compares the estimates for Engineering and Computer Science presented in panel (a) with the results obtained using the ACS.

Figure 3: Heterogeneity by Gender



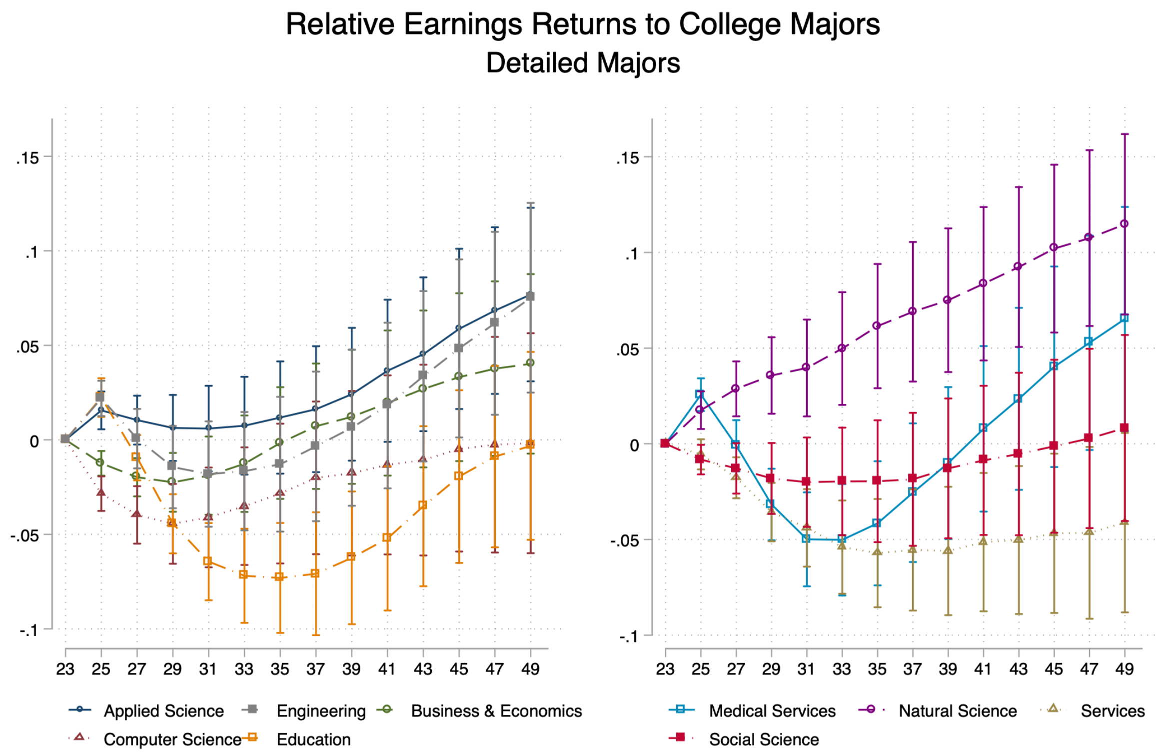
Notes: This figure shows estimates and 95% confidence intervals of $\beta_{m,a} - \beta_{m,23}$ in equation (1), separately estimated for men and women, using LEHD annual earnings as the dependent variable. The sample consists of college graduates with a valid major who are not enrolled and do not have a graduate degree observed in the ACS between 2009 and 2019 linked to annual earnings in the LEHD 2014 snapshot. The LEHD earnings data is limited to workers: ages 23-50, ≥ 3 quarters of earnings, and above the 1st percentile of earnings. Classification of majors follows Deming and Noray (2020). The regression includes worker, year, and age-group fixed effects, plus indicators of age interacted with race. Observations are weighted using the ACS person weights. Standard errors are clustered at the major-by-age level.

Figure 4: Heterogeneity by Race



Notes: This figure shows estimates and 95% confidence intervals of $\beta_{m,a} - \beta_{m,23}$ in equation (1), separately estimated by race, using LEHD annual earnings as the dependent variable. The sample consists of college graduates with a valid major who are not enrolled and do not have a graduate degree observed in the ACS between 2009 and 2019 linked to annual earnings in the LEHD 2014 snapshot. The LEHD earnings data is limited to workers: ages 23-50, ≥ 3 quarters of earnings, and above the 1st percentile of earnings. Classification of majors follows Deming and Noray (2020). The regression includes worker, year, and age-group fixed effects, plus indicators of age interacted with gender. Observations are weighted using the ACS person weights. Standard errors are clustered at the major-by-age level.

Figure 5: Earning Growth Estimates Using an Alternative Major Classification



Notes: This figure shows estimates and 95% confidence intervals of $\beta_{m,a} - \beta_{m,23}$ in equation (1), using LEHD annual earnings as the dependent variable. The sample consists of college graduates with a valid major who are not enrolled and do not have a graduate degree observed in the ACS between 2009 and 2019 linked to annual earnings in the LEHD 2014 snapshot. The LEHD earnings data is limited to workers: ages 23-50, ≥ 3 quarters of earnings, and above the 1st percentile of earnings. We classify majors into ten groups (Applied Science, Business and Economics, Computer Science, Education, Engineering, Humanities, Medical Services, Natural Science, Services, and Social Science) following Altonji, Kahn, and Speer (2016) and leaving Humanities as the reference category. The regression includes worker, year, and age-group fixed effects, plus indicators of age interacted with gender and race. Observations are weighted using the ACS person weights. Standard errors are clustered at the major-by-age level.

Table 1: Summary Statistics, ACS 2009-2019

	$\geq$ BA	Only BA & not enrolled	>= 27 weeks & Above 1% earnings
Log Earnings	10.84	10.78	10.92
Age	36.7	36.5	36.6
% Female	53.2	51.5	50.6
% Non-white	21.5	19.6	19.4
Observations	3,537,433	2,038,161	1,917,287
% Engineering & CS	13.15	13.55	13.82
% Business	20.67	25.51	25.80
% Life & Physical Science	8.81	5.90	5.88
% Social Science	7.52	6.81	6.78
% Humanities	17.38	18.46	18.15
% Others	32.47	29.7	29.58

Notes: ACS data is extracted from the Integrated Public Use Microdata Series (IPUMS) 1% samples (Ruggles et al., 2021). The first column includes all respondents aged 23-50 with at least a bachelor's degree who report a valid major. The second column excludes individuals enrolled in school or who report receiving a graduate degree. The final column further excludes individuals working less than 27 weeks or those earning below the first percentile of earnings.

Table 2: Summary Statistics, LEHD and Matched ACS

Unit		LEHD	Matched ACS
Person	% Born < 1960	27.4	1.2
	% $1960 \leq$ Born < 1970	24.3	28.4
	% $1970 \leq$ Born < 1980	23.8	34.1
	% Born ≥ 1980	24.5	36.2
	% White	79.2	77.0
	% Male	47.9	49.0
	% Engineering & CS	12.6	13.9
	% Business	25.4	25.9
	% Life & Physical Science	5.7	5.7
	% Social Science	6.9	6.9
	% Humanities	18.2	18.2
	% Other	31.2	29.4
	Total Persons	3,640,000	1,195,000
Person-Year	Earnings	57,500	69,500
	Weeks worked		42.14
	Quarters worked	3.9	
	Years per person	9.2	1
	% Before 1995	8.4	0
	% 1995-1999	18.4	0
	% 2000-2004	23.9	0
	% 2005-2009	24.7	17.0
	% After 2010	24.6	83.0
	Total Person-Years	33,640,000	1,195,000

Notes: The LEHD sample includes all matched individuals from the 2009–2019 ACS waves with at most a BA degree who also report a valid major. The Matched ACS sample includes only individuals in our baseline ACS sample (degree, major, age, and work restrictions) between 2009 and 2015 who also appear in the LEHD in those years.

Table 3: Earnings Growth Estimates, ACS

		$\beta_{m,a} - \beta_{m,23}$					
Major m	Age a	(1)	(2)	(3)	(4)	(5)	(6)
Engineering & CS	29-30	-0.069	-0.132	-0.145	-0.153	-0.141	-0.183
		(0.034)	(0.033)	(0.030)	(0.031)	(0.030)	(0.023)
	39-40	-0.131	-0.198	-0.222	-0.225	-0.209	-0.278
		(0.054)	(0.046)	(0.045)	(0.047)	(0.044)	(0.033)
	49-50	-0.179	-0.237	-0.248	-0.230	-0.216	-0.254
		(0.058)	(0.047)	(0.047)	(0.047)	(0.045)	(0.031)
Business	29-30	-0.109	-0.075	-0.078	-0.066	-0.052	-0.096
		(0.032)	(0.025)	(0.025)	(0.024)	(0.023)	(0.010)
	39-40	-0.146	-0.092	-0.101	-0.080	-0.067	-0.138
		(0.050)	(0.040)	(0.040)	(0.038)	(0.036)	(0.015)
	49-50	-0.176	-0.117	-0.121	-0.092	-0.076	-0.115
		(0.055)	(0.040)	(0.041)	(0.039)	(0.038)	(0.017)
L&P Science	29-30	0.198	0.145	0.116	0.072	0.065	0.022
		(0.076)	(0.051)	(0.043)	(0.044)	(0.042)	(0.037)
	39-40	0.412	0.314	0.160	0.102	0.099	0.028
		(0.125)	(0.101)	(0.063)	(0.057)	(0.056)	(0.045)
	49-50	0.419	0.322	0.175	0.124	0.129	0.090
		(0.115)	(0.087)	(0.059)	(0.054)	(0.055)	(0.044)
Social Science	29-30	0.038	0.037	0.036	0.013	0.013	-0.030
		(0.031)	(0.025)	(0.025)	(0.024)	(0.023)	(0.010)
	39-40	0.098	0.076	0.031	0.018	0.018	-0.052
		(0.049)	(0.040)	(0.040)	(0.037)	(0.036)	(0.015)
	49-50	0.080	0.056	-0.006	-0.001	-0.002	-0.041
		(0.054)	(0.040)	(0.041)	(0.039)	(0.038)	(0.017)
	N	3,537,433	3,174,188	2,038,161	1,932,838	1,917,282	1,917,282

Notes: This table presents estimates of equation (1) where π_{mc} and α_i are part of the composite error. The baseline sample is all four-year college graduates between 23-50 years old in 2009-2019 American Community Survey. Column (1) presents estimates from a specification identical to Deming and Noray (2020) but adds individuals observed in the 2018 and 2019 ACS rounds who report a valid college degree. Column (2) excludes individuals currently enrolled in school. Column (3) further limits the sample to individuals holding only a Bachelor's degree. In column (4) we exclude individuals working fewer than 27 weeks and include extra controls. Column (5) excludes individuals earning in the 1st percentile. Column (6) splits Humanities from the Other major category. Observations are weighted using the ACS person weights. In all columns standard errors are clustered at the major-by-age level.

Table 4: Earnings Growth Estimates, Matched ACS and LEHD

		$\beta_{m,a} - \beta_{m,23}$					
		Matched ACS		LEHD			
Major m	Age a	(1)	(2)	(3)	(4)	(5)	(6)
Engineering & CS	29-30	-0.175	-0.166	-0.046	-0.023	-0.048	-0.027
		(0.017)	(0.020)	(0.012)	(0.014)	(0.012)	(0.011)
	39-40	-0.251	-0.246	-0.060	-0.010	-0.062	-0.002
		(0.015)	(0.022)	(0.016)	(0.020)	(0.016)	(0.021)
	49-50	-0.209	-0.170	-0.007	0.063	-0.013	0.053
		(0.024)	(0.026)	(0.016)	(0.021)	(0.016)	(0.027)
Business	29-30	-0.096	-0.095	-0.057	-0.052	-0.058	-0.031
		(0.014)	(0.018)	(0.006)	(0.007)	(0.006)	(0.008)
	39-40	-0.132	-0.137	-0.057	-0.038	-0.058	-0.001
		(0.016)	(0.016)	(0.013)	(0.014)	(0.013)	(0.018)
	49-50	-0.098	-0.090	-0.014	0.016	-0.014	0.026
		(0.019)	(0.025)	(0.013)	(0.015)	(0.013)	(0.024)
L&P Science	29-30	0.031	0.076	0.044	0.023	0.043	0.030
		(0.016)	(0.017)	(0.011)	(0.011)	(0.011)	(0.011)
	39-40	0.054	0.082	0.075	0.056	0.074	0.064
		(0.021)	(0.021)	(0.019)	(0.017)	(0.019)	(0.021)
	49-50	0.143	0.181	0.143	0.135	0.144	0.107
		(0.027)	(0.029)	(0.018)	(0.018)	(0.018)	(0.026)
Social Science	29-30	-0.011	-0.022	0.006	0.006	0.005	0.022
		(0.017)	(0.014)	(0.008)	(0.011)	(0.008)	(0.011)
	39-40	-0.053	-0.063	0.013	0.037	0.012	0.060
		(0.025)	(0.022)	(0.014)	(0.017)	(0.014)	(0.022)
	49-50	-0.015	-0.028	0.007	0.080	0.005	0.086
		(0.026)	(0.036)	(0.018)	(0.019)	(0.018)	(0.029)
Others	29-30	-0.074	-0.051	-0.025	-0.025	-0.025	-0.033
		(0.016)	(0.013)	(0.008)	(0.008)	(0.008)	(0.008)
	39-40	-0.111	-0.097	-0.033	-0.019	-0.034	-0.036
		(0.016)	(0.018)	(0.015)	(0.013)	(0.015)	(0.018)
	49-50	-0.049	-0.024	0.039	0.072	0.040	0.014
		(0.021)	(0.023)	(0.014)	(0.015)	(0.014)	(0.025)
	N (millions)	1.2	1.0	33.3	33.3	33.3	33.3

Notes: This table presents estimates of equation (1) using various samples and specifications. In columns (1) and (2) we use a sample of individuals who appear concurrently in the ACS and LEHD. The outcome in column (1) is the log of ACS measure of earnings and in column (2) it is the log of the LEHD earnings measure. Columns (3)-(6) utilize the full panel of earnings in the LEHD. Column (3) excludes cohort-by-major, year-by-major, or worker fixed effects, while columns (4)-(6) respectively include one of these types of controls. Observations are weighted using the ACS person weights. Standard errors are clustered at the major-by-age level.

Table 5: Cohort-by-Major and Year-by-Major Fixed Effects Estimates

	Engineering & CS	Business	Life & Physical Science	Social Science	Others
	(1)	(2)	(3)	(4)	(5)
Panel A: Cohort-by-Major estimates					
Before 1940	0.109	0.106	0.076	0.105	0.003
	(0.011)	(0.007)	(0.012)	(0.010)	(0.015)
1941-1945	0.044	0.050	0.026	0.073	0.012
	(0.008)	(0.006)	(0.009)	(0.006)	(0.006)
1951-1955	0.043	0.030	0.011	0.073	0.017
	(0.002)	(0.003)	(0.004)	(0.003)	(0.004)
1956-1960	0.075	0.031	0.031	0.110	0.021
	(0.005)	(0.004)	(0.006)	(0.004)	(0.006)
1961-1965	0.059	0.038	0.018	0.138	0.032
	(0.007)	(0.006)	(0.010)	(0.007)	(0.009)
1966-1970	0.095	0.057	0.046	0.152	0.056
	(0.009)	(0.008)	(0.012)	(0.009)	(0.013)
1971-1975	0.104	0.063	0.050	0.149	0.061
	(0.011)	(0.009)	(0.013)	(0.011)	(0.014)
1976-1980	0.109	0.052	0.006	0.134	0.037
	(0.013)	(0.010)	(0.013)	(0.014)	(0.015)
1981-1985	0.141	0.057	-0.031	0.126	0.038
	(0.018)	(0.013)	(0.014)	(0.015)	(0.015)
1986-1990	0.231	0.079	-0.050	0.169	0.052
	(0.024)	(0.014)	(0.022)	(0.020)	(0.018)
Panel B: Year-by-Major estimates					
1996-2000	-0.012	-0.023	-0.065	0.004	-0.057
	(0.012)	(0.006)	(0.009)	(0.009)	(0.009)
2001-2005	0.000	-0.005	-0.035	0.032	-0.033
	(0.011)	(0.007)	(0.010)	(0.010)	(0.008)
2006-2010	0.026	0.006	-0.023	0.053	-0.010
	(0.010)	(0.008)	(0.010)	(0.010)	(0.008)
2011-2015	0.059	0.018	-0.029	0.055	-0.003
	(0.010)	(0.006)	(0.010)	(0.009)	(0.006)

Notes: Panel A presents estimates of equation (1) using the LEHD that includes cohort-by-major effects. The specification is identical to that of column (4) of Table 4. Panel B presents estimates of equation (1) using the LEHD that includes year-by-major effects. The specification is identical to that of column (5) of Table 4. Observations are weighted using the ACS person weights. Standard errors are clustered at the major-by-age level.

A Appendix

A.1 Linking ACS and LEHD Data

The LEHD infrastructure contains different files with information about workers and the firms where they are observed. In this paper, we employ the Employment History Files (EHF). For each state included in the LEHD 2014 snapshot, the state-specific EHF contains quarterly employment and earnings records for all individuals that appear in the UI records during the corresponding period linked to an employer. Each individual in the LEHD is represented by a unique identifier called PIK (Protected Identification Key). Similarly, each individual in the ACS is represented by a combination of household (CMID) and individual (PNUM) identifiers. We employ the BOC PIK Crosswalk American Community Survey, provided by the Census Bureau, to link both datasets. We exclude cases where an individual in the ACS is linked to more than one PIK identifier.

After linking our sample of college graduates interviewed in the ACS, we constructed a panel with one observation per person per year. We construct annual earnings as the sum of quarterly earnings across quarters, jobs, and states during the corresponding year. Table 2 shows that, on average, we observe 9.2 observations per individual.

A.2 Additional Tables and Figures

Table A1: Majors Classification

Category	Majors (Five-group)	Majors (Six-group)
Engineering and CS	Communication Technologies (20), Computer and Information Sciences (21), Engineering (24), Engineering Technologies (25), Military Technologies (38), Nuclear, Industrial Radiology, and Biological Technologies (51),Electrical and Mechanic Repairs and Technologies (57), Precision Production and Industrial Arts (58), Transportation Sciences and Technologies (59)	Same
Business	Business (62)	Same
Life and Physical	Environment and Natural Resources (13), Biology and Life Sciences (36), Physical Sciences (50)	Same
Social Science	Social Sciences (55)	Same
Humanities		Commercial Art and Graphic Design (6004), French, German, Latin and Other Common Foreign Language Studies (2602), Other Foreign Languages (2603), Music (6002), Drama and Theater Arts (6001), Communications (1901), Mass Media (1903), Advertising and Public Relations (1904), English Language and Literature (3301), Liberal Arts (3401), Humanities (3402), Linguistics and Comparative Language and Literature (2601), Composition and Speech (3302), History (6402), United States History (6403), Fine Arts (6000), Art History and Criticism (6006), Philosophy and Religious Studies (4801), Theology and Religious Vocations (4901), Journalism (1902), Visual and Performing Arts (6003), Film, Video and Photographic Arts (6005), Studio Arts (6007)
Other	All other codes	All other codes

Notes: This table shows the categorization of majors used in different sections of the paper. Majors correspond to the variable DEGFIELD in the ACS 2009-2019 (https://usa.ipums.org/usa-action/variables/DEGFIELD#codes_section). Each column shows the specific general and detailed codes included in each group.

Table A2: LEHD Earnings Growth Estimates, Cohort Heterogeneity

		$\beta_{m,a} - \beta_{m,23}$		
Major m	Age a	All	Up to 1968	After 1968
Engineering & CS	29-30	-0.027	-0.095	-0.022
		(0.011)	(0.029)	(0.010)
	39-40	-0.002	-0.067	0.004
		(0.021)	(0.036)	(0.019)
	45-46	0.031	-0.035	0.048
		(0.025)	(0.038)	(0.017)
	49-50	0.053	-0.013	
		(0.027)	(0.038)	
Business	29-30	-0.031	-0.067	-0.029
		(0.008)	(0.024)	(0.007)
	39-40	-0.001	-0.037	-0.001
		(0.018)	(0.033)	(0.017)
	45-46	0.019	-0.018	0.016
		(0.023)	(0.035)	(0.014)
	49-50	0.026	-0.011	
		(0.024)	(0.036)	
Life & Physical Science	29-30	0.030	-0.020	0.032
		(0.011)	(0.027)	(0.010)
	39-40	0.064	-0.004	0.079
		(0.021)	(0.032)	(0.023)
	45-46	0.092	0.028	0.117
		(0.024)	(0.033)	(0.019)
	49-50	0.107	0.041	
		(0.026)	(0.034)	
Social Science	29-30	0.022	0.032	0.022
		(0.011)	(0.036)	(0.009)
	39-40	0.060	0.073	0.053
		(0.022)	(0.043)	(0.021)
	45-46	0.078	0.089	0.076
		(0.027)	(0.045)	(0.016)
	49-50	0.086	0.098	
		(0.029)	(0.046)	
Others	29-30	-0.033	-0.098	-0.032
		(0.008)	(0.027)	(0.007)
	39-40	-0.036	-0.119	-0.024
		(0.018)	(0.034)	(0.021)
	45-46	-0.002	-0.083	-0.002
		(0.023)	(0.035)	(0.018)
	49-50	0.014	-0.068	
		(0.025)	(0.036)	
	N (millions)	33.3	17.9	15.4

Notes: This table presents estimates of equation (1) with worker fixed effects using the LEHD sample. Column (1) includes all individuals and is a repeat of the results from column (6) of Table 4. In column (2) we include individuals born in 1968 or earlier, and in column (3) we include individuals born after 1968. Observations are weighted using the ACS person weights. Standard errors are clustered at the major-by-age level.

Table A3: IPEDS Major Classification

Category	CIP Codes
Engineering & CS	Communications Technologies, Computer and Information Sciences, Engineering, Engineering-Related Technologies, Military Technologies, Science Technologies
Business	Marketing Operations/Marketing and Distribution, Business Management and Administrative Services
Life and Physical Sciences	Agricultural Sciences, Conservation and Renewable Natural Resources, Biological Science/Life Sciences, Physical Sciences
Social Science	Social Sciences and History
Humanities and Other	Agricultural Business and Production, Architecture and Related Programs, Area, Ethnic and Cultural Studies, Communications, Personal and Miscellaneous Services, Education, Foreign Languages and Literatures, Home Economics-General, Vocational Home Economics, Law and Legal Studies, English Language and Literature/Letters, Liberal Arts and Studies, General Sciences and Humanities, Library Science, Mathematics, Multi/Interdisciplinary Studies, Parks, Recreation, Leisure and Fitness Studies, Philosophy and Religion, Theological Studies and Religious Vocations, Psychology, Protective Services, Public Administration and Services, Construction Trades, Mechanics and Repairers, Precision Production Trades, Transporation and Material Moving Workers, Visual and Performing Arts, Health Professions and Related Sciences, Undesignated

Notes: This table shows the mapping of CIP codes in the IPEDS to our field classification.

Table A4: Share of Detailed Engineering and CS Majors by Birth Cohort

Field of degree	Born $<$ 1968	Born $\geq$ 1968
Communication Technologies	0.76	2.05
Computer and Information Systems	3.51	7.85
Computer Programming and Data Processing	0.54	0.64
Computer Science	12.71	19.39
Information Sciences	1.17	2.23
Computer Information Management and Sec	0.53	1.52
Computer Networking and Telecommunications	0.66	1.41
General Engineering	9.86	6.62
Aerospace Engineering	1.53	1.33
Biological Engineering	0.81	0.73
Architectural Engineering	0.43	0.33
Biomedical Engineering	0.13	0.84
Chemical Engineering	4.62	3.67
Civil Engineering	9.09	6.71
Computer Engineering	1.36	5.72
Electrical Engineering	17.52	11.4
Engineering Mechanics, Physics, and Sci	0.47	0.33
Environmental Engineering	0.2	0.48
Geological and Geophysical Engineering	0.18	0.09
Industrial and Manufacturing Engineering	3.49	2.65
Materials Engineering and Materials Sci	0.58	0.45
Mechanical Engineering	14.38	11.39
Metallurgical Engineering	0.47	0.09
Mining and Mineral Engineering	0.37	0.12
Naval Architecture and Marine Engineering	0.51	0.21
Nuclear Engineering	0.21	0.2
Petroleum Engineering	0.63	0.3
Miscellaneous Engineering	1.29	1.34
Engineering Technologies	0.82	0.77
Engineering and Industrial Management	1.64	0.43
Electrical Engineering Technology	2.03	1.75
Industrial Production Technologies	2.44	1.11
Mechanical Engineering Related Technology	0.63	0.73
Miscellaneous Engineering Technologies	1.27	1.62
Military Technologies	0.12	0.05
Nuclear, Industrial Radiology, and Biol	0.19	0.33
Electrical and Mechanic Repairs and Tech.	0.33	0.34
Precision Production and Industrial Art	0.02	0.01
Transportation Sciences and Technologies	2.49	2.76

Notes: Shares based on ACS data from 2009 and 2019.

Table A5: Share of Detailed Humanities Majors by Birth Cohort

Field of degree	Born $<$ 1968	Born $\geq$ 1968
Communications	9.89	16.88
Journalism	6.46	5.46
Mass Media	2.11	4.16
Advertising and Public Relations	1.64	3.47
Linguistics and Comparative Language an	1.06	0.97
French, German, Latin and Other Common	3.89	2.77
Other Foreign Languages	0.92	0.77
English Language and Literature	17.92	13.57
Composition and Speech	0.57	1.18
Liberal Arts	9.74	7.03
Humanities	0.78	0.57
Philosophy and Religious Studies	3.01	2.88
Theology and Religious Vocations	4.51	2.75
Fine Arts	9.59	6.62
Drama and Theater Arts	1.9	3.02
Music	4.22	3.71
Visual and Performing Arts	0.48	1.02
Commercial Art and Graphic Design	5.54	8.55
Film, Video and Photographic Arts	1.02	2.65
Art History and Criticism	1.4	1.28
Studio Arts	0.95	1.42
Miscellaneous Fine Arts	0.05	0.26
History	12.01	8.84
United States History	0.35	0.16

Notes: Shares based on ACS data from 2009 and 2019.

Table A6: Earnings Growth Estimates: Robustness Checks

		$\beta_{m,a} - \beta_{m,23}$				
		Baseline	Age>25	No Trimming	Trim 2.5%	+ Graduates
Major m	Age a	(1)	(2)	(3)	(4)	(5)
Engineering & CS	29-30	-0.027	-0.028	-0.029	-0.018	-0.024
		(0.011)	(0.007)	(0.012)	(0.009)	(0.010)
	39-40	-0.002	-0.002	0.010	0.002	-0.022
		(0.021)	(0.019)	(0.023)	(0.020)	(0.021)
	49-50	0.053	0.052	0.067	0.057	0.007
		(0.027)	(0.024)	(0.029)	(0.025)	(0.028)
Business	29-30	-0.031	-0.014	-0.036	-0.018	-0.025
		(0.008)	(0.006)	(0.009)	(0.007)	(0.007)
	39-40	-0.001	0.016	0.005	0.009	-0.011
		(0.018)	(0.017)	(0.020)	(0.017)	(0.019)
	49-50	0.026	0.044	0.035	0.038	0.001
		(0.024)	(0.023)	(0.027)	(0.023)	(0.026)
L&P Science	29-30	0.030	0.011	0.036	0.023	0.044
		(0.011)	(0.007)	(0.012)	(0.010)	(0.008)
	39-40	0.064	0.045	0.084	0.051	0.185
		(0.021)	(0.018)	(0.022)	(0.019)	(0.019)
	49-50	0.107	0.088	0.129	0.095	0.214
		(0.026)	(0.023)	(0.028)	(0.024)	(0.025)
Social Science	29-30	0.022	0.013	0.021	0.028	0.033
		(0.011)	(0.007)	(0.012)	(0.009)	(0.009)
	39-40	0.060	0.049	0.068	0.061	0.081
		(0.022)	(0.020)	(0.024)	(0.021)	(0.022)
	49-50	0.086	0.076	0.095	0.089	0.093
		(0.029)	(0.026)	(0.032)	(0.027)	(0.029)
Others	29-30	-0.033	-0.045	-0.031	-0.037	-0.027
		(0.008)	(0.006)	(0.009)	(0.007)	(0.007)
	39-40	-0.036	-0.045	-0.018	-0.049	-0.039
		(0.018)	(0.017)	(0.020)	(0.017)	(0.018)
	49-50	0.014	0.004	0.040	-0.003	-0.011
		(0.025)	(0.024)	(0.027)	(0.024)	(0.025)
	N (millions)	33.3	31.1	33.6	32.8	54.2

Notes: This table presents estimates of equation (1) with worker fixed effects using the LEHD sample. Column (1) is our preferred specification (ages 23-50, not enrolled, no graduate degree, and above 1% of earnings) and is a repeat of the results from column (6) of Table 4. Columns (2)-(5) make individual deviations from our preferred model by excluding workers below 25, including bottom 1% of earners, excluding the bottom 2.5% of earners, and including graduate degree holders respectively. Observations are weighted using the ACS person weights. Standard errors are clustered at the major-by-age level.

Table A7: Detailed Classification of College Majors

Category	Majors
Applied Science	Precision Production and Industrial Arts, Environmental Studies, Multidisciplinary or General Science, Architecture, Agriculture or Agricultural Science, Earth and Other Physical Science
Business and Economics	Economics, Finance, Miscellaneous Business and Medical Support, Accounting, Marketing, Business Management and Administration
Computer Science	Computer and Information Technology, Computer Programming
Education	Secondary Education, Library Science and Education
Engineering	All Other Engineering, Mechanical Engineering, Electrical Engineering, Civil Engineering, Chemical Engineering, Engineering Technology
Humanities	Commercial Art and Design, Foreign Language, Music and Speech/Drama, Communications, Letters: Literature, Writing, Other, Art History and Fine Arts, Philosophy and Religion, Journalism, Film and Other Arts, History
Medical Services	Medical Technology, Public Health, Nursing, Other Medical/Health Services
Natural Science	Mathematics, Physics, Chemistry, Biological Sciences
Services	Fitness and Nutrition, Leisure Studies and Basic Skills, Protective Services, Social Work and Human Resources
Social Science	Family and Consumer Science, Psychology, Other Social Sciences, Area, Ethnic, and Civil Studies, Political Science, International Relations, Public Administration and Law

Notes: This table shows the categorization of majors used in section 4.4. Majors included in each cell correspond to the classification used by Altonji, Kahn, and Speer (2016).

A.3 NSCG

The NSCG (National Survey of College Graduates) is a biennial survey conducted by the National Center for Science and Engineering Statistics, which is part of the National Science Foundation. The 1993 and 2003 NSCG use a stratified random sampling method to select individuals who reported having a bachelor's degree or higher in the 1990 and 2000 Decennial Census Long Form, were younger than 76 years old, and resided in the United States. Since 2010, the NSCG has employed a rotating panel design, which means that the survey includes both returning sample cases from the previous NSCG survey and new sample cases from the American Community Survey (ACS). The NSCG 2010 mostly consists of new samples from the 2009 ACS, and the 2013 NSCG includes a subsample of the 2010 NSCG and the 2011 ACS. The NSCG 2015, 2017, and 2019 follow the same survey design. In our analysis, we rely on the NSCG waves from 1993, 2003, and 2010-2019 as they are representative of all college graduates in the United States under 76 years old. [A1]

The NSCG is primarily a cross-sectional survey that covers a longer time period than the ACS. This reduces the reliance on cross-cohort comparisons when estimating age-earnings profiles since cohorts of young workers in 1993 will also be represented as older workers in 2019. It is important to point out that while the NSCG starts in 1993, only 36% of the data is from post ACS years (after 2009). So while the NSCG is representative within wave, and it is not representative of all cohorts working between 1993 and 2019. Yet it still provides a supplement to the analysis using the LEHD, since young workers are overrepresented in our sample of workers in the early years of the LEHD.

Table A8 provides some basic information about the individuals in the NSCG data. In terms of age, gender, and race, the NSCG sample looks similar to the ACS. The distribution of majors also matches the ACS, with engineering and computer science majors accounting for roughly 13% of the sample and business majors accounting for more than a quarter of

[A1] The NSCG data is available at the NCSES webpage (https://nsf.gov/statistics/srvygrads/#tabs-2). We augment the 1993 NSCG using a version from the Inter-university Consortium for Political and Social Research (ICPSR). The ICPSR version provides information about work hours and weeks from the 1990 census. We exclude the NSCG waves focused only on science and engineering graduates.

the sample.

In Table A9, we display estimates of equation (1) using the NSCG. Throughout the analysis we include only individuals ages 25-50 since relatively few individuals below 25 are surveyed. In column (1) we estimate a version of equation (1) excluding cohort-by-major effects. This is the same specification we used for the ACS displayed in column (1) of Table 3. Similar to the ACS results, technical and business majors experience slower earnings growth over the life cycle relative to humanities, though the effects are somewhat muted. In columns (2)-(4) we limit the sample to focus only on BA recipients who are attached to the labor force ($\geq$ 27 weeks worked and >1% of earnings) with similar patterns emerging. In columns (5) and (6) we allow the returns to major to vary by cohorts and years, respectively. Similar to our analysis based on the LEHD, once we allow the returns to major to vary by cohort, earnings grow faster over the life cycle for technical and business majors relative to humanities. The inclusion of major-by-year effects does not yield important differences relative to the model without them, again similar to what we find in the LEHD.

The broad takeaway is that the age-earnings profile estimates based on the NSCG are quite similar to the estimates based on the LEHD. This is despite the fact that we are unable to include worker fixed effects. The key is to have a long enough panel or repeated cross-section to credibly identify changes in the returns to major by cohort. Once these features are taken into account, there is little evidence that wage growth is slower for engineers, computer scientists, and business majors.

Table A8: Summary Statistics, NSCG 1993-2019

	$\geq$ BA	Only BA & not enrolled	$\geq$ 27 weeks & Above 1% earnings
Log Earnings	11.03	10.92	11.01
Age	37.72	37.31	37.32
% Female	51.21	50.15	49.12
% Non-white	27.29	26.49	26.16
Observations	385,499	211,546	202,691
% Engineering & CS	12.95	13.14	13.46
% Business	23.44	27.79	28.09
% Life & Physical Science	8.98	6.26	6.27
% Social Science	13.72	11.59	11.49
% Humanities	17.63	18.3	18.11
% Others	23.28	22.92	22.58

Notes: The NSCG 1993-2019 is extracted from the National Center for Science and Engineering Statistics. The NSCG 1993 is further augmented by a version from the Inter-university Consortium for Political and Social Research. The first column includes all respondents aged 25-50 with at least a bachelor's degree who report a valid major. The second column excludes individuals who report receiving a graduate degree. The final column further excludes individuals working less than 27 weeks or those earning below the first percentile of earnings.

Table A9: Earnings Growth Estimates, NSCG

		$\beta_{m,a} - \beta_{m,25}$					
Major, m	Age, a	(1)	(2)	(3)	(4)	(5)	(6)
Engineering & CS	29-30	0.010	0.031	-0.001	-0.016	0.046	0.000
		(0.028)	(0.044)	(0.041)	(0.050)	(0.068)	(0.049)
	39-40	-0.123	-0.095	-0.120	-0.149	0.004	-0.136
		(0.033)	(0.055)	(0.064)	(0.063)	(0.062)	(0.064)
	49-50	-0.075	-0.083	-0.143	-0.148	0.028	-0.138
		(0.049)	(0.053)	(0.067)	(0.064)	(0.077)	(0.066)
Business	29-30	0.018	0.004	0.017	-0.072	-0.005	-0.059
		(0.047)	(0.069)	(0.066)	(0.051)	(0.065)	(0.051)
	39-40	-0.042	-0.053	-0.035	-0.088	0.066	-0.074
		(0.074)	(0.104)	(0.107)	(0.085)	(0.079)	(0.085)
	49-50	-0.051	-0.095	-0.126	-0.161	0.009	-0.150
		(0.061)	(0.076)	(0.081)	(0.062)	(0.066)	(0.064)
L & P Science	29-30	0.108	0.147	0.127	0.080	0.088	0.081
		(0.060)	(0.085)	(0.095)	(0.051)	(0.064)	(0.050)
	39-40	0.260	0.231	0.221	0.147	0.118	0.145
		(0.059)	(0.071)	(0.092)	(0.080)	(0.070)	(0.079)
	49-50	0.315	0.269	0.215	0.133	0.118	0.128
		(0.060)	(0.068)	(0.085)	(0.072)	(0.075)	(0.074)
Social Science	29-30	0.068	0.072	0.073	0.053	0.064	0.057
		(0.042)	(0.061)	(0.058)	(0.056)	(0.061)	(0.054)
	39-40	0.081	0.121	0.074	0.063	0.082	0.064
		(0.055)	(0.075)	(0.082)	(0.071)	(0.056)	(0.071)
	49-50	0.109	0.041	0.015	0.005	0.002	0.009
		(0.061)	(0.080)	(0.077)	(0.068)	(0.070)	(0.070)
Others	29-30	-0.042	-0.038	0.002	-0.033	0.025	-0.029
		(0.020)	(0.041)	(0.041)	(0.039)	(0.058)	(0.039)
	39-40	-0.071	-0.079	-0.075	-0.118	-0.037	-0.115
		(0.034)	(0.057)	(0.067)	(0.065)	(0.064)	(0.065)
	49-50	-0.082	-0.107	-0.118	-0.137	-0.048	-0.131
		(0.039)	(0.041)	(0.064)	(0.062)	(0.067)	(0.064)

Notes: This table presents estimates of equation (1) using different specifications. The sample is all four-year college graduates between 25-50 years old in the 1993-2019 National Survey of College Graduates. Column (1) presents estimates from a specification identical to Deming and Noray (2020) using the NSCG sample. Column (2) uses the same specification as column (1) limiting the sample to individuals holding a Bachelor's degree. Column (3) limits the sample to those working more than 26 weeks and some extra controls; (4) trims the lowest percentile; (5) controls cohort fixed effects; (6) controls year fixed effects instead of cohort fixed effects. Standard errors are clustered at the major-by-year level.