College Majors and Earnings Growth*

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Abstract

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. We find that engineering, computer science, and business majors have similar or faster earnings growth relative to education, humanities, and social science majors. This is in stark contrast with Deming and Noray (2020), who estimate age-earning profiles using the ACS and find that earnings for engineering, computer science, and business majors decline rapidly over the lifecycle with respect to all other majors.

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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 the past fifteen years, three lengthy reviews describe researchers rapid advances in this area (Altonji, Blom, and Meghir, 2012; Altonji, Arcidiacono, and Maurel, 2016; Patnaik, Wiswall, and Zafar, 2021). Two empirical facts lie behind the widespread interest in the returns to major. First, the number of high school graduates who matriculate to 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.[2] Three recent papers, Andrews et al. (2024), Martin (2022), and Deming and Noray (2020), use different data and empirical approaches to show that the returns to major vary significantly with age. The findings in Deming and Noray (2020) have been particularly influential given the surprising nature of their result and its publication in one of the field's most prominent journals. 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 earnings gaps close considerably over the life cycle. The authors provide supporting evidence that this pattern may be driven by human capital de-

[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] Heterogeneity in earnings growth across majors is important since in an economy with credit constraints, variation in age-earnings profiles can have meaningful welfare consequences holding fixed average lifetime returns. Hampole (2024) 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. 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.

preciation, as computer science and engineering graduates tend to work in occupations that experience frequent changes in skill requirements over time.

A potential concern with using the ACS alone to estimate major-specific earnings profiles is the relatively short time dimension of the sample. 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. The results in Andrews et al. (2024) suggest that this could be a concern for interpreting the findings in Deming and Noray (2020). Andrews et al. (2024) show that engineering and business majors experience faster wage growth relative to liberal arts majors for a sample of Texas high school graduates between 1996 and 2002. By focusing on a few cohorts as they age, Andrews et al. (2024) 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.

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 market outcomes are observed over a significantly longer period, from 1985 to 2019, and that the same workers can be followed over time.

We match ACS and LEHD data to generate a long panel of earnings for the same workers analyzed in Deming and Noray (2020) and estimate age-earnings profiles by major. The simplest specification mimics the regression employed by Deming and Noray (2020), except the model includes multiple earnings for the same individual. This alone greatly reduces heterogeneity in age-earnings profiles by major relative to the results obtained using only the ACS cross-section. After including worker fixed effects, computer science and engineering majors have the same or steeper age-earnings profiles relative to most other 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 or even expand over the life cycle. While workers with a business major maintain slower wage growth relative to other majors based on a model with worker fixed effects, this pattern disappears after including labor supply controls. We provide evidence that business majors are more likely to be working full-time at the beginning of their careers relative to other majors and that this gap disappears with age. As a result, if labor supply is not accounted for, one might mistakenly attribute slower earnings growth among business majors to relative skill decay as opposed to increases in labor supply among non-business graduates.

The remainder of our paper focuses on the factors driving differences in age-earnings profiles estimated using the short panel of repeated cross-sections in the ACS versus the long worker panel in the LEHD. We provide evidence that the earnings premium associated with obtaining a technical degree, such as engineering or computer science, or a 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.

The main takeaway of our paper is that engineering, computer science, and business majors do not experience slower earnings growth across the lifecycle relative to most other majors. This result contradicts the main prediction of the theoretical framework developed in Deming and Noray (2020). However, we cannot assess their secondary prediction that college graduates in fast-changing careers will exit them over time. The LEHD lacks data on occupation, and as a result, we are unable to determine whether cohort differences might play a role in the estimated shifts out of STEM occupations documented by Deming and Noray (2020) using the ACS. More broadly, the evidence Deming and Noray (2020) presents that job skills change much faster in technology-intensive careers is persuasive, and it remains possible that this is leading to flatter age-earnings profiles in technically-oriented fields. However, our results suggest that variation in skill demand within majors over time is not enough to drive earnings convergence across majors over the lifecycle.

2 Data

There are two primary data sources used in this paper, the ACS and LEHD. The following paragraphs outline the key details of each sample.

We collect ACS data from the Integrated Public Use Microdata Series (IPUMS) 1% samples (Ruggles et al., 2021) covering the period from 2009-2019. In our initial analysis, we select a sample that is as similar to Deming and Noray (2020) as possible. This means limiting ourselves to individuals who appear in the ACS prior to 2018, are between the ages of 23 and 50, have at least a four-year college degree and valid major, and have non-missing and non-military occupations and earnings. Following Deming and Noray (2020), we aggregate majors into five categories: engineering and computer science, business, life and physical science, social science, and other (e.g., humanities, education, health, vocational).[3]

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 2022, though the initial year varies by state. We restrict our sample to pre-2020 earnings to avoid complications arising from the Covid-19 pandemic. Annual earnings are constructed as the sum of earnings across quarters, jobs, and states in a given year. While we analyze annual earnings, we also keep track of the number of quarters a worker has positive earnings in a given year. 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]

For most of the paper, we only match individuals that are present in the original

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

[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 A.1 for details about the construction of the matched database.

Deming and Noray (2020) ACS sample to the LEHD for comparability purposes. However, we report estimates of additional regressions at the end of the paper where we modify this matching to include all workers in the 2009-2019 ACS between the ages of 30 and 60. Importantly, when we run our regressions using the LEHD data, we still limit the analysis to workers who are between the ages of 23 and 50. The rationale for matching workers older than 30 in the ACS is to ensure that they have completed their education. We include individuals younger than 60 to avoid potential differential survival rates across majors. We refer to this as the Extended LEHD sample. In our final regressions using the Extended LEHD sample, we also consider an alternate degree field aggregation where we allow for ten different major groups.

Table 1 provides summary statistics for the three samples, the ACS, the LEHD, and the Extended LEHD. The top panel demonstrates that individual characteristics do not vary significantly across samples, including the distribution of college majors. Close to half of each sample has a degree in the other major category, which includes humanities, education, and health related majors. These three groups account for nearly 70% of the other major group.

In contrast, the bottom panel of Table 1 demonstrates that the structure of the samples is quite different. The LEHD necessarily contains fewer individuals since we only have access to information for 27 states. But the panel nature of the LEHD implies that these fewer individuals are observed over a longer time horizon leading to dramatically more observations. On average, each individual in the LEHD is observed for 18.3 years, while each individual is observed only once in the ACS. The Extended LEHD contains more individuals than the baseline ACS and LEHD samples. This is a result of using two additional years of the ACS to match with the LEHD and the inclusion of individuals who are between the ages of 50 and 60 when they appear in the ACS. The long panel of the LEHD also affects the temporal dimension of the earnings data. Almost all of the ACS earnings observations occur after 2010, while the LEHD and Extended LEHD earnings observations are more evenly distributed between 1995 and 2020.

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

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

where Earnings_{imat} reflects annual earnings for individual i, with major m, at age a, during year t. X_{it} always includes gender, race, age groups interacted with gender, US citizenship and veteran status, and controls for graduate degrees.[6] θ_t and δ_a correspond to year and age fixed effects, respectively. The key parameters in the above equation are $\beta_{m,a}$, which are coefficients on the interactions of two-year age bins with major m.[7] $\beta_{m,a}$ capture the earnings gap between major m and the excluded major at age a, while δ_a should be interpreted as the earnings growth profile for the excluded major category. Including college major dummies among the regressors, as we do in most specifications, changes the interpretation of these parameters. In this case, $\beta_{m,a}$ can be interpreted as the excess earnings growth of major m at age a with respect to the baseline major at age 23.

Following Deming and Noray (2020), our initial regressions estimate Equation (1), assuming orthogonality of the residual. We then depart by decomposing the residual ϵ_{imat} using the panel dimension of the LEHD sample. Our main specifications decompose:

$$\epsilon_{imat} = \alpha_i + u_{imat}$$

where the α_i are individual fixed effects. The α_i can be correlated with the other regressors described above, and are differenced away using a standard fixed effects estimator. When we estimate the model with individual fixed effects, $\beta_{m,a}$ is always interpreted as the excess wage growth of major m at age a with respect to the baseline major at age 23.[8]

[6]Race is captured by a series of mutually exclusive indicator variables for Black, Asian, Native American, Hawaiian and Other, plus a dummy for Hispanic. For education, we include indicators for having a Master's, Professional, or Doctoral degree.

[7]Following Deming and Noray (2020), $\beta_{m,a} = \beta_{m,a+1}$ if a is odd.

[8]When worker fixed effects are included, it is not possible to identify all age effects (δ_a) and year effects

3.2 Results

We begin by replicating the age-earnings profiles reported in Deming and Noray (2020), based on their sample criteria for the ACS. We estimate Equation (1) by OLS and cluster the standard errors at the major-by-age level. Figure 1 displays the point estimates and confidence intervals for $\beta_{m,a}$. The reference major group is all other degree fields, with more than half consisting of humanities and education majors. 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 the other major group 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.

Column (1) of Table 2 reports the same information as Figure 1, except in a slightly different format. More precisely, it displays estimates of earnings growth at ages 30, 40, and 50 relative to age 23. The main difference between these results and Figure 1 is that we include major dummies in the specification and therefore the estimates of $\beta_{m,a}$ should be interpreted as the excess wage growth of major m with respect to the baseline major at age 23. Between the ages of 23 and 50, earnings for engineering and computer science majors decline by 0.167 log-points relative to other degree fields, consistent with the drop in Figure 1.

Column (2) of Table 2 displays estimates from the same specification as in column (1), but restricts the sample to those individuals in the ACS that can be matched to the LEHD. The primary difference between the two columns is geographical since we only have access to 27 states in the LEHD. While the numbers are similar, the patterns for engineering and computer science are a bit more pronounced. Overall, it seems that the geographical differences between the ACS and LEHD samples are not a concern for our analysis.

The remaining columns in Table 2 utilize the LEHD data to examine how earnings vary

(θ_t), even when one age and year effect are normalized to zero. The demeaning process of the fixed effect estimator makes the two sets of controls collinear. We opt for setting one additional year effect equal to zero, meaning that the baseline age effects are only identified as a result of this normalization. This does not impact our analysis since we are not interested in δ_a, just the differences in earnings growth over the lifecycle, $\beta_{m,a}$.

over the lifecycle by major. In column (3), we replace the outcome variable, ACS earnings, with LEHD earnings holding fixed the estimation sample and regressors relative to column (2). As we shift from the ACS to the LEHD, we are shifting from self-reported annual earnings, to earnings based on unemployment insurance data. Comparing the second and third columns of Table 2 indicates that any differences in the earnings measures between the ACS and LEHD have little impact on age-earnings profile estimates by major. Through column (3), the main message of Deming and Noray (2020) persists, technical and business degree holders have statistically significant slower earnings growth over the life cycle relative to other majors.

Despite the apparent robustness of the earnings growth penalty experienced by technical and business degree holders, a key empirical concern remains. Estimating lifecycle 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 partially address this concern in column (4), estimating age-earnings profiles by major using the panel dimension of the LEHD. As a reminder, the individuals included in column (4) are the same as those included in columns (2) and (3), except we now use their earnings information from all years and not just the year in which they appear in the ACS.

When we exploit the panel dimension of the LEHD sample, the estimated age-earnings profiles change considerably, especially for technical degree holders. While engineering and computer science majors still see slower earnings growth over the life cycle with respect to the excluded major group, the magnitude of the gap is much smaller and statistically insignificant. For example, instead of a relative decline of 0.085 log-points for individuals aged 29-30, column (4) shows a negligible gap for this group. When workers are aged 49-50, the gap reduces from 0.165 log points to 0.032 log-points and it is not statistically significant. Simply adding earnings observations across the life cycle for many workers leads to a significant change in the age-earnings profiles.

The final column of Table 2 uses the same observations as column (4), but allows for permanent, unobserved individual heterogeneity in earnings. Once worker fixed effects are included, relative earnings growth for technical majors are positive at ages 30, 40 and 50, but only statistically different from zero at ages 49-50. While the estimates for technical degrees change dramatically between columns (1) and (5), the estimates for business majors remain negative and large. Additionally, life and physical science majors and social science majors experience significant wage growth over the lifecycle relative the excluded group.

The results in Table 2 mimic Deming and Noray (2020) in sample selection criteria and model specification, other than the inclusion of individual fixed effects in column (5). In Table 3 we depart from their specification. Our concern, also shared by Deming and Noray (2020), is that earnings growth estimates across majors are capturing not just changes in the value of human capital across the lifecycle, but other lifecycle differences by major related to additional education and labor supply.[9]

The first change we make is to allow age-earnings profiles to vary with the individual's highest level of education. The original Deming and Noray (2020) regression includes dummies for graduate degrees, but it assumes that workers with the same undergraduate major have similar age-earnings profiles on average, regardless of the final education level. We relax this assumption by interacting age group indicators with an indicator for whether the worker has a graduate degree (masters and others separately). Column (2) in Table 3 presents the results. While all the age-earnings profile estimates change, the largest difference is for life and physical science majors. The estimates are dramatically smaller, consistent with the fact that individuals with these undergraduate degrees are more likely to obtain a graduate degree and graduate degree holders tend to have steeper age-earnings profiles. Table 4 shows that 55% of workers with life and physical science undergraduate degrees hold a graduate degree, as opposed to at most 36% for the baseline major. The fact that the coefficients for the business majors become less negative is also consistent with this feature of the data, given that business majors are less likely to hold a graduate degree.

The second change we make is to incorporate controls for labor supply. Following Deming and Noray (2020), we use log yearly earnings as our dependent variable. However,

[9] Deming and Noray (2020) address graduate education and labor supply in footnotes 23 and Online Appendix Figures A6 and A7, but do not present results in the main paper.

there is substantial variation in how much workers work within a given year. The LEHD does not have precise information on labor supply, but we do know the number of quarters with positive earnings in a given year. In column (3) of Table 3, we present estimates from a model that includes indicator variables for number of quarters worked. Controlling for labor supply generates large differences relative to the baseline results in column (1), particularly for business majors. At ages 49-50, the earnings decline in business relative to the excluded category drops from 0.158 log-points to 0.041 log-points. The drop in the business major penalty over the lifecycle is explained by the fact that labor supply varies by major with age. In Table 5, we report the fraction of workers with at least three quarters of positive earnings by age and major. All majors report 95-96% "full-time" rates at ages 49-50, but business majors have a significantly higher full-time rate at the beginning of their career. As a result, business majors experience relatively slower earnings growth over the lifecycle, but this is mostly the result of working full-time when young while other majors are less attached to the labor market.

The results in column (4) of Table 3 are from a model where we simultaneously allow age-earnings profiles to vary with highest degree and control for labor supply. The estimates show that technical and business degree holders do not have different wage growth profiles from the excluded major category, and the gap with social sciences and life and physical science majors is smaller than in previous specifications. For technical degrees, the point estimate is 0.047 log-points smaller than social science majors and 0.15 log-points smaller than life and physical sciences at age 49-50.[10]

Figure 2 provides a detailed summary of our findings thus far. In the top panel, we illustrate excess earnings growth for each major with respect to the excluded category. The estimates correspond to column (4) in Table 3, but include all age bins. In the bottom panel, we compare these same estimates for technical and business majors to those obtained using LEHD earnings, but only relying on the same cross-section available in the ACS and

[10]For comparison, Table A2 shows how controlling for age interacted with graduate degree and labor supply impact age-earnings profiles when using just the repeated cross-sections in the ACS. Similar patterns emerge where the penalty for business majors relative to the excluded major group shrinks, and the earnings growth of life and physical science majors declines relative to other majors.

excluding age interacted with graduate degrees and labor supply controls. The solid lines are the same as in the top panel, while the dashed lines are constructed from the estimates in column (3) of Table 2. The top panel indicates that engineering, computer science and business majors have wage growth on par with the excluded major group, while the bottom panel shows that without a long panel this result is obscured.

3.3 Interpretation

As the previous section demonstrates, estimates of age-earnings profiles by major change considerably when we shift from the ACS to a panel of worker earnings in the LEHD. This is most pronounced when we include worker fixed effects, but just including additional observations without accounting for worker unobserved heterogeneity also leads to important changes, especially for technical degree holders. In this section, we investigate the mechanisms driving the sensitivity of age-earning profiles across samples and specifications. There are three primary 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. Below we provide evidence that changes in returns to major across cohorts is the most likely explanation.

To help guide and interpret our empirical analysis, consider the following simplified model of expected earnings for major m at age a:

$$E\left(\ln \text{Earnings} \mid a, m, Y, R\right) = \beta_0^m + \beta_1^m a + \delta^m \times Y + (\pi_0^m + \pi_1^m a) \times R. \qquad (2)$$

Y is an indicator variable equal to one if earnings are from a recent year, say post 2009, and R is an indicator variable equal to one if earnings are for workers from a recent cohort, say born after 1970. These two variables allow for shifts in the returns to major across time and cohort.[11] This framework can provide insight into how the existence of the three alternative mechanisms described above, cohort-major trends, year-major trends, and cohort-specific

[11] This simplified model of earnings differs from the empirical model we estimate. In particular, the β_j^m coefficients relate to the level of earnings for major m, while in our estimated model they capture the gap between major m and a baseline major. This normalization is without loss of generality and is made primarily for convenience.

earnings profiles, can impact age-earnings profiles estimates as the estimation sample and specification change.

In the analysis below, we separately consider how changes in the returns to major across cohorts and time impact estimates of age-earnings profiles. In a fully saturated model, age is collinear with time and birth cohort. As a result, one cannot separately identify the effect of age from the effect of time or birth cohort without further restrictions.

3.3.1 Cohort-Major Trends

We consider first a setting where the level of returns for major m changes across cohorts and there are no time effects. These changes could occur through differential selection into majors and/or variability in skill development within major across cohorts. In this case, Equation (2) simplifies such that expected earnings are given by

$$E\left(\ln \text{Earnings} \,|\, a, m, Y, R\right) = \beta_0^m + \beta_1^m a + \pi_0^m \times R.$$

This specification allows, for example, more recent STEM graduates in majors like engineering or computer science to have higher returns ($\pi_0^m > 0$). Identifying π_0^m is difficult with cross-sectional data since the full age-earnings profile isn't observed for young and old cohorts. In fact, our cross-sectional regressions that mimic the approach in Deming and Noray (2020) do not include R for this reason.

However, excluding R in the ACS sample will lead to biases in age-earnings profiles if $\pi_0^m \neq 0$. Because the ACS only includes earnings in recent years, the indicator for being in a recent cohort will be negatively correlated with age. More precisely, when $R = 0$ (older cohort), a tends to be large (older age). Using linear projections, $R = -\lambda_0 a + v_0$, where $\lambda_0 > 0$ represents the absolute value of the projection of an indicator for $R = 0$ on a.[12] Thus, omitting R from the model will lead to the following conditional expectation:

$$E\left(\ln \text{Earnings} \,|\, a, m\right) = \beta_0^m + \left(\beta_1^m - \lambda_0 \pi_0^m\right) a.$$

[12]While the projection coefficient could be major specific, this variation is minimal so we omit this from the discussion. We adopt this simplification throughout this analysis.

If the returns to technical majors have shifted up in more recent cohorts, then we would expect the ACS to produce downward biased estimates. In contrast to the cross-sectional approach, using the LEHD panel with worker fixed effects flexibly captures changes in the returns to major across cohorts. In the worker fixed effect model, the cohort specific terms are subsumed into the worker effects since major and birth cohort are time invariant within worker.

To demonstrate the potential role of cohort-major effects as outlined above, consider Table 6. The first three columns demonstrate how age-earnings profiles change as we shift from a cross-sectional sample (the ACS sample using LEHD earnings) to panel data (multiple observations per worker in the LEHD) to a model with worker fixed effects.[13] Note that all models include age bins interacted with graduate degrees and indicators for labor supply. In moving from column (1) to column (2), we already observe a large change in the age-earnings profiles for engineering and computer science. This change is consistent with cohort effects since the correlation between R and a will be dramatically reduced relative to using just a recent cross-section. In particular, the older cohorts are now also observed when they are young. The age-earnings profiles for technical majors increase further from column (2) to column (3) as we now explicitly allow for cohort effects through worker fixed effects. Though less dramatic, similar patterns are seen for business majors when moving from columns (1) to (3).

To provide more direct evidence on changes in returns across cohorts, we estimate a version of our model with cohort-by-major indicator variables. We add to Equation (1) interactions between major indicators and and birth cohort indicators, where birth cohorts are defined in three year intervals. Although including birth cohort indicators instead of worker fixed effects is less flexible, it allows us to directly estimate how the returns to major have changed across cohorts. The estimates for the cohort-by-major indicator variables are reported in Panel A of Table 7, with the corresponding age-earnings profile estimates in column (4) of Table 6. The cohort-by-major estimates indicate that technical majors have

[13]Column (3) of Table 6 is identical to column (4) of Table 3. Column (1) and (2) of Table 6 are analogous to columns (3) and (4) in Table 2 except age is interacted with graduate degrees and labor supply controls are included.

increased their initial earnings gap relative to other majors, especially for those born after 1980.

3.3.2 Year-Major Trends

An alternative to changes in skill across cohorts is changes in the returns to major across time. The key difference between the two is that in the latter case the earnings for all workers with a given major will be impacted concurrently. A likely driver of such variation is heterogeneity in skill demand over time. To investigate how changes in the returns to major across time would alter age-earnings profiles when moving from cross-sectional to panel data, assume that expected earnings are given by

$$E\left(\ln \text{Earnings} \,|\, a, m, Y\right) = \beta_0^m + \beta_1^m a + \delta^m Y.$$

When $\delta^m \neq 0$, the earnings gap across majors will change over time.

Estimating the above model using the ACS again results in a lack of identification. The ACS only includes earnings from recent years, meaning the indicator variable Y will always be equal to one. δ^m is therefore not identified. However, in this setting OLS will consistently estimate the slope coefficients β_1^m since a and Y are uncorrelated.

The LEHD sample instead merges individuals observed in recents years in the ACS with their complete labor market history. As a result, we observe earnings for most workers when they are young, but only observe earnings for some workers when they are old. In the LEHD sample there is a positive correlation between a and Y. We can express $Y = \lambda_1 a + v_1$, where $\lambda_1 > 0$ is the projection of Y on a. Not accounting for this change in returns to major over time will lead to the following conditional expectation:

$$E\left(\ln \text{Earnings}|a, m\right) = \beta_0^m + \left(\beta_1^m + \lambda_1\right) a$$

If the returns to technical majors have increased over time relative to other majors, the LEHD regressions without year-major controls will be upward biased. On the other hand, including year-major indicator variables will result in consistent estimates of β_1^m. Importantly, including year-major indicator variables in the LEHD should generate age-earnings profiles similar to those obtained using the ACS since both estimators will be consistent.

Column (2) of Table 6 reproduces our basic LEHD regressions sans worker fixed effects, while column (5) includes year-major fixed effects. To produce the results in column (5), we add interactions between major indicators and year indicators, where we group years into three-year intervals. If the returns to major are changing dramatically across time, we would expect age-earnings profiles to be significantly different across columns (2) and (5). Instead, we see that the estimates are similar. Moreover, the estimates in column (5) are not close to the cross-sectional estimates in column (1), again suggesting that year-major effects are not a key driver of the differences between the cross-sectional and panel data results. In Panel B of Table 7, we report the coefficients for the year-major indicator variables (same model as column (5) in Table 6). While the returns to technical majors have increased mildly over time, the change is not large enough to generate large biases in our results when using the LEHD.

3.3.3 Cohort Heterogeneity in Age-Earnings Profiles by Major

Of the two channels considered thus far, cohort-major effects are more consistent with the empirical patterns we observe. However, our cohort analysis only allows for level shifts in age-earnings profiles across cohorts. It remains possible that the slope of age-earnings profiles change across cohorts. This could occur if more recent vintages of STEM majors accumulate additional human capital on the job more quickly. Consider again a simplified version of Equation (2):

$$E\left(\ln \text{Earnings} \,|\, a, m, Y, R\right) = \beta_0^m + \left(\beta_1^m + \pi_1^m R\right) a.$$

In this specification, age-earnings profiles differ across workers of different cohorts. Both the ACS and the LEHD would estimate a weighted average of $\beta_1^m + \pi_1^m R$. The ACS would put more weight on the age profiles of more recent cohorts ($\beta_1^m + \pi_1^m$), while the LEHD sample would put relatively more weight on the age profile of older cohorts (β_1^m).

To investigate this we split the LEHD sample according to whether a worker is born before 1971 and re-estimate our model with worker fixed effects. In Table 8 we report estimates for the aggregated model, early cohorts, and late cohorts across columns (1)-(3) respectively. We do not find evidence to support that cohort heterogeneity in age-earnings profiles is a key explanation for the large differences between our results and Deming and Noray (2020). In particular, the coefficient on the indicator for a 47-48 year old worker with a technical degree is very similar in magnitude between the two cohorts at 0.039 and 0.040 log-points. All coefficients from column (2) and (3) are generally similar to each other.

3.3.4 Changes in STEM Majors Across Cohorts

The empirical evidence is most consistent with computer science and engineering degree fields experiencing cross-cohort increases in earnings levels relative to other majors. 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 other fields. 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 other majors. 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. We aggregate degrees of study to best resemble the classification utilized in this paper. Additionally, we use the sum of the 75th percentile math and verbal SAT scores from 2019 to rank schools according to enrollee test scores.[14] Two patterns suggest that technical majors

[14]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

have become more positively selected relative to most majors over time. First, growth in STEM related fields is occurring at the most selective institutions. 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, growth in humanities and other majors is occurring at the least selective institutions. 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 consistent with recent cohorts of technical degree holders being relatively more selected than other majors.

There is also evidence that the type of skills being developed within technical and other majors, like education and humanities, has changed across cohorts. Using detailed degree data available in the ACS, we examine how the distribution of majors within each of the five broad categories has shifted.[15] Among technical degree holders, there has a been a shift towards computer related fields. Technical degree holders born in 1970 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 1970. The detailed technical majors whose shares have shrunk the most in relative terms across birth cohorts are general engineering, electrical engineering, and mechanical engineering. Among other majors, there has been shift towards communications and psychology and away from education, literature and history across birth cohorts born before and after 1970. Other notable changes include an increase in marketing and finance and decline in business management among business degree holders, and an increase in biology and decline in chemistry for life and physical science majors. 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

rank is based only on the 2019 data, and is thus fixed across the 1992 and 2019 data.

[15] Table A3 show the share of the most common detailed major within each of the five categories by birth cohort respectively.

skill prices. Further disentangling the sorting and skill mechanisms behind the changes in returns to major across birth cohorts is left for future work.

3.4 Extended Sample and Detailed Majors

For comparability purposes, our analysis to this point has utilized precisely the same individuals included in Deming and Noray (2020), aside from some geographical limitations of the LEHD. We now turn to the Extended LEHD sample as defined in the Data section, which differs from the LEHD sample in three dimensions. First, it includes individuals from the ACS who had a missing wage or occupation in the year they were surveyed. Second, the Extended LEHD sample includes the 2018 and 2019 ACS rounds. Finally, it includes all workers in the ACS who were between 30 and 60 years old in the survey year. Excluding workers younger than 30 increases the likelihood that they have completed their education. Excluding workers above 60 helps avoid major-specific survival bias. Summary statistics for the Extended LEHD sample are available in Table 1.

In column (2) of Table 9, we report age-earnings profile estimates using the Extended LEHD. The model includes worker fixed effects and is thus comparable to the estimates from column (4) of Table 3, whose estimates are reported in column (1) to facilitate comparisons. While no dramatic change is observed, it is interesting to see that in this larger sample, estimates for technical and business degrees are marginally higher, while those for social science marginally lower. In particular, the point estimates indicate that workers with an engineering or computer science degree have earnings profiles on par or steeper than all other majors except those with life and physical science degrees.

Our approach to aggregating majors is also driven by the choices in Deming and Noray (2020). However, as Andrews et al. (2024) discuss, the use of a different or more detailed classification of majors could alter our results if there exists variation in returns to detailed fields within each major classification. Furthermore, the residual category contains half the sample and is an aggregation of diverse majors ranging from humanities (the biggest group) to health related majors, education, vocational and even STEM majors like mathematics and statistics. While this is not a problem per se, it does make interpretation more challenging. For this reason, we consider an alternative, more disaggregated classification based on the characterization of college majors used by Altonji, Kahn, and Speer (2016).[16] Specifically, we define the following groups: applied science, business and economics, computer science, education, engineering, humanities, medical services, natural science, services, and social science. Table A4 shows the sub-categories included in each group.

Using this alternative classification, we re-estimate Equation (1), including worker fixed effects, leaving humanities as the reference category. Table 10 shows estimates of age-earnings profiles for each group and Figure 3 graphically depicts how relative earnings change across the lifecycle. 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. Engineering in particular displays one of the steepest profiles across all majors. Workers with a natural science major have the steepest profile. Workers with medical related majors, a group that was part of the other major category in the previous classification, also have steep slopes. In Table A5, we also report estimates without worker fixed effects to show how large the initial earnings gaps are across the detailed major categories. Engineering, computer science, and business have the largest initial gaps with respect to humanities, followed by medical services and natural science.

3.5 NSCG

An alternative approach for estimating age-earnings profiles 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. Deming and Noray (2020) use the NCSG as a robustness check and continue to find slower earnings growth over the lifecycle for engineering, computer science, and business majors.

For our purposes, 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. This longer

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

time dimension makes it possible to explicitly allow for cohort-major effects.[17] 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 other 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 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 vary across the life cycle 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. (2024) 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 most other majors. Andrews et al. (2024) 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. 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. (2024), we find that technical and business majors experience faster wage growth relative to most other majors over the full life cycle and across the US. The discrepancy in results between Deming and Noray (2020) and Andrews et al. (2024) is driven by our finding that recent cohorts of engineering, computer science, and business

[17] Although the NSCG has a panel structure with restricted access, it tracks each individual for at most four waves and does not extend as far back as the LEHD. Therefore, we prefer our estimates based on the LEHD.

majors earn a higher premium relative to humanities, education, and social science 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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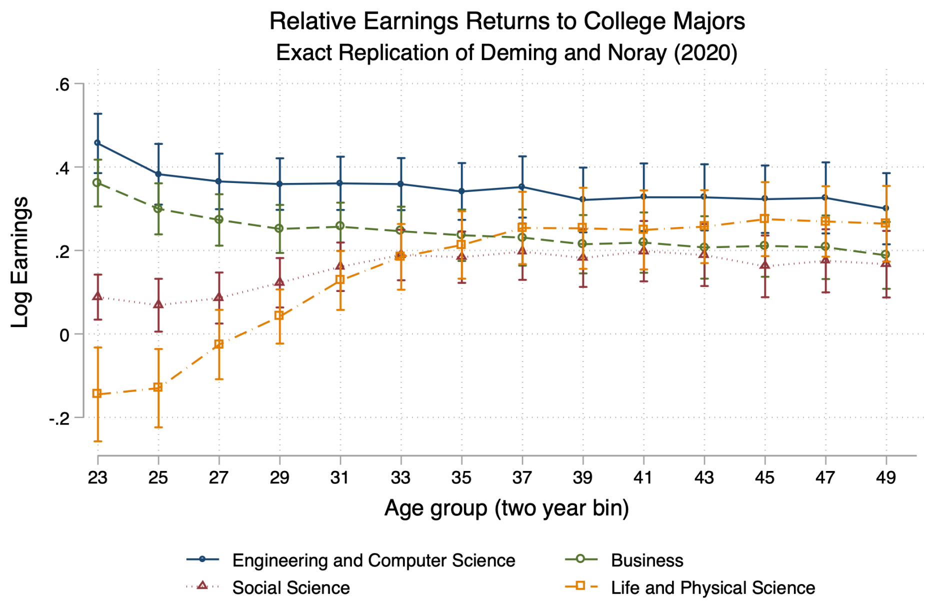
Figures and Tables

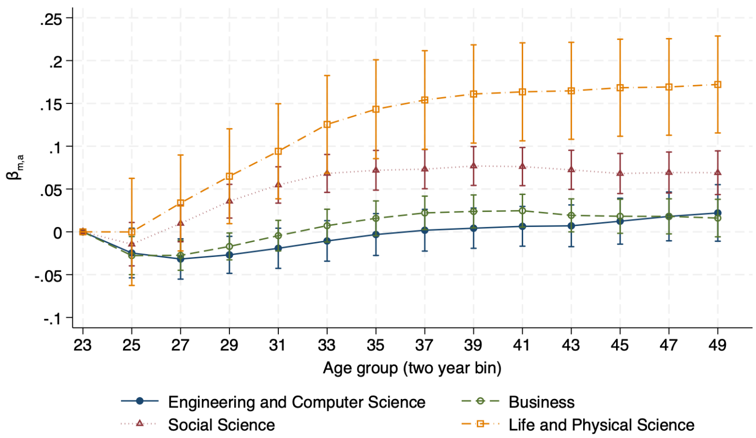
Figure 1: Replication of Deming and Noray (2020), Figure V



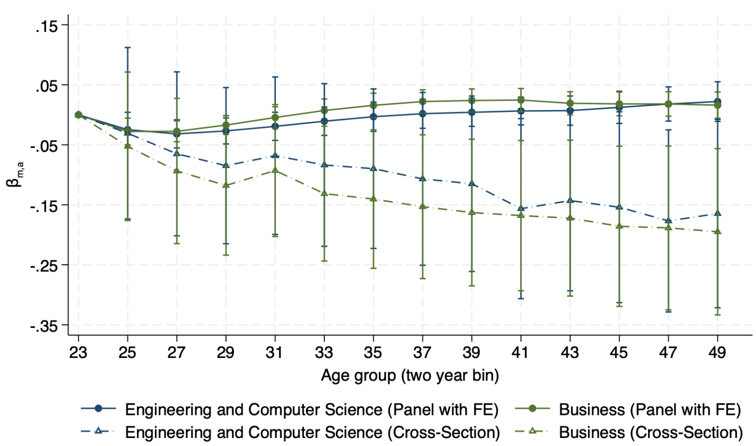
Notes: This plot replicates Figure V in Deming and Noray (2020). Each coefficient and 95% confidence interval corresponds to estimates of $\beta_{m,a}$ in Equation (1) (without major dummies) using annual log earnings as the dependent variable. The sample is all four-year graduates observed in the 2009-2017 American Community Survey between 23 and 50 year old with a valid major and occupation, excluding military. 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, U.S. citizenship, veteran status, and an indicator for having any graduate school education. Observations are weighted using the ACS person weights. Standard errors are clustered at the major-by-age bin level.

Figure 2: LEHD Gaps in Earnings Growth Relative to Excluded Majors

(a) Estimates with Worker FE

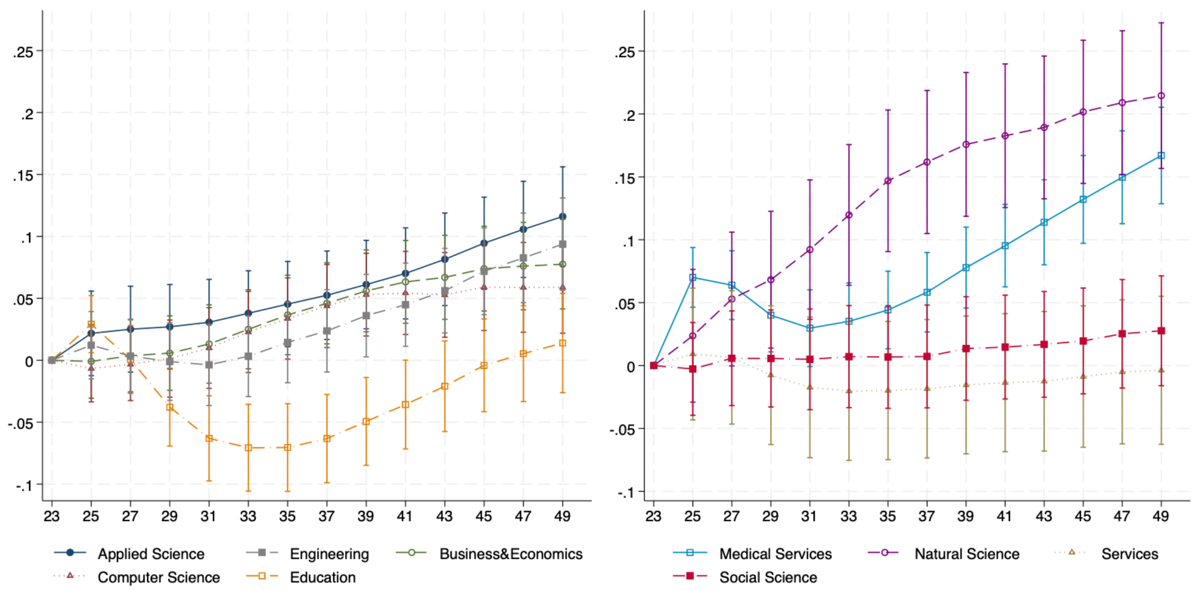


(b) Cross-Section and Panel Estimates for Technical and Business Majors



Notes: Panel (a) plots estimates and 95% confidence intervals of $\beta_{m,a}$ in Equation (1) using LEHD annual earnings as dependent variable. Only individuals included in our replication of Deming and Noray (2020)'s results are included in this sample. The regression includes individual fixed effects, sex-by-age indicators, age and year fixed effects, race and ethnicity, U.S. citizenship, and veteran status. It also include interactions of age with graduate school education and a control for the number of quarters worked in a given year. Observations are weighted using the ACS person weights. Standard errors are clustered at the major-by-age bin level and at the individual level. Panel (b) compares the estimates for Engineering and Computer Science and Business presented in panel (a) with the results obtained using LEHD earnings for the cross-sectional sample available in the ACS. The dashed lines correspond to the results in column (3) of Table 2.

Figure 3: LEHD Gaps in Earnings Growth Relative to Humanities



Notes: This figure shows estimates and 95% confidence intervals of $\beta_{m,a}$ in Equation (1), using LEHD annual earnings as the dependent variable. The sample consists of college graduates between 30 and 60 years old in the ACS between 2009 and 2019 linked to annual earnings in the LEHD. The LEHD earnings regression is limited to workers aged between 23 and 50. 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 individual fixed effects, sex-by-age indicators, age and year fixed effects, race and ethnicity, U.S. citizenship, and veteran status. It also includes interactions of age with graduate school education and a control for the number of quarters worked in a given year. Observations are weighted using the ACS person weights. Standard errors are clustered at the major-by-age bin level and at the individual level.

Table 1: Summary Statistics, ACS and LEHD

Unit		ACS	LEHD	Extended LEHD
Person	% Male	46.9	46.8	46.6
	% White	78.8	74.8	75.8
	% Engineering & CS	13.1	13.5	13.0
	% Business	20.9	20.5	20.9
	% Life & Physical Science	8.7	8.7	8.7
	% Social Science	7.6	7.5	7.6
	% Others	49.7	49.8	49.8
	Total Persons	2,808,501	2,398,000	5,901,000
Person-Year	Years per person	1.0	18.3	17
	% Before 2005	0.0	28	39.7
	% 2005-2009	10.7	22.4	22.2
	% 2010-2014	53.6	26.4	20.7
	% After 2015	35.7	23.2	17.5
	Total Person-Years	2,808,501	38,020,000	76,450,000

Notes: The ACS sample includes all respondents surveyed between 2009 and 2017 aged 23-50 with at least a bachelor's degree who report a valid major. ACS data is extracted from the Integrated Public Use Microdata Series (IPUMS) 1% samples (Ruggles et al., 2021). The LEHD sample includes all matched individuals from the 2009–2017 ACS waves who report valid major and occupation. The Extended LEHD sample includes all matched individuals from the 2009–2019 ACS waves who are aged 30-60 during the ACS survey and report a valid major.

Table 2: Log Earnings Growth Estimates, ACS and LEHD

		$\beta_{m,a}$				
		ACS		LEHD		
Major m	Age a	(1)	(2)	(3)	(4)	(5)
Engineering & CS	29-30	-0.050	-0.107	-0.085	0.002	0.025
		(0.059)	(0.057)	(0.066)	(0.059)	(0.037)
	39-40	-0.126	-0.167	-0.115	-0.009	0.065
		(0.071)	(0.067)	(0.075)	(0.068)	(0.039)
	49-50	-0.167	-0.216	-0.165	-0.032	0.071
		(0.075)	(0.073)	(0.080)	(0.076)	(0.043)
Business	29-30	-0.103	-0.100	-0.118	-0.111	-0.095
		(0.054)	(0.051)	(0.059)	(0.051)	(0.018)
	39-40	-0.149	-0.133	-0.163	-0.145	-0.116
		(0.062)	(0.058)	(0.062)	(0.057)	(0.022)
	49-50	-0.182	-0.167	-0.195	-0.182	-0.158
		(0.068)	(0.065)	(0.071)	(0.063)	(0.024)
L&P Science	29-30	0.213	0.192	0.158	0.207	0.190
		(0.091)	(0.089)	(0.075)	(0.077)	(0.054)
	39-40	0.428	0.361	0.391	0.432	0.425
		(0.103)	(0.094)	(0.079)	(0.084)	(0.058)
	49-50	0.430	0.391	0.424	0.462	0.457
		(0.102)	(0.098)	(0.085)	(0.088)	(0.057)
Social Science	29-30	0.053	0.052	0.019	0.070	0.076
		(0.054)	(0.052)	(0.060)	(0.051)	(0.022)
	39-40	0.112	0.074	0.094	0.136	0.146
		(0.062)	(0.058)	(0.062)	(0.057)	(0.026)
	49-50	0.093	0.046	0.065	0.104	0.131
		(0.067)	(0.065)	(0.071)	(0.063)	(0.029)
	N	2,808,501	2,398,000	2,398,000	38,020,000	38,020,000
	Worker FE	N	N	N	N	Y
	R^2	0.197	0.207	0.176	0.197	0.591

Notes: This table presents estimates of Equation (1) using various samples and specifications. Column (1) presents estimates from the ACS sample used by Deming and Noray (2020) with the addition of major dummies. In column (2), we limit the ACS sample to those individuals who also appear in the LEHD. The sample in column (3) is identical to column (2), but the outcome is based on LEHD earnings. Columns (4)-(5) include the same workers as in columns (2) and (3), but use the full earnings panel in the LEHD. Column (5) also includes worker fixed effects. All regressions include major dummies, sex-by-age indicators, age and year fixed effects, race and ethnicity, U.S. citizenship, and veteran status. Observations are weighted using the ACS person weights. Standard errors are clustered at the major-by-age bin level and at the individual level. CS: Computer Science, L&P Science: Life and Physical Science.

Table 3: LEHD Log Earnings with Graduate Degree Profiles and Labor Supply Controls

		$\beta_{m,a}$			
			Graduate degree profiles	Labor supply controls	Both
Major m	Age a	(1)	(2)	(3)	(4)
Engineering & CS	29-30	0.025	0.037	-0.036	-0.027
		(0.037)	(0.028)	(0.013)	(0.011)
	39-40	0.065	0.093	-0.014	0.004
		(0.039)	(0.029)	(0.013)	(0.012)
	49-50	0.071	0.104	-0.001	0.022
		(0.043)	(0.033)	(0.020)	(0.017)
Business	29-30	-0.095	-0.062	-0.037	-0.017
		(0.018)	(0.016)	(0.009)	(0.008)
	39-40	-0.116	-0.043	-0.023	0.024
		(0.022)	(0.020)	(0.010)	(0.010)
	49-50	-0.158	-0.074	-0.041	0.016
		(0.024)	(0.023)	(0.012)	(0.011)
L&P Science	29-30	0.190	0.125	0.106	0.065
		(0.054)	(0.033)	(0.042)	(0.028)
	39-40	0.425	0.258	0.269	0.161
		(0.058)	(0.034)	(0.046)	(0.029)
	49-50	0.457	0.269	0.297	0.172
		(0.057)	(0.035)	(0.044)	(0.029)
Social Science	29-30	0.076	0.055	0.049	0.036
		(0.022)	(0.021)	(0.010)	(0.010)
	39-40	0.146	0.098	0.107	0.077
		(0.026)	(0.024)	(0.012)	(0.012)
	49-50	0.131	0.080	0.103	0.069
		(0.029)	(0.027)	(0.013)	(0.013)
	N	38,020,000	38,020,000	38,020,000	38,020,000
	Worker FE	Y	Y	Y	Y
	R^2	0.591	0.595	0.788	0.790

Notes: This table presents estimates of Equation (1) using the full panel of earnings in the LEHD and incorporating worker fixed effects. Column (1) is a repeat of the results from column (5) of Table 2. Column (2) includes interactions between age group and advanced degree indicators (holding a master's degree and holding a professional degree or Ph.D.). Column (3) includes separate indicator variables for the number of quarters worked each year. Column (4) includes both sets of controls. Observations are weighted using the ACS person weights. Standard errors are clustered at the major-by-age bin level and at the individual level. CS: Computer Science, L&P Science: Life and Physical Science.

Table 4: Share of Advanced Degrees by College Major

Major m	Share in LEHD	Share with Advanced Degree
Engineering & Computer Science	13.5	35.9
Business	20.5	22.3
Life & Physical Science	8.7	54.5
Social Science	7.5	40.0
Others	49.8	36.3

Notes: This table shows the distribution of majors in the LEHD sample, as in column (1) of Table 1. The second column displays the share of individuals with a graduate degree by major category.

Table 5: Share of Full-time Work by College Major and Age Group

	Major m				
Age a	Engineering & CS	Business	Life & Physical Science	Social Science	Others
23-24	77.8	84.4	74.7	77.8	81.1
25-26	86.5	89.8	80.8	84.0	87.1
27-28	89.2	91.4	84.9	87.5	89.6
29-30	91.2	92.5	88.4	89.9	91.0
31-32	92.7	93.3	90.5	91.5	91.8
33-34	93.9	93.8	92.0	92.5	92.5
35-36	94.5	94.1	93.2	93.0	93.0
37-38	95.0	94.3	94.1	93.4	93.6
39-40	95.3	94.6	94.6	93.8	94.0
41-42	95.6	94.8	95.1	94.2	94.5
43-44	95.8	95.0	95.3	94.5	94.9
45-46	96.0	95.2	95.5	94.5	95.2
47-48	96.1	95.3	95.8	94.7	95.4
49-50	96.0	95.3	95.7	94.7	95.5

Notes: This table shows the share of individuals in the LEHD sample with positive earnings in at least three quarters in a given year for each age group and major combination. CS: Computer Science.

Table 6: LEHD Log Earnings Estimates, Mechanisms

		$\beta_{m,a}$				
		Cross-Section	Without Worker FE	Worker FE	Cohort-by-major FE	Year-by-major FE
Major m	Age a	(1)	(2)	(3)	(4)	(5)
Engineering & CS	29-30	-0.137	-0.041	-0.027	-0.031	-0.048
		(0.071)	(0.068)	(0.011)	(0.067)	(0.068)
	39-40	-0.177	-0.059	0.004	-0.039	-0.071
		(0.079)	(0.071)	(0.012)	(0.071)	(0.072)
	49-50	-0.196	-0.064	0.022	-0.033	-0.087
		(0.081)	(0.078)	(0.017)	(0.078)	(0.079)
Business	29-30	-0.059	-0.025	-0.017	-0.022	-0.026
		(0.048)	(0.043)	(0.008)	(0.043)	(0.043)
	39-40	-0.055	-0.005	0.024	-0.003	-0.007
		(0.056)	(0.052)	(0.010)	(0.051)	(0.052)
	49-50	-0.065	-0.015	0.016	-0.008	-0.018
		(0.063)	(0.059)	(0.011)	(0.059)	(0.059)
L&P Science	29-30	0.078	0.077	0.065	0.072	0.080
		(0.074)	(0.058)	(0.028)	(0.057)	(0.058)
	39-40	0.193	0.178	0.161	0.161	0.184
		(0.076)	(0.062)	(0.029)	(0.061)	(0.063)
	49-50	0.244	0.198	0.172	0.187	0.209
		(0.081)	(0.067)	(0.029)	(0.066)	(0.068)
Social Science	29-30	0.009	0.028	0.036	0.028	0.028
		(0.049)	(0.042)	(0.010)	(0.042)	(0.042)
	39-40	0.036	0.066	0.077	0.059	0.067
		(0.055)	(0.049)	(0.012)	(0.049)	(0.050)
	49-50	0.027	0.049	0.069	0.050	0.055
		(0.061)	(0.056)	(0.013)	(0.056)	(0.056)
	N	2,398,000	38,020,000	38,020,000	38,020,000	38,020,000
	R^2	0.510	0.517	0.790	0.517	0.517

Notes: This table presents estimates of Equation (1) using LEHD earnings as the dependent variable for various samples and specifications. All columns also include age by graduate degree indicators and quarters worked indicators. Column (1) uses a sample of individuals who appear concurrently in the ACS and LEHD. Columns (2)-(5) use the same workers as in column (1), but all earnings observations. Column (2) presents estimates without worker fixed effects. Column (3) includes worker fixed effects. Columns (4) and (5) replace worker fixed effects with cohort-by-major and year-by-major fixed effects, respectively. Observations are weighted using the ACS person weights. Standard errors are clustered at the major-by-age bin level and at the individual level. CS: Computer Science, L&P Science: Life and Physical Science.

Table 7: Cohort-by-Major and Year-by-Major Fixed Effects Estimates

	Engineering & CS (1)	Business (2)	Life & Physical Science (3)	Social Science (4)
Panel A: Cohort-by-Major estimates				
up to 1960	0.022	-0.010	0.011	0.033
	(0.010)	(0.009)	(0.015)	(0.018)
1961-1963	0.011	-0.014	0.016	0.028
	(0.010)	(0.009)	(0.015)	(0.017)
1964-1966	0.003	-0.009	-0.010	0.042
	(0.012)	(0.009)	(0.016)	(0.016)
1967-1969	0.018	-0.001	-0.010	0.044
	(0.013)	(0.010)	(0.016)	(0.017)
1970-1972	0.045	0.005	0.027	0.061
	(0.013)	(0.010)	(0.016)	(0.018)
1973-1975	0.032	0.006	0.024	0.048
	(0.014)	(0.011)	(0.017)	(0.019)
1976-1978	0.016	-0.013	-0.003	0.016
	(0.014)	(0.012)	(0.018)	(0.019)
1979-1981	0.048	-0.005	-0.005	0.034
	(0.015)	(0.013)	(0.019)	(0.019)
1982-1984	0.045	-0.010	-0.033	0.007
	(0.016)	(0.014)	(0.021)	(0.020)
1985-1987	0.073	-0.006	-0.044	0.025
	(0.019)	(0.014)	(0.023)	(0.022)
1988 and after	0.134	0.040	-0.051	0.062
	(0.031)	(0.015)	(0.025)	(0.022)
Panel B: Year-by-Major estimates				
up to 1997	0.040	0.025	-0.032	0.033
	(0.011)	(0.008)	(0.009)	(0.009)
1998-2000	0.088	0.037	-0.019	0.067
	(0.015)	(0.011)	(0.013)	(0.013)
2001-2003	0.030	0.020	-0.015	0.047
	(0.010)	(0.008)	(0.012)	(0.009)
2004-2006	0.036	0.027	-0.026	0.048
	(0.012)	(0.009)	(0.012)	(0.010)
2007-2009	0.038	0.011	-0.024	0.031
	(0.014)	(0.009)	(0.014)	(0.010)
2010-2012	0.066	0.022	-0.023	0.027
	(0.014)	(0.010)	(0.015)	(0.011)
2013-2015	0.070	0.024	-0.035	0.029
	(0.015)	(0.010)	(0.014)	(0.011)
2016 and after	0.074	0.027	-0.040	0.035
	(0.014)	(0.010)	(0.015)	(0.011)

Notes: Panel A presents estimates of Equation (1) using the LEHD sample with cohort-by-major effects. The specification is identical to that of column (4) of Table 6. Panel B presents estimates of Equation (1) using the LEHD sample and year-by-major effects. The specification is identical to that of column (5) of Table 6. Observations are weighted using the ACS person weights. Standard errors are clustered at the major-by-age bin level and at the individual level. CS: Computer Science.

Table 8: Log Earnings Estimates by Birth Cohort

			By Birth Cohort	
		LEHD	Born ≤ 1970	Born > 1970
Major m	Age a	(1)	(2)	(3)
Engineering & CS	29-30	-0.027	0.017	-0.035
		(0.011)	(0.017)	(0.011)
	39-40	0.004	0.021	0.011
		(0.012)	(0.017)	(0.012)
	47-48	0.018	0.039	0.040
		(0.015)	(0.018)	(0.015)
	49-50	0.022	0.046	
		(0.017)	(0.020)	
Business	29-30	-0.017	0.005	-0.019
		(0.008)	(0.014)	(0.008)
	39-40	0.024	0.038	0.027
		(0.010)	(0.016)	(0.010)
	47-48	0.018	0.031	0.032
		(0.010)	(0.015)	(0.011)
	49-50	0.016	0.032	
		(0.011)	(0.015)	
L&P Science	29-30	0.065	0.049	0.065
		(0.028)	(0.029)	(0.029)
	39-40	0.161	0.143	0.163
		(0.029)	(0.026)	(0.030)
	47-48	0.169	0.153	0.172
		(0.029)	(0.026)	(0.031)
	49-50	0.172	0.156	
		(0.029)	(0.026)	
Social Science	29-30	0.036	0.080	0.032
		(0.010)	(0.014)	(0.010)
	39-40	0.077	0.125	0.071
		(0.012)	(0.015)	(0.012)
	47-48	0.069	0.116	0.076
		(0.012)	(0.015)	(0.013)
	49-50	0.069	0.118	
		(0.013)	(0.015)	
	N	38,020,000	14,640,000	23,380,000
	R^2	0.790	0.789	0.787

Notes: This table presents estimates of Equation (1) using the full panel of earnings in the LEHD separately by birth cohort. Column (1) is a repeat of the results from column (4) of Table 3. Columns (2) and (3) present separate estimates for the subsample of individuals born in 1970 or earlier, and after 1970, respectively, using the same specification. Observations are weighted using the ACS person weights. Standard errors are double clustered at the major-by-age bin level and at the individual level. CS: Computer Science, L&P Science: Life and Physical Science.

Table 9: Log Earnings Estimates for Extended LEHD Sample

		$\beta_{m,a}$	
Major m	Age a	LEHD (1)	Extended LEHD (2)
Engineering & CS	29-30	-0.027	0.002
		(0.011)	(0.012)
	39-40	0.004	0.042
		(0.012)	(0.013)
	49-50	0.022	0.054
		(0.017)	(0.018)
Business	29-30	-0.017	-0.001
		(0.008)	(0.011)
	39-40	0.024	0.041
		(0.010)	(0.014)
	49-50	0.016	0.028
		(0.011)	(0.016)
L&P Science	29-30	0.065	0.065
		(0.028)	(0.029)
	39-40	0.161	0.163
		(0.029)	(0.031)
	49-50	0.172	0.173
		(0.029)	(0.031)
Social Science	29-30	0.036	0.043
		(0.010)	(0.014)
	39-40	0.077	0.077
		(0.012)	(0.017)
	49-50	0.069	0.056
		(0.013)	(0.019)
	N	38,020,000	76,450,000
	R^2	0.790	0.803

Notes: This table presents estimates of Equation (1) with worker fixed effects using the LEHD and Extended LEHD samples. Column (1) is a repeat of the results from column (4) of Table 3. Column (2) uses the sample of matched individuals from the 2009-2019 ACS waves aged 30-60 when interviewed and who reported a valid major and the same specification as column (1). Observations are weighted using the ACS person weights. Standard errors are clustered at the major-by-age bin level and at the individual level. CS: Computer Science, L&P Science: Life and Physical Science.

Table 10: Log Earnings Estimates by Detailed Major Classification

Major m	Age a	$\beta_{m,a}$	Major m	Age a	$\beta_{m,a}$
Applied Science	29-30	0.027	Medical Services	29-30	0.040
		(0.017)			(0.015)
	39-40	0.061		39-40	0.078
		(0.018)			(0.016)
	49-50	0.116		49-50	0.167
		(0.020)			(0.020)
Engineering	29-30	-0.001	Natural Science	29-30	0.068
		(0.016)			(0.028)
	39-40	0.036		39-40	0.176
		(0.017)			(0.029)
	49-50	0.094		49-50	0.215
		(0.019)			(0.030)
Business & Economics	29-30	0.006	Services	29-30	-0.008
		(0.015)			(0.028)
	39-40	0.056		39-40	-0.015
		(0.017)			(0.028)
	49-50	0.078		49-50	-0.004
		(0.018)			(0.030)
Computer Science	29-30	0.001	Social Science	29-30	0.006
		(0.016)			(0.020)
	39-40	0.053		39-40	0.014
		(0.017)			(0.021)
	49-50	0.059		49-50	0.028
		(0.019)			(0.022)
Education	29-30	-0.038			
		(0.016)			
	39-40	-0.049			
		(0.018)			
	49-50	0.014			
		(0.020)			
N			76,450,000		
R^2			0.803		

Notes: This table presents estimates of Equation (1) with worker fixed effects using the same sample and controls as column (2) of Table 9, but a more detailed classification of majors. We classify majors into ten groups following Altonji, Kahn, and Speer (2016), leaving Humanities as the reference category. Observations are weighted using the ACS person weights. Standard errors are clustered at the major-by-age bin level and at the individual 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 2022 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 the 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 construct 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 1 shows that, on average, we observe 18.3 observations per individual.

A.2 Additional Tables

Table A1: Majors Classification

Category from Deming and Noray (2020)	Majors
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)
Business	Business (62)
Life and Physical	Environment and Natural Resources (13), Biology and Life Sciences (36), Physical Sciences (50)
Social Science	Social Sciences (55)
Other	Agriculture(11), Architecture (14), Area, Ethnic, and Civilization Studies 15 Communications (19), Cosmetology Services and Culinary Arts (22), Education Administration and Teaching (23), Linguistics and Foreign Languages (26), Family and Consumer Sciences (29), Law (32), English Language, Literature, and Composition (33), Liberal Arts and Humanities (34), Library Science (35), Mathematics and Statistics (37), Interdisciplinary and Multi-Disciplinary (40), Physical Fitness, Parks, Recreation (41), Philosophy and Religious Studies (48), Theology and Religious Vocations (49), Psychology (52), Criminal Justice and Fire Protection (53), Public Affairs, Policy, and Social Work (54), Construction Services (56), Fine Arts (60), Medical and Health Sciences and Service (61), History (64)

Notes: This table shows the categorization of majors used by Deming and Noray (2020) and in most of this paper. Majors correspond to the variable DEGFIELD in the ACS 2009-2019 (https://usa.ipums.org/usa-action/variables/DEGFIELD#codes_section).

Table A2: ACS Log Earnings with Graduate Degree Profiles and Labor Supply Controls

		$\beta_{m,a}$			
			Graduate degree profiles	Labor supply controls	Both
Major m	Age a	(1)	(2)	(3)	(4)
Engineering & CS	29-30	-0.050	-0.059	-0.069	-0.068
		(0.059)	(0.060)	(0.058)	(0.059)
	39-40	-0.126	-0.131	-0.143	-0.141
		(0.071)	(0.069)	(0.065)	(0.063)
	49-50	-0.167	-0.168	-0.158	-0.152
		(0.075)	(0.072)	(0.069)	(0.067)
Business	29-30	-0.103	-0.106	-0.050	-0.053
		(0.054)	(0.053)	(0.045)	(0.044)
	39-40	-0.149	-0.134	-0.082	-0.071
		(0.062)	(0.061)	(0.051)	(0.049)
	49-50	-0.182	-0.164	-0.100	-0.086
		(0.068)	(0.067)	(0.055)	(0.054)
L&P Science	29-30	0.213	0.185	0.091	0.064
		(0.091)	(0.093)	(0.055)	(0.056)
	39-40	0.428	0.349	0.267	0.201
		(0.103)	(0.096)	(0.070)	(0.061)
	49-50	0.430	0.353	0.281	0.216
		(0.102)	(0.098)	(0.069)	(0.063)
Social Science	29-30	0.053	0.047	0.020	0.013
		(0.054)	(0.053)	(0.046)	(0.045)
	39-40	0.112	0.092	0.059	0.041
		(0.062)	(0.059)	(0.051)	(0.049)
	49-50	0.093	0.074	0.047	0.030
		(0.067)	(0.065)	(0.055)	(0.053)
	N	2,808,501	2,808,501	2,808,501	2,808,501
	R^2	0.197	0.203	0.470	0.475

Notes: This table presents estimates of Equation (1) using the ACS sample and various specifications. Column (1) is a repeat of the results from column (1) of Table 2. Column (2) includes interactions between age group and advanced degree indicators. Column (3) includes indicators for each interval of weeks worked per year. Column (4) includes both. Observations are weighted using the ACS person weights. Standard errors are clustered at the major-by-age bin level. CS: Computer Science, L&P Science: Life and Physical Science.

Table A3: Share of Detailed Majors by Birth Cohort

Field of degree	Born $\leq$ 1970	Born $>$ 1970
Engineering and Computer Science		
Computer Science	11.91	19.03
Electrical Engineering	19.13	13.03
Mechanical Engineering	14.55	11.89
Computer and Information Systems Managers	3.18	6.90
Civil Engineering	8.96	6.84
General Engineering	9.86	6.48
Computer Engineering	1.75	6.16
Chemical Engineering	5.56	4.43
Business		
Business Management	33.87	28.57
General Business	22.76	17.70
Accounting	20.48	16.63
Marketing	8.58	12.61
Finance	7.09	11.79
Hospitality Management	1.14	2.83
Management Information Systems and Statistics	1.27	2.42
Human Resources and Personnel Management	2.05	2.22
Life and Physical Sciences		
Biology	34.94	41.30
Chemistry	17.96	10.48
Multi-disciplinary or General Science	9.71	7.69
Biochemical Sciences	2.84	5.47
Physics	8.00	5.21
Environmental Science	1.92	5.08
Physiology	1.33	2.96
Geology and Earth Science	5.05	2.75
Social Sciences		
Political Science and Government	30.12	31.45
Economics	28.3	25.03
Sociology	23.29	20.91
Anthropology and Archeology	4.82	7.20
International Relations	2.36	4.75
Geography	3.77	3.91
General Social Science	5.23	3.04
Criminology	1.43	3.04
Other		
Psychology	6.88	10.32
Nursing	7.67	6.96
English Language and Literature	6.29	5.73
Elementary Education	9.87	5.62
Communications	2.63	5.36
General Education	9.13	4.56
Criminal Justice and Fire Protection	2.04	4.27
History	4.48	3.88

Notes: Shares of the eight most common detailed majors for each one of the five categories as defined in Deming and Noray (2020), based on ACS data from 2009 and 2019.

Table A4: 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 3.4. Majors included in each cell correspond to the classification used by Altonji, Kahn, and Speer (2016).

Table A5: Log Earnings Estimates, Detailed Major, OLS

Major m	Age a	$\beta_{m,a}$	Major m	Age a	$\beta_{m,a}$
Applied Science	29-30	0.023	Medical Services	29-30	0.042
		(0.066)			(0.058)
	39-40	0.043		39-40	0.081
		(0.070)			(0.058)
	49-50	0.087		49-50	0.194
		(0.076)			(0.058)
	Major Indicator	0.069		*Major Indicator*	0.115
		(0.040)			(0.036)
Engineering	29-30	-0.005	Natural Science	29-30	0.089
		(0.064)			(0.087)
	39-40	-0.022		39-40	0.199
		(0.067)			(0.082)
	49-50	0.001		49-50	0.250
		(0.069)			(0.083)
	Major Indicator	0.460		*Major Indicator*	0.074
		(0.042)			(0.064)
Business & Economics	29-30	0.000	Services	29-30	-0.005
		(0.063)			(0.086)
	39-40	0.030		39-40	-0.009
		(0.064)			(0.089)
	49-50	0.047		49-50	0.020
		(0.062)			(0.090)
	Major Indicator	0.269		*Major Indicator*	0.005
		(0.037)			(0.062)
Computer Science	29-30	0.027	Social Sciences	29-30	0.008
		(0.056)			(0.070)
	39-40	0.048		39-40	0.021
		(0.057)			(0.071)
	49-50	0.057		49-50	0.041
		(0.057)			(0.070)
	Major Indicator	0.368		*Major Indicator*	0.031
		(0.033)			(0.042)
Education	29-30	-0.043			
		(0.058)			
	39-40	-0.069			
		(0.058)			
	49-50	0.002			
		(0.058)			
	Major Indicator	-0.051			
		(0.036)			
N			76,450,000		
R^2			0.537		

Notes: This table presents estimates of Equation (1) without worker fixed effects using the full panel of earnings in the LEHD and detailed classification of majors. The final row of each major shows the wage gap estimate of the major with respect to humanities at age 23. Observations are weighted using the ACS person weights. Standard errors are clustered at the major-by-age bin level and at the individual level.

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.[A2] 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, 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 A6 provides some basic information about the individuals in the NSCG data. In

[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.

[A2]The NSCG has a panel component, as it surveys a subset of interviewees up to four times. In the 1990s and 2000s, it only followed individuals whose field of degree or occupation was related to science and engineering in their first survey. Starting in 2010, there is sample overlap, with some cases included in the 2010 NSCG also appearing in survey waves through 2017, in the 2013 NSCG also appearing in waves through 2019, and so on. This longitudinal structure is available within a restricted environment.

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 around 20% of the sample.

In Table A7, we display estimates of Equation (1) using the NSCG. Throughout the analysis we include only individuals aged 25-50 since relatively few individuals under 25 are surveyed. In column (1) we estimate a version of Equation (1) excluding cohort-by-major effects, year-by-major effects, and worker fixed effects. This specification matches the one used for the ACS displayed in column (1) of Table 2. Similar to the ACS results, technical and business majors experience slower earnings growth over the life cycle relative to other majors, though the effects are somewhat muted. In columns (2), we include dummies for working week intervals and the interaction between dummies of age groups and graduate degrees. In columns (3) and (4) we allow the returns to majors 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 significant 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 of repeated cross-sections 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 A6: Summary Statistics, NSCG 1993-2019

	ACS	LEHD	NSCG
% Male	46.9	46.8	48.8
% White	78.8	74.8	72.7
% Engineering & CS	13.1	13.5	13.2
% Business	20.9	20.6	20.7
% Life & Physical Science	8.7	8.7	8.8
% Social Science	7.6	7.5	9.1
% Others	49.7	49.8	48.2
Total Persons	2,808,501	2,398,000	385,499

Notes: The first two columns repeat summary statistics of the ACS and the LEHD sample in Table 1. 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 sample includes all respondents aged 25-50 with at least a bachelor's degree who report a valid major. CS: Computer Science.

Table A7: Log Earnings Estimates, NSCG

		$\beta_{m,a}$			
Major, m	Age, a	NSCG (1)	Graduate degree and labor supply controls (2)	Cohort-by-major FE (3)	Year-by-major FE (4)
Engineering & CS	29-30	0.007	0.015	0.047	0.031
		(0.091)	(0.094)	(0.106)	(0.093)
	39-40	-0.124	-0.113	0.026	-0.096
		(0.091)	(0.089)	(0.102)	(0.089)
	49-50	-0.069	-0.060	0.092	-0.047
		(0.097)	(0.094)	(0.110)	(0.095)
Business	29-30	-0.001	0.009	-0.008	0.018
		(0.078)	(0.078)	(0.087)	(0.078)
	39-40	-0.058	-0.026	0.059	-0.013
		(0.074)	(0.071)	(0.083)	(0.071)
	49-50	-0.059	-0.040	0.034	-0.032
		(0.085)	(0.080)	(0.094)	(0.081)
L&P Science	29-30	0.111	0.133	0.157	0.142
		(0.091)	(0.091)	(0.097)	(0.091)
	39-40	0.249	0.214	0.255	0.231
		(0.086)	(0.085)	(0.093)	(0.085)
	49-50	0.305	0.268	0.336	0.280
		(0.100)	(0.095)	(0.105)	(0.096)
Social Science	29-30	0.027	0.039	0.062	0.047
		(0.079)	(0.077)	(0.079)	(0.077)
	39-40	0.015	-0.007	0.080	0.006
		(0.074)	(0.071)	(0.076)	(0.071)
	49-50	0.048	0.022	0.077	0.034
		(0.085)	(0.078)	(0.084)	(0.078)
	N	385,499	385,499	385,499	385,499
	R^2	0.185	0.233	0.235	0.233

Notes: This table presents estimates of Equation (1) using various samples and specifications. The baseline 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) includes working weeks and interaction between age group and advanced degree indicators. Column (3)-(4) include cohort-by-major fixed effects and year-by-major fixed effects respectively in addition to column (2). Standard errors are clustered at the major-by-age bin level. CS: Computer Science, L&P Science: Life and Physical Science.