Heterogeneity in STEM Coursework Within and Across College Majors: Do College Graduates' Earnings Depend on Major, STEM Credits, or Both?

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Abstract: We use data for over 200,000 bachelor's degree recipients to contribute new evidence on the relationship between STEM training and earnings. In contrast to studies that identify the expected earnings premium associated with any STEM degree or with specific college majors, we account for workers' majors *and* the percent of total college credits completed in STEM courses (STEM intensity). We find that STEM intensity is an important determinant of log-earnings for many STEM *and* non-STEM majors, and that estimated earnings gaps between pairs of majors can change dramatically when STEM intensity is accounted for. In light of this evidence, we believe policy initiatives focused on drawing students into STEM should emphasize the potential value of STEM coursework for non-STEM majors.

Keywords: STEM training, college major, human capital, wage differentials, college coursework

1. Introduction

Efforts to attract students into science, technology, engineering and mathematics (STEM) have been central to U.S. education policy since soon after October 1957, when the Soviet Union's launch of the Sputnik satellite heightened fears that the U.S. had fallen behind in those fields. Although policy initiatives related to STEM education have varied over the ensuing decades, the over-arching goal has been to maintain a pipeline of workers with the skills needed to produce scientific and technological innovation and, in turn, economic growth. Current STEM policies at both the federal and state levels are far too numerous to summarize, but in the state of Ohio (the source of administrative data used for this study), current STEM programs include a large-scale "Choose Ohio First" scholarship program for college students pursuing STEM degrees and a "STEM Learning Network" that helps prepare students for STEM degrees and careers.[1]

To support these longstanding policy goals, researchers have sought to understand what drives college students to choose STEM degrees and how those degrees are valued in the labor market. Recent examples of this wide-ranging research agenda include Card and Payne (2021), Castleman *et al*. (2018), Delaney and Deverieux (2019), Gottfried and Bozick (2016), Jiang (2021), Swiderski (2024), and Wang (2015). A related literature looks more broadly at college major choice and post-college earnings differentials among majors (*e.g*., Altonji *et al.* 2016; Arcidiacono 2004; Lemieux 2014; Webber 2016; Wiswall and Zafar 2015). A third strand of the literature extends the analysis of earnings payoffs by accounting for actual coursework or credit accumulations (*e.g.,* Hamermesh and Donald 2008; James *et al*. 1989; Light and Rama 2019; Light and Schreiner 2019). In the current study, we contribute new evidence on the relationship between STEM training and earnings by using a novel hybrid of each of these approaches.

Using Ohio administrative data, we construct a sample of over 200,000 recent bachelor's degree recipients for whom we can link detailed transcript data with longitudinal, post-college earnings records. In contrast to studies that identify the expected earnings payoff(s) associated with *any* STEM major or, alternatively, a set of STEM and non-STEM majors, we consider two dimensions of STEM training: (a) college major, which we classify into 15 STEM and 26 non-

[1] See https://highered.ohio.gov/initiatives/affordability/choose-ohio-first/cof-overview/cof and https://osln.org/ for information on these Ohio programs, Herold (1974) and Steeves *et al.* (2009) for discussions of the effects of Sputnik on education policy, and https://www.ed.gov/stem for information on "YOU Belong in STEM," an example of current federal STEM education policy.

STEM fields; and (b) STEM intensity**,** which we define as the percentage of total college credits completed in STEM courses.[2] By characterizing college training in this way—and by estimating flexible earnings models in which each major has its own intercept and nonlinear STEM intensity slope—we are able to address several questions that have received scant attention in the existing literature: Do STEM degrees necessarily entail highly intensive STEM training? More generally, how do various STEM and non-STEM degrees compare in STEM intensity? How does the earnings payoff associated with additional STEM training vary across STEM and non-STEM majors? Can students who choose non-STEM majors expect to earn more in the labor market by adding STEM courses to their college curricula? Our data are well-suited to answering these questions because college students in Ohio (and throughout the U.S.) can easily switch majors and/or complete a considerable amount of coursework in fields unrelated to their major; *e.g.,* the average student in our sample completes 70% of all credits *outside* the major. In contrast, data for non-U.S. college students, who often have far less flexibility in their curricular choices, would be unlikely to provide the within-major variation in STEM training that we exploit for our analysis.

We believe our findings are informative despite our reliance on "selection on observables" to control for ability and other confounding factors in our earnings models—a strategy that dominates the literature on cross-major earnings variation (Altonji *et al*. 2016), given the lack of viable methods for dealing with a large number of endogenous variables. Evidence from robustness checks suggests that we control adequately for ability in our regression analysis, yet our estimates invariably reflect both the causal effects of skills acquired in college *and* the effects of unobserved factors such as preferences and expectations. As such, our estimates for a given major and given level of STEM intensity represent the earnings payoff that students can expect to receive *if* they possess levels of unobserved factors that are typical among students making similar choices. For example, we identify the estimated log-earnings associated with a given level of STEM intensity among engineering majors, and interpret this as the payoff a typical engineering might receive. We do *not* suggest that a typical arts major could expect the same payoff if forced to switch to

[2]As detailed in section 3, for our primary definition of STEM we match course-specific, six-digit Classification of Instructional Program (CIP) codes from each student's transcript to CIP codes identified by the Department of Homeland Security as STEM fields. We also consider a stricter definition in which STEM majors and courses are confined to six fields: biological sciences, computer and information sciences, engineering, engineering technology, mathematics and statistics, and physical sciences.

engineering and increase her STEM intensity, given that her unobserved factors are likely to differ from those of a typical engineering student.

We uncover a number of striking patterns in the data that we hope will spur further discussion and analysis. STEM intensity varies dramatically across majors: even among the six "extreme" STEM majors listed in footnote 2, the mean level of STEM intensity ranges from 79% for engineering to only 56% for computer and information science. Computer science exemplifies the considerable *within*-major variation seen in our data, with STEM-intensity ranging from 29% at the 10th percentile to 77% at the 90th percentile. This 10th percentile value is below the 90th percentile level of STEM intensity of 33% for philosophy majors, which means a subset of computer science majors lag behind select philosophy majors in their STEM intensity. We also find that estimated log-earnings gaps between STEM and non-STEM majors are often sensitive to STEM intensity. For example, the estimated gap between engineering (the highest-paid major, on average) and languages (among the lowest-paying majors) is 0.71 when STEM intensity is ignored, but only 0.59 when we use our flexible specification to compare a low STEM intensity engineering major to a high STEM-intensity languages major. Our evidence suggests that the augmentation of a lower-paying, non-STEM degree with STEM training can, in some cases, lead to substantial labor market rewards.

2. Related literature

Our analysis relates to prior research that identifies earnings benefits associated with a STEM degree or with an array of college majors, as well as studies that incorporate measures of college coursework into earnings models. In this section, we overview a sampling of those studies to illustrate how the current study complements and extends existing research.

Among studies that examine the STEM earnings premium, the focus is often on differences between men and women. For example, Olitsky (2014) identifies separate STEM effects for men and women at each quartile in the ability distribution, using propensity score matching to account for the endogenous choice of a STEM or non-STEM major. He finds a particularly pronounced gender gap in the STEM wage premium among high-ability workers. Jiang (2021) follows up on this issue as part of a broader study that employs a latent skills approach to modeling binary choices between STEM and non-STEM majors *and* occupations. She finds that the average treatment effect of STEM degrees increases in skill for both men and women, with insignificant differences across genders. Even *et al.* (2023) is a rare example of a recent study that does not examine gender or racial/ethnic gaps; instead, the authors compare the "overall" STEM earnings premium across OECD countries to identify the importance of education levels, union levels, and other factors. Among their key take-aways is that the STEM wage premium in the U.S. is substantially higher than the average premium for other OECD countries.

Among studies with a focus on the STEM wage premium, Light and Rama (2019) is a precursor to ours insofar as they introduce a continuous measure of STEM intensity in lieu of an orthodox, binary STEM/non-STEM indicator. Aside from that commonality, the current study differs dramatically from Light and Rama (2019), who focus on gender differences in the log-earnings associated with interactions between each worker's college STEM training and occupational STEM requirements. In contrast to our study, Light and Rama (2019) also ignore college major (except to use a binary STEM major dummy in a "straw man" specification that excludes STEM intensity) and use data from the 1997 National Longitudinal Survey of Youth. In the current study we do not pursue a gender comparison, nor do we control for post-college occupations or the STEM requirements of those occupations because our administrative data lack occupational identifiers. Instead, we borrow the measure of STEM intensity used by Light and Rama (2019) to explore the joint relationship between college major, STEM intensity, and earnings.

Specifically, we use our continuous STEM intensity measure to augment log-earnings models that control for either a binary STEM degree indicator or 41 major-specific intercepts. The latter approach to identifying "returns" to college major has been widely used, but without the inclusion of STEM intensity. Most studies in this literature account for the endogeneity of college majors by incorporating a rich vector of controls (including academic ability) in an earnings model (*e.g.,* Altonji *et al.* 2016; Chevalier 2011; Hamermesh and Donald 2008; James *et al.* 1989; Light and Schreiner 2019; Light and Wertz 2022; Loury and Garman 1995; Sloane, Hurst and Black 2021; Webber 2016). Some analysts estimate a structural model (Arcidiacono 2004; Beffy *et al.* 2012; Kinsler and Pavan 2015) or use a regression discontinuity design (Bleemer and Mehta, 2022; Hastings *et al.* 2014; Kirkeboen *et al.* 2016) to contend with endogeneity, although the cost of these strategies is a severe reduction in the number of college majors that can be analyzed. Overall, this literature provides clear evidence that earnings vary widely across college majors and that predicted earnings for select non-STEM majors can exceed those of select STEM majors. For example, Altonji *et al.* (2016) estimate a log-earnings model with 19 major-specific intercepts and find that engineering majors have the highest predicted log-earnings (0.392 relative to education) followed by accounting (0.328), computer/mathematical sciences (0.327), economics (0.313), and nursing (0.312). However, the exent to which STEM coursework affects the relative returns to college majors, both STEM and non-STEM, has not previously been assessed.

The primary contribution of our current study is to reexamine existing evidence of earnings effects of college majors in a manner that reveals how the evidence changes when we account for STEM intensity. In using this measure, however, we join a relatively small group of studies that include measures of college coursework in earnings models. Examples of this approach include James *et al.* (1989), who control for the number of college math credits along with separate intercepts for six aggregate majors, and Hamermesh and Donald (2008), who control for upper-level science and math credits (as well as grades) along with 11 major-specific intercepts. Light and Schreiner (2019) include intercepts for 12 college majors along with student-specific measures of "major intensity," defined as the percentage of total college credits completed within the major. In a similar vein, Light and Wertz (2022) control for the occupational specificity of each major in decomposing each student's total college credits (weighted by occupational specificity) into within-major, within-discipline, and outside the discipline. They find that students majoring in nonvocational fields such as English can expect to increase their post-college earnings significantly by taking occupationally specific credits outside their discipline.

As our brief review demonstrates, studies that exploit detailed college credit information (as we do in the current study) are rare, presumably because these analyses require course-specific information obtained from college transcripts. Given that the requisite data are becoming increasingly available—and that studies exploiting such data, including the current study, point to important relationships between college coursework and post-college earnings *conditional* on major—we expect this sub-literature to grow substantially in years to come.

3. Data

3.1 Data sources

We use college transcript data from Ohio's Higher Education Information System (HEI) combined with earnings records from Ohio's Unemployment Insurance (UI) data; both are restricted-use, administrative databases made available by the Ohio Longitudinal Data Archive (OLDA). HEI data contain detailed transcript records for all students who enroll in Ohio's public two- and/or four-year colleges and universities from 1999 onward. UI data report quarterly earnings, weeks worked, and industry of employment by employer from 1995 onward. Our merged HEI-UI records span 1999 through the third quarter of 2019, which is the last quarter for which UI records were available when we were given access to the data.

Although merged HEI-UI data are well-suited for our analysis, they are not without shortcomings. First, transcript data are only available for public colleges and universities in Ohio, so we miss coursework for students who transferred from a private or non-Ohio college to their degree-granting institution. Second, UI earnings data are only available for workers whose employers participate in Ohio's UI system. As a result, we lack earnings records for anyone working outside Ohio, as well as for the relatively small number of Ohio workers whose employers are excluded from UI coverage (*e.g.*, employees of the federal government or select religious organizations, and a subset of self-employed workers). Third, our data lack occupation identifiers, so we are unable to explore the match between college training and post-college occupations, which previous studies have shown to be potentially important (*e.g.,* Jiang 2021; Lemieux, 2014; Light and Rama 2019; Robst 2007). Our sample selection criteria and robustness checks are designed, in part, to contend with the first two data limitations.

3.2 Sample selection

Although several million Ohio college students appear in the HEI database, we begin by reducing the sample to 426,559 individuals who earn a bachelor's degree from one of Ohio's 13 public, four-year institutions from 2010 onward.[3] We impose the latter criterion to focus on both recent graduation cohorts and post-college earnings within, at most, nine years of graduation. Due to employer learning (Altonji and Pierret 2001), career interruptions (Blau and Kahn 2017; Spivey 2005) and other factors, we believe relationships between college coursework and earnings are best assessed soon after graduation.[4]

We also drop students (a) who earn their degree after age 26, given that they are likely to have significant, pre-college work histories; (b) with unusually high credit concentrations in

[3]The 13 Ohio universities are Bowling Green State U., Central State U., Cleveland State U., Kent State U., Miami U., Ohio State U., Ohio U., Shawnee State U., U. of Akron, U. of Cincinnati, U. of Toledo, Wright State U. and Youngstown State U.

[4]Webber (2016) finds that net benefits to college investments do not arise for many years among students faced with high costs and/or debt, but we focus on earnings rather than "return on investment." Note that our use of a 2010 cutoff has the added advantage of allowing us to skirt the 2008-2009 recession.

nonacademic subjects (*e.g.*, "construction trades") because they may not have been pursuing a conventional four-year degree; and (c) whose degree field appears to be miscoded. In addition, we drop students whose college records show fewer than 108 credits accumulated towards a bachelor's degree (90% of the 120 credits typically needed to earn a degree); it appears that these incomplete records arise when transfer credits are omitted from HEI records made available to researchers. Finally, we drop students with no post-college earnings during the observation window that begins with the first calendar quarter after college graduation and ends with the third quarter of 2019 (when our UI records end). For individuals who reenroll in school, we terminate the earnings window with the last calendar quarter preceding reenrollment.[5]

Our final sample consists of 2,717,057 quarterly earnings observations for 209,137 individuals. These panel data are unbalanced, with the earliest (2010) graduation cohort contributing *far* more quarterly observations, on average, than the latest (2019) cohort. An unbalanced panel is not inherently problematic, but our robustness checks in section 6.3 include estimates based on a subsample of workers with at least four years of post-college earnings.

3.3 Defining college majors, STEM majors, and STEM intensity

HEI uses six-digit 2010 Classification of Instructional Programs (CIP) codes to record each student's *primary* major.[6] The 209,137 students in our sample complete majors with 428 different six-digit CIP subject codes that distinguish, for example, between general microbiology and cellular molecular biology within the two-digit biological sciences field. The analysis of 428 six-digit majors (or, alternatively, 195 four-digit majors) is impractical for our purposes, given that we intend to compare STEM coursework across majors and estimate log-earnings models with major-specific regressors. In addition, an examination of websites for the 13 Ohio universities in our sample reveals numerous cases where multiple six-digit majors are granted by the same department and are differentiated primarily by the choice of upper-level courses offered by the department.

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[5]The data appendix provides additional details on sample selection and other data issues discussed in this section.

[6]We do not attempt to account for double majors, minors, and other types of concentrations because these options differ across institutions and are not consistently identified in our data. Our assessment of the data leads us to believe that switching majors is a more important contributor to variation in STEM intensity than is earning a double major, and that neither phenomenon is likely to account for more than a small portion of the tremendous cross-student heterogeneity in STEM intensity.

To obtain a manageable number of majors, we aggregate the 428 six-digit majors in our sample to fields that correspond, in most cases, to CIP two-digit codes (biological sciences, education, business, social sciences, *etc.*). Although the CIP taxonomy includes 47 two-digit codes, we are left with 32 after eliminating vocational and "basic skills" fields in which bachelor's degrees are not rewarded, reassigning three fields in which only a handful of sample members obtain degrees, and disaggregating the popular two-digit major that spans a variety of health fields into five majors: speech and hearing, medical sciences, public health, nursing, and health and rehabilitation sciences.

Our next task is to designate each major and college course as STEM or non-STEM; this results in further revisions to our set of college majors. There is no consensus in the literature as to which college majors and courses fall under the "science, technology, engineering and mathematics" umbrella, but we use the "U.S. Department of Homeland Security (DHS) STEM Designated Degree Program List," which provides six-digit CIP codes for fields that DHS considers to be STEM and that, as a result, qualify international degree-recipients for visa extensions to pursue optional practical training.[7] We use this STEM list for two reasons. First, it is a widely-accepted STEM definition that is not viewed as extremely narrow or broad. Second, although none of the 13 Ohio universities in our sample appears to have an official list of STEM majors, the rare references to STEM majors that we were able to find on these universities' websites use the DHS definition.

While most of our 32 majors based on two-digit CIP codes consist *entirely* of six-digit majors that are designated STEM (*e.g.,* engineering, biological sciences) or non-STEM (*e.g.,* English, arts), nine majors (*e.g.,* agriculture, business) contain a mix of six-digit STEM and non-STEM majors. In these cases, we split the major into STEM and non-STEM versions and rely on each student's six-digit CIP code to determine whether she is a STEM or non-STEM major. Stated differently, rather than naively aggregate our six-digit majors to the two-digit fields given by CIP, we aggregate to the largest group within each two-digit field that avoids combining STEM and non-STEM majors. Within the two-digit agriculture field, for example, students majoring in plant science, animal science, or food science are deemed to be STEM agriculture majors, while students

[7]This list, dated January 21, 2022, is disseminated by U.S. Immigration and Customs Enforcement and is available at https://www.ice.gov/doclib/sevis/pdf/stemList2022.pdf. Recent studies that used this STEM definition include Jiang (2021), Light and Rama (2019), and Smith *et al.* (2021).

majoring in agricultural management, agricultural operations, and agricultural economics are among those categorized as non-STEM agriculture majors.[8]

A careful perusal of six-digit CIP codes and our sample members' coursework reveals that courses designated as STEM are, with few exceptions, highly scientific and technical. Nonetheless, the notion that a subset of degrees in agriculture, business, and even social sciences and criminal justice are STEM might be at odds with policy initiatives designed to encourage students to earn degrees in engineering, mathematics, and other "extreme" STEM fields. Therefore, we repeat a portion of our analysis using an alternative STEM definition in which all nine "split" majors (and all the courses falling within those fields) are designated as non-STEM. This leaves us with six STEM majors (biological sciences, computer and information sciences, engineering, engineering technology, mathematics and statistics, and physical sciences) that are unquestionably considered STEM under any definition or policy initiative.

Our primary STEM definition yields a set of 41 majors: six are "pure" STEM, nine are split into both STEM and non-STEM versions, and 17 are "pure" non-STEM; *i.e.,* we have 15 STEM and 26 non-STEM majors. For our robustness checks based on a stricter STEM definition, we have six STEM and 26 non-STEM majors. Tables 2 and A2-A3 list our 41 majors.

In addition to categorizing majors as STEM or non-STEM, we must determine each student's total credit accumulation and the percentage of those total credits completed in STEM fields. HEI data include the title, completion status, credits earned, term, and six-digit CIP code for each course. For our primary STEM definition, we simply compute each sample member's total completed credits and the percentage of those total credits completed in DHS-designated STEM courses, based on six-digit CIP codes for each course. For our stricter STEM definition, the numerator is confined to credits completed in DHS-designated STEM courses in biological sciences, computer and information sciences, engineering, engineering technology, mathematics and statistics, and physical sciences. We refer to these variables as *total credits* and *STEM intensity*, with the latter measured two ways. We choose to focus on the estimated effect on log-

[8]Two additional two-digit majors could be split into STEM and non-STEM versions, but are not due to sample size concerns. As a result, computer and information science (a STEM major with 3,907 sample members) includes four individuals with a six-digit, non-STEM major (CIS support services) and architecture (a non-STEM major with 1,574 sample members) includes 12 students with a six-digit STEM major (architectural/building sciences and technology). Every estimate reported in our analysis is invariant to the inclusion in our sample of these 16 reclassified students.

earnings of STEM intensity (conditional on total credits) rather than total STEM credits because an increment of, say, three STEM credits is quite different for students who complete only 108 total credits than for those who complete 160 or more total credits.

3.4 Additional variables used for log-earnings models

The dependent variable for our regression analysis is the natural logarithm of real, average weekly earnings; additional details are in the data appendix. The key explanatory variables are a binary STEM major indicator, 41 major dummies, and measures of total credits and STEM intensity. These variables—which we include in different combinations in our regression models—are described in section 3.3. In the remainder of this section, we describe the set of baseline regressors included in every specification. Table 1 shows summary statistics for most of these baseline regressors plus the dependent variable.

Our baseline regressors include indicators of whether the sample member is male, Hispanic, white (the omitted group), Black, Asian, or of another/unknown race. We would ideally include a pre-college measure of academic ability, but our HEI data do not include high school grades or scores for college admission tests. In the absence of that information, we follow Ost, Pan and Webber (2018) and use each student's grade point average in the first term of undergraduate enrollment as a measure of "early" academic ability.[9] We also control for the percentage of first-term attempted college credits that are completed, and whether the student completed more than three credits in the first term in basic skills, vocational, or personal enrichment courses.

To account for heterogeneity in college enrollment patterns, we include indicators of whether the student attended a single, four-year college (the omitted group) or underwent (a) one two-year to four-year transfer; (b) one four-year to four-year transfer; or (c) multiple transfers. We also control for whether the student attended multiple campuses of the same institution, and for associate degree receipt. Our final measure related to college enrollment is the student's age at bachelor's degree receipt. Although we confine our sample to individuals who graduate by age 26, this variable captures remaining variation in enrollment discontinuity and time to degree.

We also control for fixed effects for the year in which the bachelor's degree was awarded and, importantly, the degree-granting institution. Institution fixed effects enable us to eliminate any

[9]Our preferred regression specifications include college major dummy variables, and *all* specifications include university fixed effects, so differences in grading standards across majors and institutions are accounted for.

cross-institution heterogeneity in average student ability, average course difficulty, grading policies, credit requirements, and course and major offerings.

Our remaining baseline controls are years of post-college work experience and its square. We construct an "actual experience" measure by summing the number of calendar quarters with positive earnings from college graduation through the quarter associated with the given earning observation, and dividing by four.

4. Regression strategy

Our analytic strategy involves comparing predicted log-earnings for individuals with different college majors and levels of STEM intensity. We base these predictions on alternative versions of the following log-earnings model:

$$\ln Y_{isyt} = \alpha + \beta Z_i + \gamma X_{it} + \delta_s + \rho_y + e_{it}, \tag{1}$$

where Y_{isyt} is real, average weekly earnings in quarter t for individual i who graduates from school s in calendar year y, Z_i represents one or more of the key regressors defined in section 3.3, and X_{it} is the set of baseline controls described in section 3.4; δ_s and ρ_y are school and graduation-year fixed effects, respectively. We discuss the extent to which key regressors might be correlated with the time-varying residual, e_{it}, later in this section.

In our first specification, Z_i is a binary indicator of whether the individual's college major is STEM or non-STEM; this specification takes no account of college coursework and identifies an average log-earning gap between all STEM majors and all non-STEM majors. In specification 2, we replace the STEM indicator in specification 1 with a set of 40 major dummies (with non-STEM agriculture as the omitted major) to assess how predicted log-earnings vary among the majors that specification 1 treats as two homogenous groups. In specifications 1' and 2', we augment specifications 1-2 by adding controls for total credits and its square, and STEM intensity (the percentage of total credits completed in STEM fields) and its square. We use quadratic functions because there is considerable nonlinearity in the credit-earnings relationships, yet experimentation reveals that higher-order polynomials are unnecessary; for comparison, we also summarize estimates based on a linear function when presenting our findings in section 6. Specification 2" introduces additional flexibility by interacting the STEM intensity measures with major dummies, thus allowing each major to have its own intercept and nonlinear STEM intensity gradient.

We use our regression estimates to address three issues. First, using specifications 1 and 2, we demonstrate that a simple classification of majors as STEM or non-STEM masks tremendous variation in predicted log-earnings within the two groups. Second, using specifications 2 and 2', we show how each major's predicted log-earnings compares to its mean STEM intensity and how inferences about the relative "return" to each major change when STEM intensity is taken into account. Third, using specifications 2, 2', and 2", we assess predicted log-earnings gaps between select pairs of majors. For example, we compute the predicted gap between an engineering major with an unusually low level of STEM intensity and an observationally equivalent business major with an unusually high level of STEM intensity—and we compare this predicted gap to one that reverses each major's assumed STEM intensity and to one based on a specification that does not account for STEM intensity. By considering several pairs of majors and alternative levels of STEM intensity, we gain a clear sense of how STEM coursework relates to post-college earnings.

We use ordinary least squares (OLS) to estimate the log-earnings models described above, and account for nonindependence of the residuals among multiple observations for each individual in computing the standard errors. Clearly, our key regressors are self-selected on the basis of academic ability, noncognitive traits, preferences, and expectations about the post-college job market, and some of these factors are invariably related to post-college wages and curriculum choice. We use a "selection on observables" strategy to reduce this endogeneity problem by including a rich set of ability-related regressors and fixed effects (see section 3.4) that, we believe, absorb a large portion of the cross-student and cross-institution variation in ability among bachelor's degree recipients.

Nonetheless, we acknowledge that our estimated OLS coefficients for key variables are likely to reflect the confounding effects of individual preferences, expectations, and noncognitive traits. Unfortunately, we lack a viable econometric strategy for reducing these sources of endogeneity. We would have to reduce the number of majors to three or four to incorporate a structural approach similar to that of Arcidiacono (2004), Beffy *et al.* (2012) Jiang (2021), or Kinsler and Pavan (2015). We cannot use a regression discontinuity strategy to identify causal effects of college major on earnings because we lack the idiosyncratic admissions policies exploited by Bleemer and Mehta (2022), Hastings *et al.* (2014) and Kirkeboen *et al.* (2016).

Even if we were to view our continuous STEM intensity measure as our sole endogenous variable, we lack a suitable instrumental variable. Changes in institutional policies related to general education and major-specific credit requirements are rare, and a careful examination of select policy changes reveals virtually no first-stage explanatory power. We believe this is due to the *tremendous* latitude given to college students in their curriculum decisions, especially in fulfilling nonmajor credit requirements that, for the mean student in our sample, account for 70% of total credits. Because this flexibility extends to major requirements as well, we are also unable to distinguish with sufficient confidence between STEM courses that are required by the major and those taken as electives or general education requirements. However, as discussed below, we experiment with STEM intensity measures based only on courses taken either "early" or "late" in the four-year program as an indirect way to hone in on STEM courses that are likely to be upper-level and/or required by the major.

Although all identification strategies have advantages and disadvantages, it is worth noting that our "selection on observables" approach not only dominates the existing literature, but provides informative evidence. The ideal causal effect on earnings of, say, an engineering degree is often thought to be based on a hypothetical experiment in which a randomly-chosen student is assigned to an engineering major; the identification strategy that mimics this experiment produces an estimated "return" that is wholly attributable to the skills acquired from an engineering degree. However, if this randomly-chosen student has abilities and preferences that are roughly halfway between those of engineering-oriented students and, say, arts-oriented students, the causal effect is not a meaningful representation of what either type might gain from an engineering degree. We believe our estimated OLS earnings effect of an engineering degree *is* informative (as long as we adequately eliminate the confounding effect of ability), even though it represents what a randomly-chosen student can expect to earn from an engineering degree as a result of skill acquisition *and* the preferences, traits, and expectations that characterize students who choose that particular major.

We attempt to dispel any doubts about the usefulness of our estimates with a series of robustness checks. First, to absorb any remaining variation in student ability, we add each student's final, cumulative grade point average as a regressor and, alternatively, eliminate students who attend multiple institutions and/or campuses. Second, we reduce the sample to individuals who contribute earnings observations for at least the first four years following college graduation to focus on workers who are likely to be career-oriented, holding jobs that use their college degrees, and not simply biding time before entering graduate school. Third, we experiment with three alternative measures of STEM intensity that only consider credits completed in the first, second, or last year of college. These experiments reveal whether relationships between STEM intensity and log-earnings differ for general education versus upper-level STEM courses. Fourth, we replicate a subset of our findings using the stricter definition of STEM described in section 3.3.

5. Summary statistics

Before presenting estimates of log-earnings models, we document the considerable heterogeneity in STEM intensity within and across majors. We begin with the first set of columns in table 2, which summarize the distributions of our STEM intensity variable for each major. Majors are ranked by their mean STEM intensity within STEM and non-STEM groups.

Table 2 reveals a mean level of STEM intensity of 69.3% among all STEM majors (indicating that the typical STEM major completes over two-thirds of her total credits in STEM courses), which is 3.5 times higher than the corresponding mean of 19.8% among non-STEM majors. While this comparison is unsurprising, the corresponding standard deviations (14.7 and 11.4 for STEM and non-STEM majors, respectively) and 10th-90th percentile ranges (34.1 and 27.1) reveal substantial variation within each group.

Focusing first on the 15 STEM majors, table 2 reveals that the highest mean levels of STEM intensity are for engineering (79.1%), health and rehabilitation sciences (72.2%), engineering technology (71.4%), and physical sciences (66.7%). These relatively high means reflect not only the STEM-intensive nature of the training needed to complete bachelor's degrees in these fields but also the likelihood that students choosing these majors favor STEM courses when completing general education and other non-major credit requirements. The least STEM-intensive STEM majors, at the mean, are communications (17.5%), criminal justice (35.7%), business (36.6%), and social sciences (44.5%). Each of these is notable for being among nine "split" majors defined in section 3.3. Because these are nontraditional STEM fields, it is unsurprising that their mean levels of STEM intensity are relatively low—yet we are reassured to see that, for all nine "split" fields, the mean level of STEM intensity for the STEM major exceeds the mean level for the non-STEM counterpart (*e.g.*, 44.5% vs. 18.9% for STEM and non-STEM social sciences majors). It is important to note that cross-major variation in STEM intensity among STEM majors is not solely due to the inclusion of nontraditional majors: even among the six majors that meet our restrictive definition of STEM, the mean level of STEM intensity ranges from 79.1% for engineering to 55.6% for computer and information sciences.

Turning to non-STEM majors, we learn from table 2 that the highest mean levels of STEM intensity are for environmental studies (53.2%), medical sciences (44.7%), agriculture (41.1%), and psychology (33.2%). Aside from psychology, five of the six most STEM-intensive non-STEM majors are not only "split" fields but are outside the humanities and social sciences. Unsurprisingly, humanities and social sciences are well represented among non-STEM majors with the *lowest* mean levels of STEM intensity: Arts is the least STEM-intensive of all majors with a mean of 10.1%, followed by legal studies (11.4%), military studies (11.8%), communications (13.8%), and English (13.9%).

As discussed in section 3.3, each college course that contributes to our STEM intensity measure (based on the DHS definition of STEM) appears to cover scientific or technical subject matter, yet we acknowledge that STEM courses offered in business, agriculture, and other "split" fields are not always the focus of STEM policy. When we switch to our alternative definition in which the nine "split" majors are reclassified as non-STEM and *only* courses in the remaining six STEM fields contribute to STEM intensity, mean STEM intensity falls by 0.5 to 3.0 percentage points for 22 of 23 non-split majors, as seen in table 3, which partially replicates table 2 using the restrictive STEM definition; the exception is psychology, where the mean falls by almost half because DHS considers many psychology courses to be STEM.[10] For six of the nine "split" majors, the new sample means fall by 1.0 to 5.3 percentage points relative to the non-STEM levels in table 2. For the remaining majors (environmental studies, medical science and agriculture), the new means fall by 7.4 to 16.0 percentage points. In short, STEM intensity is sensitive to our STEM definition for four non-STEM majors and, as expected, for the nine "split" STEM majors.

Not only do we see large differences *across* majors in mean levels of STEM intensity, we also see variation in STEM intensity *within* each major. Using the difference between the 90th and 10th percentile levels as our metric, table 2 shows that this range tends to increase (decrease) as mean STEM-intensity falls among STEM (non-STEM) majors, albeit nonmonotonically. Among STEM majors, the 90th-10th percentile range is as low as 17.5 (engineering) and as high as 49 (both criminal justice and computer and information science); among non-STEM majors, it ranges from a low of 11.1 (military studies) to a high of 56.1 (medical sciences).

Table 2 also reveals that the more STEM-intensive non-STEM majors often have higher levels of STEM-intensity than many STEM majors. For example, the mean level of STEM intensity among non-STEM environmental studies majors (53.2%) falls just short of both the mean for

[10]The two-digit psychology field contains numerous six-digit STEM courses, but it is not a "split" major because none of its STEM subfields are among our sample members' majors; see the data appendix for details.

computer and information science majors (55.6%) and the 10th percentile level among physical science majors (53.8%). Moreover, the 90th percentile level among philosophy majors (31.3%) exceeds the 10th percentile level among computer and information science majors (28.8%). This latter comparison is particularly striking, given that philosophy and computer science majors are typically thought to be at opposite ends of the STEM training spectrum.

STEM majors are likely to earn a higher percentage of their STEM credits in upper-division courses than are non-STEM majors. We lack a direct way to measure the level or rigor of each STEM course or whether it fills a major-specific requirement, but in the right-most columns of table 2 we report means and standard deviations for the percentage of total STEM credits earned in the first year of college; these credits are likely to correspond to introductory courses taken to complete general education requirements. Unsurprisingly, the mean concentration of "early" STEM training is much higher among all non-STEM majors (37.1%) than among all STEM majors (21.9%). However, table 2 shows considerable variation in this measure, with the most STEM-intensive majors tending to be the least "front-loaded" even among non-STEM majors. As a result, the mean level of "early" STEM credits is lower for select non-STEM majors (*e.g.*, environmental studies (19.7%), psychology (22.6%), agriculture (24.9%)) than for select STEM majors (*e.g.,* medical sciences (29.4%), communications (30.7%), and business (32.8%)).

In principle, within- and between-major variation in STEM intensity could reflect variation in total credits (the denominator) rather than total STEM credits (the numerator). In fact, this proves not to be the case. The mean (S.D.) for "total credits" is 130.8 (19.3) among all STEM majors and 129.9 (17.7) among non-STEM majors (table 1). Among STEM majors, the major-specific mean of total credits ranges from a high of 150.5 for public health to a low of 118.5 for social sciences.[11] Among non-STEM majors, the mean ranges from 139.4 for education to 120.8 for languages, with the means for 20 of 26 majors clustered within six credits of the pooled mean of 129.9. Importantly, if we rank both STEM and non-STEM majors by their mean levels of STEM credits, the ranking is almost identical to the ranking based on mean STEM intensity shown in table 2, with a few pairs of majors with similar levels of total credits swapping positions. Although variation in total credits is not driving the patterns discussed here, we control for total credits (and its square) in all regression specifications that include STEM intensity.

[11]The major-specific numbers discussed in this paragraph are not tabulated.

6. Findings based on regression analysis

We now turn to OLS estimates for each specification of the log-earnings model described in section 4. Table 4 reports estimated coefficients for key covariates for specifications 1-2 and 1'-2', with the 41 majors ranked according to the magnitudes of their estimated coefficients for specification 2. Estimated coefficients for specification 2'' are shown in appendix table A4. It is difficult to draw inferences directly from such a highly parameterized model, so we focus our discussion of specification 2'' on estimated marginal effects for a select subset of majors (table 5).

6.1 Estimates based on specifications 1-2

Table 4 reveals that the estimated coefficient for the dichotomous STEM indicator in specification 1 is a precisely estimated 0.251. This parameter estimate—which falls midway between OLS estimates of 0.20 and 0.30 reported by Olitsky (2014) and Even *et al.* (2023), respectively, using alternative samples of U.S. workers—identifies the predicted gap in log-earnings between observationally identical workers with STEM and non-STEM bachelor's degrees, ignoring any variation in their college majors, STEM intensities, and total college credits. While this naïve estimate identifies a substantial payoff to a STEM degree, it masks considerable variation in log-earnings among workers with different majors.

Cross-major variation in log-earnings—which has been highlighted in prior studies, including Altonji *et al.* (2016), Chevalier (2011), Hamermesh and Donald (2008), and Light and Schreiner (2019)—is revealed by the estimates for specification 2, which accounts for workers' college majors but *not* their STEM intensity. As seen in table 4, STEM majors' predicted log-earnings range from a high of 0.316 (relative to non-STEM agriculture, which is the omitted major) for workers with an engineering degree to a low of -0.307 for workers with a biological sciences degree, and from a high of 0.222 (nursing) to a low of -0.450 (philosophy) among workers with non-STEM degrees. The predicted log-earnings gap between the highest- and lowest-paid STEM workers is 0.623 (0.316 – (-0.307)), while the analogous gap for non-STEM workers is 0.672 and the "global" high-low gap (engineering vs. philosophy) is 0.766.

While the estimates just discussed confirm well-known patterns, a unique feature of our analysis is that we can compare the ranking of college majors' predicted log-earnings to the ranking of their mean levels of STEM intensity. Table 4 reports each major's rank with respect to both statistics, but the relationships are more easily seen in figure 1, which plots each major's estimated coefficient for specification 2 (table 4) against its mean level of STEM intensity (table 2); STEM majors are shown in bold-face. Unsurprisingly, engineering is top-ranked with respect to both predicted earnings and mean STEM intensity, while arts has the lowest joint ranking. More interesting, in our view, are "off diagonal" majors: Nursing and business (both STEM and non-STEM) are prominent among majors with relatively large estimated coefficients relative to their mean levels of STEM intensity, while environmental studies (both STEM and non-STEM), STEM agriculture and biological sciences are among the majors that are relatively more STEM-intensive than high-earning. Clearly, the predicted log-earnings associated with each major do not always line up with the major's mean level of STEM intensity.

6.2 Estimates based on specifications 1'-2'

We now turn to specifications 1' and 2', which augment the specifications just discussed by adding STEM intensity and its square along with total credits and its square. Table 4 reveals that the addition of *actual* STEM training to the log-earnings regression has a dramatic effect on the estimates. The estimated coefficient for the binary STEM indicator falls from 0.251 in specification 1 to an imprecisely-estimated -0.011 in specification 1', while the estimated marginal effect of a 10 percentage point increase in STEM intensity (per the bottom rows of table 4) is 0.073 relative to the STEM mean of 69.3 and 0.043 relative to the non-STEM mean of 19.8. (If we were to constrain the effect of STEM intensity to be linear we would miss this "diminishing return" and would instead obtain a uniform, estimated marginal effect of 0.050.) In short, specification 1' identifies a large estimated return to STEM intensity that completely supplants the large, positive STEM major premium identified by specification 1.

As seen in the specification 2' estimates in table 4, a more nuanced pattern emerges when we add credit variables along with major dummies. The estimated marginal effect associated with a 10 percentage point increase in STEM intensity falls relative to what is seen for specification 1', from 0.073 to 0.037 when we use the relatively high STEM mean as the starting point and from 0.043 to 0.012 when we use the non-STEM mean.[12] Moreover, the estimated coefficients for every STEM major except business and communications *decrease* in magnitude, and the estimated coefficients for all but the two most STEM-intensive non-STEM majors (environmental studies

[12]When we constrain the estimated effect of STEM intensity to be linear, the estimated marginal effect (untabulated) is 0.017 which, as with specification 1', is intermediate to the two estimated effects reported in table 4. Estimated major effects are robust to whether we use a linear or quadratic function for STEM intensity but, clearly, inferences about the independent effect of STEM intensity benefit from the more flexible functional form.

and medical sciences) *increase* in magnitude. While most of the changes in major-specific coefficient estimates between specifications 2 and 2' are about 0.03 in absolute value (and some are statistically indistinguishable from zero), the increments (in absolute value) are as large as 0.06-0.11 for engineering, engineering technology, health and rehabilitation sciences, public health, medical sciences, and biological sciences. As a result, estimated log-earnings gaps change substantially for some pairs of majors when STEM intensity is taken into account, but by relatively little for other pairs. For example, the estimated engineering-philosophy gap declines from 0.766 (specification 2) to 0.623 (specification 2'), while the estimated nursing-philosophy gap changes only slightly, from 0.672 to 0.667.

We add STEM intensity to specifications 1'-2' given the evidence presented in section 5 that neither a single STEM major indicator nor a more detailed set of major dummies can adequately capture cross-student variation in STEM intensity. The changes in estimated major effects when switching from specifications 1-2 to 1'-2' indicate that STEM intensity is skill-enhancing for the average STEM major and, more specifically, for every major for which we observe a decreased coefficient estimate when switching from specification 2 to 2'. For each of these relatively STEM intensive majors, it therefore stands to reason that the estimated major coefficients are larger when (skill-enhancing) STEM intensity is excluded than when it is included. For the remaining, less STEM intensive majors, all of which have a larger coefficient estimates when STEM intensity is *included*, we cannot rule out a skill-detracting effect of STEM intensity. We will refine these inferences in section 6.4 when we switch to specification 2'', which allows the effect of STEM intensity on log-earnings to be major-specific.

6.3 Robustness checks based on specification 2'

The preceding discussion motivates our first robustness test: Because STEM intensity appears to be positively associated with log-earnings for the more STEM-intensive majors, we replace our STEM intensity variable in specification 2' with three alternatives that measure the percentage of credits completed in STEM courses during the first year of college enrollment, the first two years, and the last year. Our concern is that STEM intensity among the more STEM-intensive majors is largely due to advanced courses taken to fulfill major requirements and that these courses are inherently more earnings-enhancing than the STEM courses taken by other majors.

To explore these concerns, we begin by computing the marginal effect of a 10 percentage point increase in STEM intensity in the first and, alternatively, last year of college.[13] The first estimated marginal effect is 0.031 relative to a starting point of 15.1%, which is the mean level of STEM intensity in year 1 among STEM majors; using "late" STEM intensity, the analogous estimated marginal effect and mean are 0.018 and 11.9%. This comparison indicates that "late" STEM courses are *not* more earnings-enhancing than "early" courses for STEM majors. Moreover, we find that for virtually all STEM-intensive majors, the estimated major coefficient is largest for specification 2 (which excludes any STEM measure), followed by "late" STEM intensity, year 1 STEM intensity, years 1-2 STEM intensity, and STEM intensity based on all years of enrollment (specification 2'). This pattern reveals that controls for "late" STEM intensity do the *worst* job of removing the "omitted variable bias" inherent in specification 2 and clearly indicates that the specification 2 vs. 2' comparison is *not* driven by advanced/late STEM courses. These experiments reveal that our preferred measure captures variation in STEM intensity better than the alternatives, and produce no evidence that the timing of STEM coursework is important to our findings.

Next, we conduct the first two robustness checks described in section 4 by focusing on the estimated marginal effect of a 10 percentage point increase in STEM intensity, using the mean level of STEM intensity among STEM majors as the starting point. As shown in table 4, this estimated marginal effect is 0.037 for specification 2'. When we augment specification 2' by adding a measure of each student's final grade point average (recorded when the bachelor's degree is awarded), this estimated effect is 0.034; when we instead confine the sample to 1,692,310 students who attend a single, four-year university, the estimated effect is 0.032. Both are ad hoc attempts to reduce any remaining variation in unobserved ability. The fact that the estimated coefficients for STEM intensity (and all other parameter estimates) are largely invariant to these adjustments suggests that our preferred approach does not suffer unduly from ability bias.

For the last robustness check based on specification 2', we confine the sample to 1,795,519 individuals who contribute earnings observations in each of the first four years after graduating from college. By focusing on college graduates who work continuously, do not leave Ohio, and are not working short-term jobs before enrolling in graduate school, we are more likely to be analyzing the earnings of career-oriented workers who attempt to find good matches between their

[13]Estimates reported in this section are not tabulated. Note that our final robustness check, in which we reestimate select specifications after switching to the more restrictive STEM definition, is discussed in the next section because it focuses on specification 2''.

college training and their occupation. When we make this adjustment to the sample, the estimated marginal effect associated with a 10 percentage point increase in STEM intensity increases from 0.037 (specification 2', table 4) to 0.049. It is reassuring to find that the estimated payoff to STEM intensity is somewhat higher for this subsample of "continuous" workers than for our broader sample of college graduates, but we do not believe the difference warrants an extended examination of this special group.

6.4 Estimates based on specification 2''

Estimates for specification 2''—which allows each major to have its own intercept (as in specification 2') and also its own quadratic STEM intensity slope—appear in appendix table A4. On one hand, this is our preferred specification because its flexibility is well-suited to capturing cross-major variation in STEM intensity. On the other hand, even with our large sample size we are unable to identify all 120 (40x3) major-specific parameters precisely, so the estimates are more informative about some majors than others.

In light of this concern, we focus our discussion on estimated marginal effects for the 11 majors listed in table 5. In choosing a subset of majors for comparison, we first select the four largest STEM majors (engineering, biological sciences, computer and information sciences, and engineering technology) and the four largest non-STEM majors (business, education, communications, and nursing) based on sample sizes shown in table 2. To add representation from the arts and humanities, we also include arts and languages, and we add the STEM health and rehabilitation sciences major as a STEM counterpart to nursing. In addition to being a popular major, engineering has the highest-ranked mean level of STEM intensity of any major, as well as the highest predicted log-earnings based on the rankings shown in table 4. Using these same rankings, biological sciences has the lowest predicted log-earnings among STEM fields, nursing has the highest predicted log-earnings among non-STEM majors, and arts has the lowest mean level of STEM intensity among all majors. Thus, our subsample of 11 majors includes a number of interesting extremes.[14]

[14]Languages is the only major chosen on the basis of the estimates reported below. English, which is the largest humanities major, is arguably the more obvious choice. For both majors, the estimated relationship between STEM intensity and log-earnings proves to be positive, but the estimated effect for languages is almost twice as large as for English, and larger than for any other precisely-estimated humanities major. Thus, we use languages for our comparisons to illustrate the "upper bound" of estimated effects among humanities majors.

In computing estimated marginal effects, we use major-specific 10th percentile, mean, and 90th percentile levels to represent low, medium, and high STEM intensity. These levels (reported in table 2) vary across majors; *e.g.,* the difference between the 10th and 90th percentile levels ranges from 15 to 21 for most of our 11 majors, but STEM health and rehabilitiation sciences (32.8) and computer and information sciences (48.5) are notable outliers. We prefer major-specific definitions of low, medium, and high levels of STEM intensity to uniform definitions that do not account for differences across majors in STEM intensity distributions. If we were to uniformly define a STEM intensity of 20% as "medium," for example, it would correspond to the mean for some majors but would be unusually low for others.

The first column of numbers in table 5 shows within-major estimated marginal effects computed by incrementing STEM intensity from the major-specific 10th percentile level to the major-specific 90th percentile level, and the underlying 10th and 90th percentile levels are shown graphically in figure 2. The estimated marginal effects are positive for all five STEM majors except biological sciences, which has a slightly negative, statistically insignificant estimate. Compared to the estimated effect of 0.051 for engineering, estimates for engineering technology (0.182), computer and information science (0.266) and health and rehabilitation sciences (0.162) are 3.6, 5.2 and 3.2 times higher, despite the fact that their 10th-to-90th percentile increments in STEM intensity are only 1.1, 2.8 and 1.9 times higher than engineering's. Clearly, the predicted payoff to a "low to high" increase in STEM intensity varies dramatically among STEM majors due to both cross-major variation in estimated STEM intensity slopes *and* differences in the spread of the STEM intensity distribution. Among non-STEM majors, the estimated marginal effects range from a low of -0.094 for arts to a high of 0.160 for languages. We find a positive "return" to STEM intensity for four of six non-STEM majors listed in table 5 (business, education, communications, and languages) and for 15 of the full set of 26 non-STEM majors (not tabulated), although the effects are 0.1 or higher for only a handful (*e.g.,* languages, public health, agriculture).

The finding that increased STEM intensity is associated with *increased* log-earnings for some majors and *decreased* log-earnings for others was masked by specification 2', which identifies a uniform STEM intensity gradient for all majors. We cannot definitively identify the cause of a negative "return" to STEM intensity identified for select majors, but we conjecture that it might reflect a lack of productivity-enhancing communication skills, particularly among STEM majors. Among both STEM and non-STEM majors, this negative effect might also be due to an unusual pattern of experimenting and/or major-switching that leads to an unproductive level of STEM intensity. A rigorous exploration of cross-major differences in the “return” to STEM intensity requires more elaborate log-earnings models that account for the fields in which STEM credits are completed, the timing of STEM coursework and, ideally, the occupations in which each individual is employed; such extensions are beyond the scope of this paper.

The remaining columns in table 5 report estimated log-earnings gaps *between* pairs of majors. Specifically, we compute the difference in predicted log-earnings between engineering and each of the remaining 10 majors, holding all covariates except major and STEM intensity constant across majors. We first report estimated log-earnings gaps based on specification 2, which ignores variation in STEM intensity. These estimates, which we discussed in section 6.1, replicate evidence on cross-major log-earnings gaps reported elsewhere (Altonji 2016; Chevalier 2011; Hamermesh and Donald 2008; Light and Schreiner 2019; Loury and Garman 1995) and serve as a benchmark for the remaining estimates.

The next column of between-major estimates in table 5 are based on specification 2', which constrains the quadratic STEM intensity slope to be uniform across majors. We use the major-specific mean level of STEM intensity to compute predicted log-earnings for each major. Each predicted log-earnings gap based on specification 2' is slightly larger than the corresponding gap based on specification 2—by about 0.006 log points for most majors, but by as much as 0.01 for education and 0.03 for biological sciences. These small differences between the estimates for specifications 2 and 2' are due to differences in major-specific mean levels of STEM intensity and changes in major-specific coefficient estimates discussed earlier.

The remaining between-major estimates in table 5 are based on specification 2'', and are also shown graphically in figure 3. For the first specification 2'' estimates we continue to use major-specific mean levels of STEM intensity for direct comparison with estimates based on specification 2'. Focusing on this 2' vs. 2'' comparison, the estimated gaps decrease for three majors (nursing, computer and information science, and biological sciences) and increase for the remaining seven majors when we introduce major-specific STEM intensity slopes. Although differences between specification 2' and specification 2'' estimates are generally small in magnitude (with a maximum of 0.04 for arts), some of these changes are nontrivial in percentage terms. In particular, the predicted gap in log-earnings increases by 5% for both arts and education, 6% for business, 18% for engineering technology, and 20% for health and rehabilitation sciences. Clearly, the introduction of major-specific “returns” to STEM intensity changes our inferences about the log-earnings premiums associated with select majors, independent of any assumed changes in the level of STEM intensity.

In computing estimates for the final two columns in table 5, we introduce substantial shifts in the assumed levels of STEM intensity for each major. First, we assume the engineering major has a high level of STEM intensity (equal to the 90th percentile among engineering majors) while the comparison major has a low (10th percentile) level; we then switch from this “high-low” comparison to a “low-high” comparison in which engineering is assigned the 10th percentile level.[15] The estimated log-earnings gap between engineering and every other major except arts increases when we assign the engineering major a high level of STEM intensity and the comparison major a low level. In some cases, the estimated gap more than doubles; *e.g.,* the estimate for engineering vs. engineering technology increases from 0.099 when we use specification 2" computed at the mean to 0.208 when we use specification 2" with a “high-low” comparison. Because engineering technology majors receive such a large return to STEM intensity (per the “within” estimate in table 5), the estimated log-earnings gap increases dramatically when we “penalize” them with a low level while simultaneously increasing the level for engineering. For the same reason, estimated log-earnings gaps between engineering and both computer and information science and health and rehabilitation sciences more than double or come close to doubling when we assign “high-low” levels of STEM intensity. Estimates for other majors also change, but not nearly as much as for the three STEM majors that benefit the most in the labor market from high levels of STEM intensity.

When we switch from “high-low” to “low-high” levels of STEM intensity, the estimated log-earnings gaps are -0.025 for engineering technology, -0.037 for computer and information science, and a statistically insignificant 0.022 for health and rehabilitation sciences, indicating that highly STEM-intensive workers with these degrees can expect to earn roughly the same as engineering majors with low levels of STEM intensity. Relative to any preceding “between” estimates, the predicted gap also decreases substantially for business, education, communications, and especially language majors when we assign “low-high” levels of STEM intensity. For language majors, the

[15]Differences between the “high-low” and “low-high” estimates are systematically related to difference between the two majors’ “within” estimates. Using engineering vs. engineering technology for illustration, 0.208 – 0.051 – 0.105 = -0.025.

predicted gap declines from 0.723 when we assume mean levels of STEM intensity to 0.590 when we assign "low-high" levels. Despite being a humanities field, language majors receive a large expected payoff to STEM intensity and can substantially reduce their (predicted) earnings disadvantage by attaining the highest levels of STEM training seen among their major.

For our final robustness test we reproduce table 5 after switching to the more restrictive STEM definition discussed in section 3.3; we drop health and rehabilitation sciences from the comparison due to it no longer being a STEM major. The revised estimates, shown in table 6, can be easily summarized: Aside from the within-major, estimated marginal effects of STEM intensity for business and education, which decrease from 0.052 and 0.024, respectively (as reported in table 5) to an imprecisely estimated -0.01 and 0.01, no other estimate in table 5 changes by more than a trivial amount. This finding is unsurprising given the comparison of summary statistics (section 5) based on our two STEM definitions. Unless we focus specifically on psychology or a subset of the "split" majors, our estimates are largely insensitive to which STEM definition is used.

7. Concluding comments

In this study, we use a large sample of bachelor's degree recipients drawn from Ohio administrative records to explore relationships between college major, STEM intensity (the percentage of total college credits completed in STEM courses), and post-college earnings. While other analysts have estimated log-earnings models with binary STEM indicators or an array of college major dummies among the controls, our point of departure is to use both strategies (with 41 distinct majors, 15 of which are STEM) *plus* controls for total credits and STEM intensity. Our preferred specification allows each major to have its own intercept and nonlinear STEM intensity slope.

We find that STEM intensity varies substantially within and between majors, for both STEM *and* non-STEM majors. Many college students have relatively low (high) levels of STEM intensity despite earning their bachelor's degree in a STEM (non-STEM) field. As a result, many non-STEM majors complete a higher percentage of STEM credits than do select STEM majors. Among our most striking findings is that a philosophy major with a relatively high level of STEM intensity (equal to the 90th percentile among philosophy majors) is *more* STEM-intensive than a computer science major with a low (10th percentile) level of STEM intensity.

Our best evidence of the role of STEM intensity comes from our "fully flexible" log-earning model. Focusing on estimates for a subset of 11 popular majors, we find substantial variation among majors in the estimated log-earnings effect of a 10 percentage point increase in STEM intensity (relative to the major-specific mean), ranging from zero for biological sciences to 0.27 for computer and information science among STEM majors, and from -0.09 for arts to 0.16 for languages among non-STEM majors. As a result of this heterogeneity, predicted log-earnings gaps between pairs of majors often change significantly as the assumed level of STEM intensity varies. For example, the predicted log-earnings of a computer science major lag behind those of an engineering major by 0.12 if both are assumed to have mean levels of STEM intensity for their major, but exceed the engineering major's log-earnings by 0.04 if we assume a high (90^{th} percentile) level of STEM intensity for computer and information science and a low (10^{th} percentile) level for engineering. The predicted log-earnings of a languages major never overtake those of an engineering major, but the gap closes from 0.72 to 0.59 when the assumed levels of STEM intensity switch from major-specific means to a high (90^{th} percentile) level for languages and a low (10^{th} percentile) level for engineering.

Based on these and other findings, we conclude that the answer posed in the title is "both": College major is an important predictor of post-college earnings, but students' levels of STEM intensity are predicted to have large, positive payoffs in the labor market for many majors and slightly negative payoffs for others. While STEM majors can often (but not always) expect to benefit in the labor market by being relatively STEM-intensive in their college coursework, so can many non-STEM majors. In light of this evidence, we believe policy initiatives focused on drawing more students into STEM majors might also emphasize the potential value of STEM coursework for non-STEM majors. At the same time, we acknowledge that any policy recommendation based on our current findings is highly tentative. While our analysis rigorously demonstrates that major is not a suitable proxy for STEM intensity and that both measures have important, independent effects on post-college earnings, it must be extended in multiple dimensions before we can make precise policy prescriptions.

We conclude by noting four ways in which our analysis might be extended. First, to assess how and when non-STEM majors benefit from pursuing additional STEM coursework, we could explore the interplay between STEM intensity and major intensity, where the latter is defined as the percent of completed credits within the major as in Light and Schreiner (2019) and Light and Wertz (2022). This extension could be used to explore the tradeoffs that non-STEM majors face between "teching up" with additional STEM courses, gaining additional within-major specialization, and branching out to related non-STEM fields. Second, in a related vein, it would be worth replicating the current analysis using less restrictive definitions of STEM to determine how labor market payoffs to "soft" and "hard" STEM credits differ across majors. We chose to use the Department of Homeland Security STEM definition and a *more* restrictive definition because we believe policy initiatives designed to produce more STEM degree-holders typically have these definitions in mind, but there is much more to be learned about major-specific curriculum choices and their labor market benefits. Both the first and second extension would require more elaborate specifications of the log-earnings model to establish how major-specific "returns" to STEM intensity vary by the field and/or rigor of the STEM (and non-STEM) courses. Third, if data are available, it would be useful to identify post-college occupations and learn which occupational choices allow non-STEM majors to receive the largest rewards to their STEM coursework. Fourth, given that gender differences in STEM training are often shown to be a key determinant of gender differences in labor market outcomes, it would be of interest to apply our data and analytic strategy to a detailed gender comparison.

Declaration: This study's primary data source, the Ohio Longitudinal Data Archive, is a project of the Ohio Education Research Center (oerc.osu.edu) and provides researchers with centralized access to administrative data. The OLDA is managed by CHRR at Ohio State University (chrr.osu.edu) in collaboration with Ohio's state workforce and education agencies (olda.ohio.gov), with those agencies providing oversight and funding. The findings, conclusions, views, and opinions presented in this paper are those of the authors and do not necessarily represent the views of the U.S. Department of the Treasury or the United States government.

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Data Appendix

Sample selection: Details corresponding to the discussion in section 3.2 are in table A1.

Defining college majors, STEM majors, and STEM intensity: As discussed in section 3.3, we begin by aggregating the 428 six-digit CIP codes associated with each sample member's major to two-digit CIP codes, although for the nine two-digit codes that include both STEM and non-STEM six-digit majors (focusing only on six-digit majors associated with our sample members) we instead aggregate to both STEM and non-STEM versions of the two-digit category. The CIP taxonomy includes 18 two-digit codes corresponding to basic skills and vocational fields, none of which appear in our data because bachelor's degrees are not awarded in these fields. We combine the two-digit fields communications and communications technology into a single field because they are similar and both contain very few sample members. We eliminate the two-digit fields multi/interdisciplinary studies and science technologies after assigning each of their six-digit majors to another category (*e.g.*, medieval and renaiisance studies is assigned to history); no reassigned six-digit category contains more than a handful of sample members. Finally, as noted in section 3.3, we disaggregate the two-digit major encompassing a range of health fields into five majors (speech and hearing; medical sciences; public health, nursing; and health and rehabilitation sciences).

Tables A2 and A3 summarize the mapping between CIP codes and majors described in section 3.3.

Additional variables used for log-earnings models: To construct the dependent variable, we sum earnings and weeks worked across all employers for each calendar quarter in the post-college earnings window (starting with the first calendar quarter following the quarter in which the bachelor's degree is awarded, and ending with the third quarter of 2019 or, for individuals who reenroll, with the last nonenrolled quarter). Total, quarterly weeks worked is capped at 13. We adjust this process for a small number of quarterly observations where UI records show positive earnings but zero (or missing) weeks worked for a given employer within a given quarter. In those cases, we either (a) drop the employer-specific record if 11 or more weeks are worked for other employers in the same quarter; (b) interpolate weeks worked based on adjacent quarters for the same employer; or (c) drop the quarterly observation if neither (a) nor (b) is feasible. After incorporating this work-around for missing weeks information, we deflate quarterly earnings by the quarterly CPI-U for the Midwest and use a logarithmic transformation to obtain our dependent variable.

Table 1 reports means and standard deviations for the dependent variable and select regressors used in the log-earnings models.

Summary statistics based on alternative definition of STEM: As discussed in section 3.3, we replicate portions of our analysis using an alternative, more restrictive, definition of STEM. Specifically, we now consider the nine "split" fields listed in tables 2 and A3 to be wholly non-STEM, and we reassign six-digit CIP codes designated as STEM by DHS to be non-STEM *unless* they belong to engineering, engineering technology, physical sciences, biological sciences, mathematics/statistics, or computer/information science (the only STEM fields under our stricter definition).

For the most part, this reassignment entails moving six-digit CIP codes (and credits taken in those fields) in the nine, formerly-split fields (agriculture, health/rehabilitation sciences, *etc*.) from STEM to non-STEM. However, credits in "pure" non-STEM fields (most notably, psychology) are also moved from STEM to non-STEM if (a) they are designated as STEM by DHS; but (b) no sample member majors in those fields. To illustrate, DHS designates courses coded as cognitive psychology, experimental psychology, psychometrics, and other psychology fields to be STEM. None of our sample member major in these subfields of psychology, so psychology is not among our split fields. However, students in various majors complete credits in these psychology courses and, more generally, in many of the courses that are reassigned from STEM to non-STEM under our more restrictive STEM definition. As a result, STEM intensity changes slightly for most sample members, and often significantly for those majoring in the STEM version of a formerly-split field. For example, students majoring in plant science (agriculture) and management science (business) tend to complete many credits in those sub-fields, and thus undergo a significant drop in STEM intensity when those fields are reassigned from STEM to non-STEM.

Table 3 reports major-specific mean STEM intensity (and the difference between this mean and the analogous mean in table 2) based on the new definition of STEM.

Table 1: Summary Statistics for Dependent Variable and Select Regressors
Used in Log-Earnings Models

	Full Sample		STEM		Non-STEM	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Dependent variable						
Log-earnings[a]	5.78	.68	6.04	.64	5.72	.68
Select regressors						
Total credits	130.06	18.04	130.83	19.29	129.87	17.72
Percent of total credits in STEM	29.50	23.13	69.33	14.74	19.77	11.42
1 if male	.45		.69		.39	
1 if Hispanic	.01		.01		.01	
1 if White (omitted group)	.83		.83		.83	
Black	.07		.04		.07	
Asian	.02		.04		.02	
unknown/other race	.07		.07		.07	
1st term grade point average	3.08	.71	3.14	.67	3.06	.72
1st term percent of credits completed	.95	.12	.97	.11	.95	.12
1 if 4+ remedial credits in 1st term	.11		.11		.12	
1 if no transfer (omitted group)	.82		.86		.81	
one 2-year to 4-year transfer	.10		.08		.10	
one 4-year to 4-year transfer	.06		.05		.07	
multiple transfers	.02		.01		.02	
1 if attend multiple campuses in term	.23		.17		.24	
1 if earn associate degree	.09		.09		.09	
Age at receipt of bachelor's degree	23.04	1.12	23.15	1.09	23.01	1.12
Post-college experience (X)[a]	2.77	2.10	2.69	2.08	2.78	2.11
Number of observations	2,717,057		498,311		2,218,746	
Number of individuals	209,137		41,052		168,085	

[a]Time-varying variables; for these variables, summary statistics are computed for the time-varying sample of earnings observations (*e.g.,* 2,717,057 observations for the full sample). For all other (time-constant) variables, the "one observation per person" sample is used (*e.g.,* 209,137 for the full sample).

Note: Major-specific summary statistics are in table 2. Each specification of the log-earning model also controls for experience squared, graduation year fixed effects, and college fixed effects.

Table 2: Summary Statistics for STEM Intensity by Major
(STEM and Non-STEM majors are ranked separately by mean STEM intensity)

	Percent of Total Credits in STEM (STEM Intensity)					Pct. of STEM Credits Earned in Year 1		
	Mean	S.D.	p10	p90	p90-p10	Mean	S.D.	N
STEM majors:								
Engineering	79.1	8.1	69.8	87.3	17.5	23.0	8.4	17,274
Health/Rehab. Sciences[a]	72.2	12.7	52.9	85.6	32.8	19.1	9.3	387
Engineering Technology	71.4	8.5	60.7	80.4	19.8	16.8	7.4	2,830
Physical Sciences	66.7	9.2	53.8	77.7	23.9	20.4	9.3	2,273
Medical Sciences[a]	66.0	13.9	48.4	81.6	33.2	29.4	9.2	274
Biological Sciences	65.8	8.5	54.7	75.9	21.2	21.7	9.0	9,613
Public Health[a]	59.9	11.8	47.9	78.3	30.4	15.7	7.0	81
Agriculture[a]	59.3	12.1	44.0	76.7	32.6	19.8	9.5	1,178
Mathematics/Statistics	57.1	10.6	43.3	71.2	27.9	21.6	9.7	1,288
Environmental Studies[a]	55.6	12.0	38.9	70.5	31.6	21.0	10.9	903
Computer/Info. Sciences	55.6	17.5	28.8	77.3	48.5	20.2	10.7	3,907
Social Sciences[a]	44.5	11.3	30.3	61.0	30.8	23.5	11.8	70
Business[a]	36.6	13.5	17.1	53.3	36.2	32.8	18.3	513
Criminal Justice[a]	35.7	20.7	14.3	63.0	48.7	23.9	12.6	98
Communications[a]	17.5	15.8	2.4	42.1	39.7	30.7	29.1	363
All 15 STEM majors	69.3	14.7	50.6	84.8	34.1	21.9	9.8	41,052
Non-STEM majors:								
Environmental Studies[a]	53.2	10.7	38.6	66.9	28.3	19.7	9.7	424
Medical Sciences[a]	44.7	21.2	14.8	70.9	56.1	28.7	16.0	915
Agriculture[a]	41.1	14.5	22.4	61.5	39.1	24.9	13.9	1,280
Psychology	33.2	12.1	18.2	49.2	31.1	22.6	14.2	10,940
Public Health[a]	28.4	12.9	15.1	46.2	31.1	27.3	16.7	1,186
Health/Rehab. Sciences[a]	24.2	11.1	11.1	38.9	27.7	37.2	20.4	6,383
Nursing	22.3	8.2	14.8	30.3	15.5	53.8	23.8	13,047
Human Sciences	21.6	11.9	7.8	37.7	30.0	34.0	21.4	6,890
Multidiscip. Humanities	21.1	15.0	7.4	44.2	36.8	29.7	22.2	2,802
Business[a]	20.6	8.3	10.9	31.4	20.5	37.5	19.6	40,019
Sports/Recreation	20.6	11.2	8.5	37.2	28.7	35.9	21.3	6,060
Speech/Hearing	19.2	7.2	10.3	28.9	18.6	39.0	20.6	1,797
Social Sciences[a]	18.9	10.3	8.7	32.8	24.1	34.8	22.4	12,074
Area/Ethnic/Cult. Studies	18.6	10.7	8.5	32.8	24.4	33.5	22.1	876
Languages	17.8	11.8	7.5	33.3	25.8	37.7	24.2	2,051
Architecture	17.6	10.8	5.0	32.9	27.9	37.4	27.7	1,574
Education	17.1	12.0	6.0	35.7	29.6	39.7	25.7	19,412
Philosophy	16.9	10.1	7.2	31.3	24.1	36.2	24.8	504
Public Administration	15.2	5.6	8.8	22.5	13.7	36.6	22.9	3,120
History	15.0	7.0	8.1	23.7	15.7	38.1	24.1	2,146
Criminal Justice[a]	14.4	6.7	7.4	23.0	15.5	33.3	23.0	3,853

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Table 2: Continued

	Percent of Total Credits in STEM (STEM Intensity)					Pct. of STEM Credits Earned in Year 1		
	Mean	S.D.	p10	p90	p90-p10	Mean	S.D.	N
English	13.9	6.6	7.3	21.7	14.5	39.1	24.8	5,383
Communications[a]	13.8	7.3	5.7	23.2	17.5	37.6	26.0	15,000
Military Studies	11.8	4.5	7.2	18.3	11.1	37.0	26.0	37
Legal Studies	11.4	5.8	5.3	18.0	12.7	40.4	28.1	312
Arts	10.1	6.5	2.9	18.1	15.2	35.4	29.2	10,000
All 26 non-STEM majors	19.8	11.4	7.9	35.0	27.1	37.1	23.5	168,085

[a] "Split" majors with both STEM and non-STEM versions; see text and data appendix tables A2-3.

Table 3: Mean STEM Intensity by Major, Based on Alternative Definition of STEM (compare to table 2)

	Mean	Δ[b]	N
STEM majors:			
Engineering	78.3	0.8	17,274
Engineering Technology	70.9	0.5	2,830
Physical Sciences	64.8	1.9	2,273
Biological Sciences	62.8	3.0	9,613
Mathematics/Statistics	55.4	1.7	1,288
Computer/Info. Sciences	53.3	2.3	3,907
All 6 STEM majors	69.5	—	37,185
Non-STEM majors:			
Environmental Studies[a]	37.2	16.0	1,327
Medical Sciences[a]	35.5	9.2	1,189
Agriculture[a]	33.7	14.5	2,458
Psychology	17.0	16.2	10,940
Public Health[a]	24.3	4.1	1,267
Health/Rehab. Sciences[a]	23.2	1.0	6,770
Nursing	20.4	1.9	13,047
Human Sciences	18.8	2.8	6,890
Multidiscip. Humanities	18.3	2.8	2,802
Business[a]	15.3	5.3	40,532
Sports/Recreation	18.4	2.2	6,060
Speech/Hearing	15.7	3.5	1,797
Social Sciences[a]	15.9	3.0	12,144
Area/Ethnic/Cult. Studies	15.9	2.7	876
Languages	15.8	2.0	2,051
Architecture	15.4	2.2	1,574
Education	15.4	1.7	19,412
Philosophy	14.6	2.3	504
Public Administration	12.9	2.3	3,120
History	13.5	2.4	2,146
Criminal Justice[a]	11.9	2.5	3,951
English	12.3	1.6	5,383
Communications[a]	11.3	2.5	15,363
Military Studies	10.5	1.3	37
Legal Studies	9.8	1.6	312
Arts	9.1	1.0	10,000
All 26 non-STEM majors	16.1	3.7	171,952

[a]Majors that were split between STEM and non-STEM in table 2 and are now combined into a single, non-STEM field.
[b]Difference between the means in table 2 and this table. For non-STEM majors, the non-STEM mean from table 2 is used.
Note: Majors are listed in the same order as in table 2.

Table 4: Estimated OLS Coefficients for Select Regressors in Post-College Log-Earnings Models

Variable	STEM Intensity Rank[a]	Specification 1 Coef.	1 S.E.	2 Coef.	2 S.E.	1' Coef.	1' S.E.	2' Coef.	2' S.E.
1 if STEM major		.251	.003			-.011†	.007		
STEM intensity x10						.028	.000	-.000†	.000
STEM intensity squared x 100						.003	.000	.002	.000
Total credits x 10						-.004†	.001	-.019	.001
Total credits squared x 100						.000†	.000	.001	.000
Major[b]									
[1] **Engineering**	1			.316	.012			.206	.014
[2] **Engineering Technology**	3			.231	.014			.145	.015
[3] Nursing	21			.222	.013			.250	.013
[4] **Computer/Information Sciences**	11			.199	.014			.162	.014
[5] **STEM Health/Rehab. Sciences**	2			.195	.023			.104	.023
[6] **STEM Public Health**	7			.114	.041			.053†	.041
[7] **STEM Business**	16			.094	.023			.095	.023
[8] Business	24			.030	.013			.059	.013
[9] Agriculture (omitted group)	15			—				—	
[10] **Mathematics/Statistics**	9			-.012†	.019			-.051	.019
[11] **STEM Medical Sciences**	5			-.086	.023			-.150	.032
[12] Health/Rehab. Sciences	20			-.134	.014			-.109	.014
[13] **STEM Criminal Justice**	17			-.142	.044			-.155	.044
[14] **Physical Sciences**	4			-.151	.017			-.219	.018
[15] **STEM Social Sciences**	14			-.173	.069			-.178	.068
[16] Architecture	30			-.205	.017			-.174	.017
[17] Criminal Justice	36			-.207	.015			-.172	.015
[18] Education	32			-.212	.013			-.184	.013
[19] Medical Sciences	13			-.216	.023			-.221	.023
[20] **STEM Communications**	31			-.224	.034			-.195	.034
[21] Legal Studies	40			-.236	.027			-.199	.027
[22] **STEM Agriculture**	8			-.247	.020			-.284	.020

Continued on next page.

Table 4: Continued

Variable	STEM Intensity Rank[a]	Specification 1 Coef.	1 S.E.	2 Coef.	2 S.E.	1' Coef.	1' S.E.	2' Coef.	2' S.E.
[23] Public Administration	34			-.247	.015			-.211	.015
[24] Communications	38			-.256	.013			-.221	.013
[25] Public Health	19			-.262	.020			-.245	.020
[26] Social Sciences	27			-.273	.013			-.243	.013
[27] Human Sciences	22			-.274	.014			-.247	.014
[28] **STEM Environmental Studies**	10			-.287	.020			-.324	.020
[29] **Biological Sciences**	6			-.307	.014			-.371	.015
[30] Military Studies	39			-.311	.091			-.280	.091
[31] Multidisciplinary Humanities	23			-.328	.017			-.304	.017
[32] Sports/Recreation	25			-.343	.015			-.314	.015
[33] Area/Ethnic/Culture Studies	28			-.362	.023			-.332	.023
[34] Psychology	18			-.376	.013			-.362	.013
[35] Speech/Hearing	26			-.388	.019			-.358	.019
[36] English	37			-.389	.015			-.355	.015
[37] Languages	29			-.396	.018			-.366	.018
[38] Environmental Studies	12			-.401	.027			-.431	.027
[39] Arts	41			-.420	.014			-.383	.014
[40] History	35			-.436	.017			-.401	.017
[41] Philosophy	33			-.450	.029			-.417	.029
Estimated effect 10 ppt increase in STEM intensity:									
starting at mean level for STEM majors		—		—		.073		.037	
starting at mean level for non-STEM majors		—		—		.043		.012	

[a]Rank across all 41 majors of the major-specific mean level of STEM intensity shown in table 2.
[b]STEM majors are identified with bold-face. Majors are ranked by the magnitude of the estimated coefficient in specification 2, for comparison with the STEM-intensity rankings described in note a.
[†]Estimated coefficient is *not* statistically distinguishable from zero at a significance level of 0.05 or lower.
Note: All specifications include each variable tabulated in or summarized in the note to table 1. The sample for all specifications has 2,717,057 earnings observations for 209,137 individuals. Standard errors account for nonindependence of residuals among multiple earnings observations for each individual.

Table 5: Predicted Log-Earnings Gap Within and Between Select Majors, Based on Alternative Model Specification and Alternative Assumed STEM Intensities

	Within[b]	Between Engineering and Select Major[c]				
	Specification	Specification				
Major[a]	2"	2	2'	2"	2"	2"
Engineering	.051	—	—	—	—	—
	(.008)					
Engineering Technology	.182	.084	.090	.099	.208	-.025
	(.018)	(.008)	(.008)	(.009)	(.014)	(.011)
Nursing	-.046	.093	.099	.084	.105	.100
	(.011)	(.005)	(.005)	(.006)	(.008)	(.009)
Computer and Info. Science	.266	.117	.123	.120	.280	-.037
	(.021)	(.008)	(.008)	(.010)	(.017)	(.014)
STEM Health/Rehab. Sciences	.162	.121	.128	.145	.235	.022†
	(.045)	(.020)	(.019)	(.026)	(.032)	(.027)
Business	.052	.286	.292	.304	.337	.234
	(.007)	(.004)	(.004)	(.004)	(.007)	(.006)
Education	.024	.528	.538	.555	.564	.489
	(.010)	(.005)	(.005)	(.006)	(.008)	(.008)
Communications	.049	.571	.578	.582	.627	.527
	(.012)	(.005)	(.005)	(.006)	(.009)	(.009)
Biological Sciences	-.019†	.623	.625	.631	.646	.614
	(.018)	(.008)	(.008)	(.009)	(.013)	(.013)
Languages	.160	.712	.720	.723	.804	.590
	(.040)	(.014)	(.014)	(.016)	(.022)	(.026)
Arts	-.094	.736	.742	.776	.708	.751
	(.019)	(.007)	(.007)	(.008)	(.013)	(.011)
Level of STEM intensity						
for **engineering**		—	Mean	Mean	p90	p10
for comparison major		—	Mean	Mean	p10	p90

[a]STEM majors are identified with bold-face.

[b]Estimated increment in log-earnings (based on specification 2") for a worker with the given major whose STEM intensity increases from the major-specific 10th percentile (p10) to 90th percentile (p90) level.

[c]Estimated log-earnings gap between engineering and the given major based on specifications 2, 2' and 2". For specifications 2' and 2", workers are assigned their major-specific mean, p10, or p90 level of STEM intensity; all other regressors are held constant across majors.

†Estimated log-earnings gap is *not* statistically distinguishable from zero at a significance level of 0.05 or lower.

Note: Standard errors are in parentheses. The within and between estimates for specification 2″ are shown graphically in figures 2 and 3, respectively.

Table 6: Predicted Log-Earnings Gap Based on Alternative Definition of STEM
(compare to table 5)

	Within[b]	Between Engineering and Select Major[c]				
	Specification	Specification				
Major[a]	2''	2	2'	2''	2''	2''
Engineering	.051	—	—	—	—	—
	(.008)					
Engineering Technology	.182	.084	.089	.098	.208	-.025
	(.018)	(.008)	(.008)	(.009)	(.014)	(.011)
Nursing	-.051	.091	.096	.080	.098	.099
	(.011)	(.005)	(.005)	(.006)	(.008)	(.009)
Computer and Info. Science	.260	.117	.126	.123	.273	-.037
	(.021)	(.008)	(.008)	(.010)	(.017)	(.014)
Business	-.006†	.284	.290	.303	.306	.262
	(.007)	(.004)	(.004)	(.004)	(.006)	(.006)
Education	.013†	.526	.537	.551	.556	.493
	(.010)	(.005)	(.005)	(.006)	(.008)	(.008)
Communications	.061	.569	.576	.579	.630	.519
	(.012)	(.005)	(.005)	(.006)	(.009)	(.008)
Biological Sciences	.024†	.621	.626	.626	.664	.590
	(.018)	(.008)	(.008)	(.008)	(.012)	(.013)
Languages	.110	.710	.720	.729	.777	.617
	(.040)	(.014)	(.013)	(.016)	(.022)	(.027)
Arts	-.100	.735	.741	.771	.704	.753
	(.018)	(.007)	(.007)	(.007)	(.013)	(.011)
Level of STEM intensity						
for **engineering**		—	Mean	Mean	p90	p10
for comparison major		—	Mean	Mean	p10	p90

[abc]See notes to table 5.

†Estimated log-earnings gap is *not* statistically distinguishable from zero at a significance level of 0.05 or lower.

Note: Standard errors are in parentheses. This table replicates table 5 after switching to the more restrictive definition of STEM described in section 3.3. Health and Rehabilitation Sciences is dropped from this table because it is eliminated as a STEM major.

Table A1: Sample Selection Criteria

Criterion	No. of students
Earn bachelor's degree between 2010 and 2019[a]	426,559
Earn degree before age 20 or after age 26[b]	-75,385
	351,174
Earn <108 total credits due to missing information[c]	-43,779
	307,395
>8% of credits in basic skills and other nonacademic fields	-6,993
	300,402
Major miscoded as a field not offered at the insitition.	-352
	300,050
No post-college earnings[d]	-90,913
Final sample of recent bachelor's degree recipients	209,137

[a]The sample includes students who attended two-year institutions, multiple four-year universities, and/or multiple campuses prior to earning their bachelor's degree. Our earnings models control for these factors.

[b]Ages are approximate because our data include year of birth but not month or day of birth.

[c]Incomplete records arise when transfer credits are omitted from HEI records made available to researchers. We use a cutoff of 108, which is 90% of the 120 credits typically required for a bachelor's degree at Ohio's public institutions, to exclude highly-incomplete transcripts; because we measure STEM credits as a percentage of total credits, "slightly" incomplete transcripts are unlikely to pose a problem.

[d]UI record contains at least one quarterly earnings observation between the first calendar quarter *after* the quarter in which the degree is earned and the end of the panel (the third quarter of 2019); if the individual reenrolls, the panel ends with the last quarter *prior* to reenrollment.

Table A2: CIP Codes for Majors That are Entirely STEM or Non-STEM

Major[a]	2-digit CIP
Architecture	04
Area/Ethnic/Culture Studies (includes Gender/Group Studies)	05
Computer/Information Sciences	11
Education	13
Engineering	14
Engineering Technology	15
Language	16
Human Sciences	19
Legal Studies	22
English	23
Multidisciplinary Humanities	24
Biological Sciences (includes Biology Technician (41.01))	26
Mathematics/Statistics	27
Military Studies	29
Sports/Recreation	31
Philosophy	38
Physical Sciences (includes Phys Sci Technology (41.03))	40
Psychology	42
Public Administration	44
History (45.08 only)	45
Arts	50
Speech/Hearing (51.02 only)	51
Nursing (51.16, 51.38, 51.99 only)	51

[a]STEM majors are identified with bold-face.

Note: The master list of two-digit CIP codes associated with a few of these majors (*e.g.,* education, psychology) include 6-digit STEM fields, none of which were recorded for our sample members; therefore, these majors are entirely non-STEM rather than split between STEM and non-STEM. In addition to what is tabulated, we assigned five interdisciplinary fields within CIP code 30 (*e.g.,* peace studies, medieval studies) to military, history, or an alternative major. Table A3 contains a similar summary for majors that span both STEM and non-STEM fields.

Table A3: CIP Codes for Majors that Are Designated Both STEM and Non-STEM

Major	Designation	CIP codes[a]	Description
Agriculture	STEM	01.09.xx	Animal Science
		01.10.01	Food Science
		01.11.xx	Plant Science
	Non-STEM	Other 01	Agri. Operations, Agri. Economics, etc.
Environ. Studies/ Natural Resources	STEM	03.01.xx	Environmental Studies
		03.02.05	Water/Wetlands/Marine Science
		03.05.09	Wood Science
	Non-STEM	Other 03.02	Natural Resources Management/Policy
Communications (includes Technology)	STEM	09.07.02	Digital Communication and Media
	Non-STEM	Other 09-10	Public Relations, Journalism, etc.
Social Sciences	STEM	45.03.01	Archaeology
		45.06.03	Econometrics
		45.07.02	Geographic Information Science
	Non-STEM	Other 45	Political Science, Sociology, etc.
Criminal Justice	STEM	43.01.06	Forensic Sciences
	Non-STEM	Other 43	Law Enforcement, Fire Protection, etc.
Public Health	STEM	51.22.02	Environmental Health
	Non-STEM	51.15	Counseling
		Other 52.22	Community Health, Occup. Health, etc.
Medical Sciences	STEM	51.20.xx	Pharmaceutics
		51.22.05	Health/Medical Physics
	Non-STEM	51.11.xx	Pre-Dentristy, Pre-Medicine, etc.
		51.20.01	Pharmacy
Health/Rehabilitation Sciences	STEM	51.10.05	Clinical Laboratory Science/Technology
	Non-STEM	Other 51	Health management, Dietetics, etc.
Business	STEM	52.13.xx	Management Science, Actuarial Science
	Non-STEM	Other 52	Accounting, Marketing, Finance, etc.

[a]The xx placeholder refers to multiple six-digit codes within the given four-digit code.
Note: Table A2 contains a similar summary for majors that are entirely STEM or non-STEM.

Table A4: Estimated OLS Coefficients for Select Regressors in Specification 2"

Variable	Direct Effect[a]		Interaction with: STEM Intensity[a]		Interaction with: STEM Intensity^2 [a]	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
STEM intensity x 10	-.064†	.044	—		—	
STEM intensity^2 x 100	.016	.005	—		—	
Total credits x 10	-.015	.005	—		—	
Total credits squared x 100	.001	.000	—		—	
Major[b]						
[1] **Engineering**	-.491	.136	.025	.005	-.026	.005
[2] **Engineering Technology**	-.093†	.273	.007†	.009	-.009†	.007
[3] Nursing	.104†	.100	.024	.005	-.060	.008
[4] **Computer/Information Sciences**	-.062†	.116	.011	.005	-.015	.006
[5] **STEM Health/Rehab. Sciences**	.245†	.344	-.000†	.011	-.007†	.009
[6] **STEM Public Health**	.722†	.993	-.015†	.031	.003†	.025
[7] **STEM Business**	-.038†	.144	.010†	.008	-.014†	.010
[8] Business	.025†	.094	.006†	.005	-.008†	.006
[9] Agriculture omitted group)	—		—		—	
[10] **Mathematics/Statistics**	-.520†	.381	.021†	.014	-.025	.012
[11] **STEM Medical Sciences**	-.543†	.555	.025†	.018	-.032	.015
[12] Health/Rehab. Sciences	-.230	.098	.019	.005	-.045	.007
[13] **STEM Criminal Justice**	.079†	.237	-.013	.008	.012†	.022
[14] **Physical Sciences**	-.565†	.448	.018†	.014	-.023	.012
[15] **STEM Social Sciences**	-1.01†	1.16	.030†	.052	-.023†	.055
[16] Architecture	-.154†	.297	-.002†	.006	.011†	.011
[17] Criminal Justice	-.220	.099	.009†	.006	-.017†	.012
[18] Education	-.186	.093	.004†	.005	-.008†	.005
[19] Medical Sciences	-.035†	.118	-.001†	.006	-.009†	.008
[20] **STEM Communications**	-.080†	.106	-.014	.008	.018†	.012
[21] Legal Studies	-.298	.130	.018†	.014	-.047†	.044
[22] **STEM Agriculture**	-.531	.297	.024	.011	-.036	.010
[23] Public Administration	-.223	.106	.007†	.008	-.022†	.018
[24] Communications	-.287	.094	.011	.005	-.023	.007
[25] Public Health	-.342	.121	.010†	.007	-.016	.009
[26] Social Sciences	-.293	.095	.009	.005	-.016	.006
[27] Human Sciences	-.237	.094	.005†	.005	-.014	.006
[28] **STEM Environmental Studies**	-.169†	.277	-.001†	.011	-.006†	.011
[29] **Biological Sciences**	-.552	.255	.016	.009	-.024	.008
[30] Military Studies	.254†	.554	-.061†	.079	.148†	.250
[31] Multidisciplinary Humanities	-.432	.098	.013	.005	-.019	.006
[32] Sports/Recreation	-.222	.097	-.004†	.005	.005†	.008
[33] Area/Ethnic/Culture Studies	-.421	.114	.010†	.007	-.014†	.012
[34] Psychology	-.348	.098	.006†	.005	-.015	.006
[35] Speech/Hearing	-.318	.128	.005†	.010	-.022†	.023

Continued on next page.

Table A4: continued

	Interaction with:					
	Direct Effect[a]		STEM Intensity[a]		STEM Intensity^{2} [a]	
Variable	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
[36] English	-.392	.098	.009†	.006	-.023	.011
[37] Languages	-.481	.103	.012	.006	-.015	.009
[38] Environmental Studies	.521†	.580	-.029†	.023	.017†	.022
[39] Arts	-.291	.094	-.014	.005	.052	.010
[40] History	-.461	.106	.009†	.007	-.013†	.013
[41] Philosophy	-.368	.135	-.004†	.011	.018†	.024

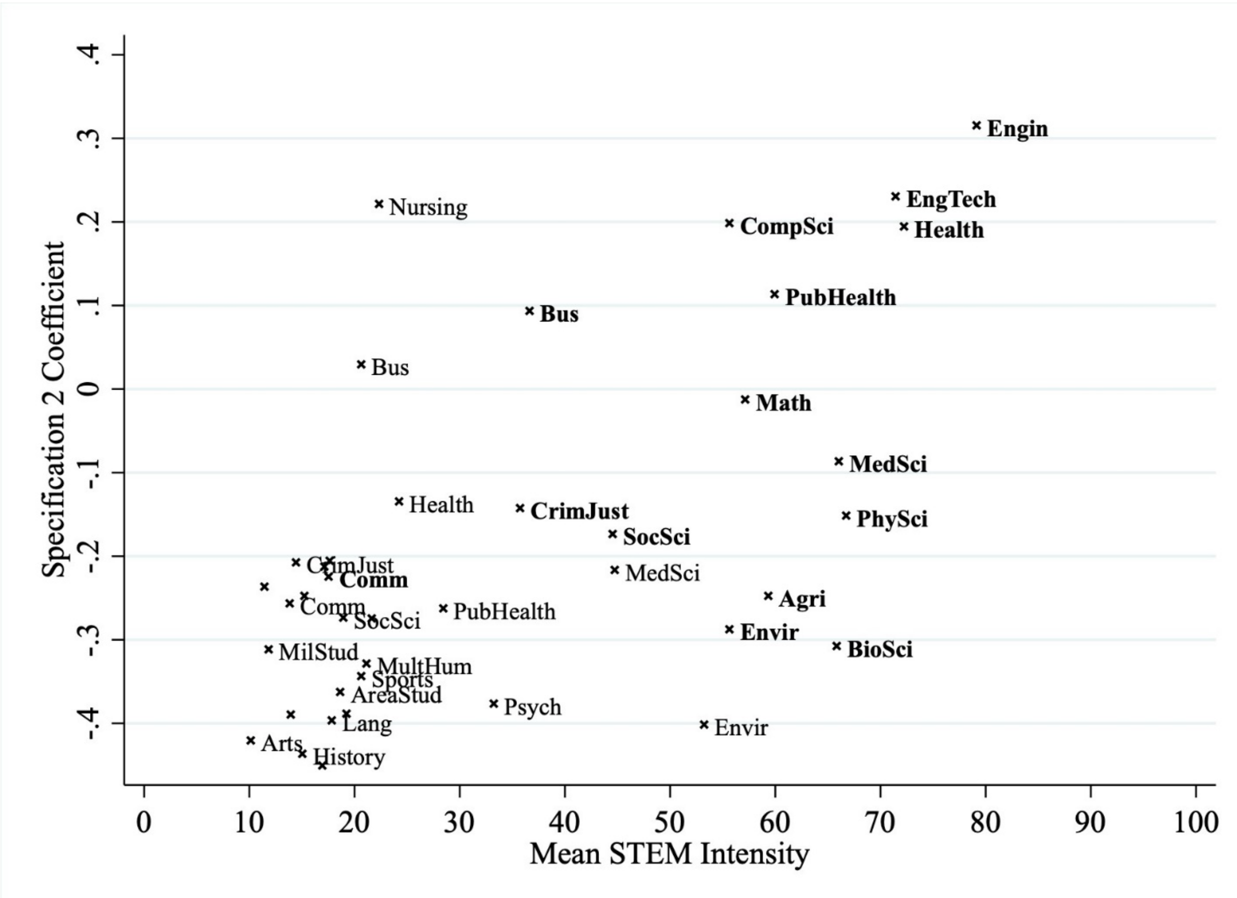
[a]All estimates are from a single regression. Direct effects are estimated coefficients for STEM intensity and its square, total credits and its square, and major dummies. Interactions are estimated coefficients for *interactions* between each major and STEM intensity and STEM intensity squared; the latter are multiplied by 100, as are the corresponding standard errors.

[b]STEM majors are identified with bold-face. Majors are ranked in the same order as in table 2.

†Estimated coefficient is *not* statistically distinguishable from zero at a significance level of 0.10 or lower.

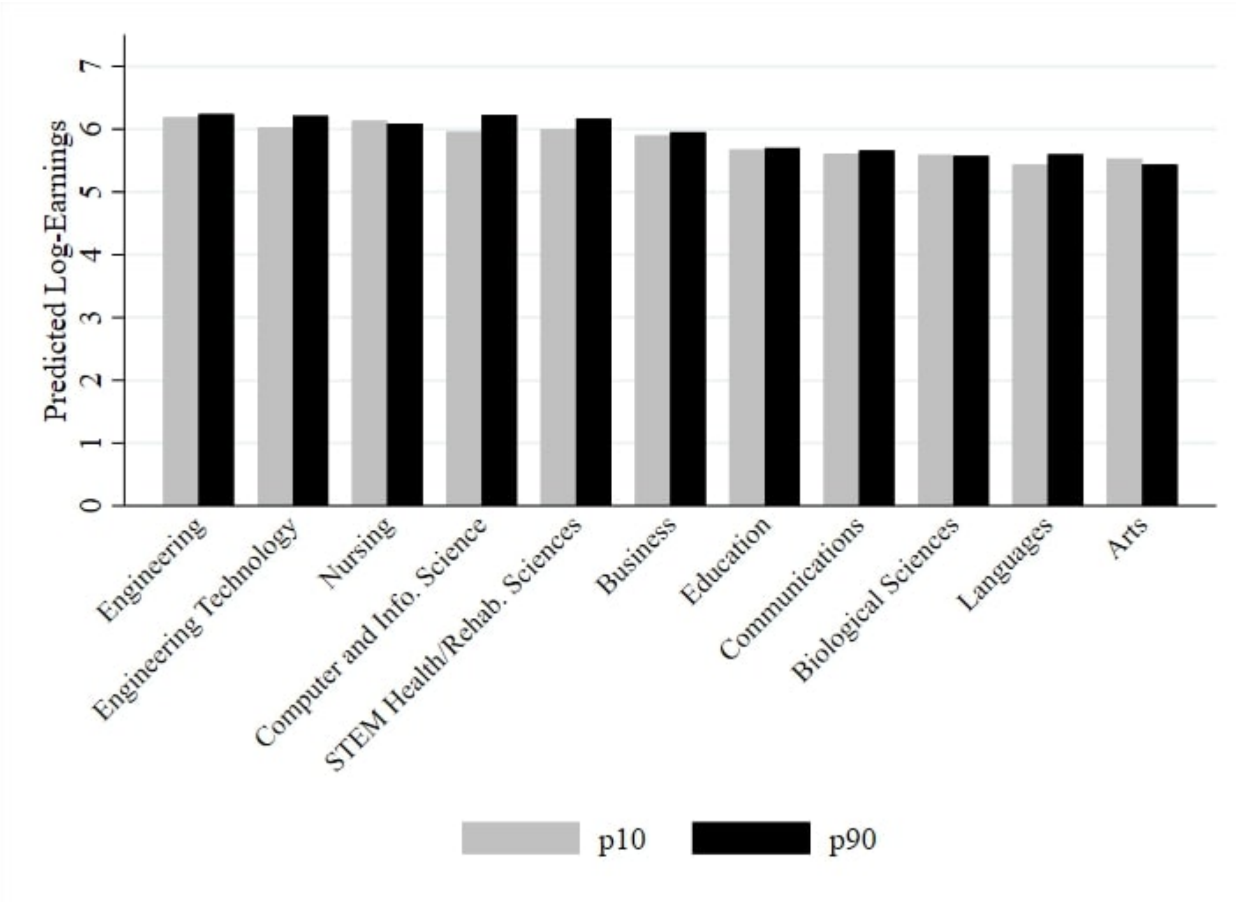
Note: Specification 2" also includes each variable tabulated in or summarized in the note to table 1. The sample has 2,717,057 earnings observations for 209,137 individuals. Standard errors account for nonindependence of residuals among multiple earnings observations for each individual.

Figure 1: Relationship Between Major-Specific Estimated Log-Earning Coefficient and Mean STEM Intensity



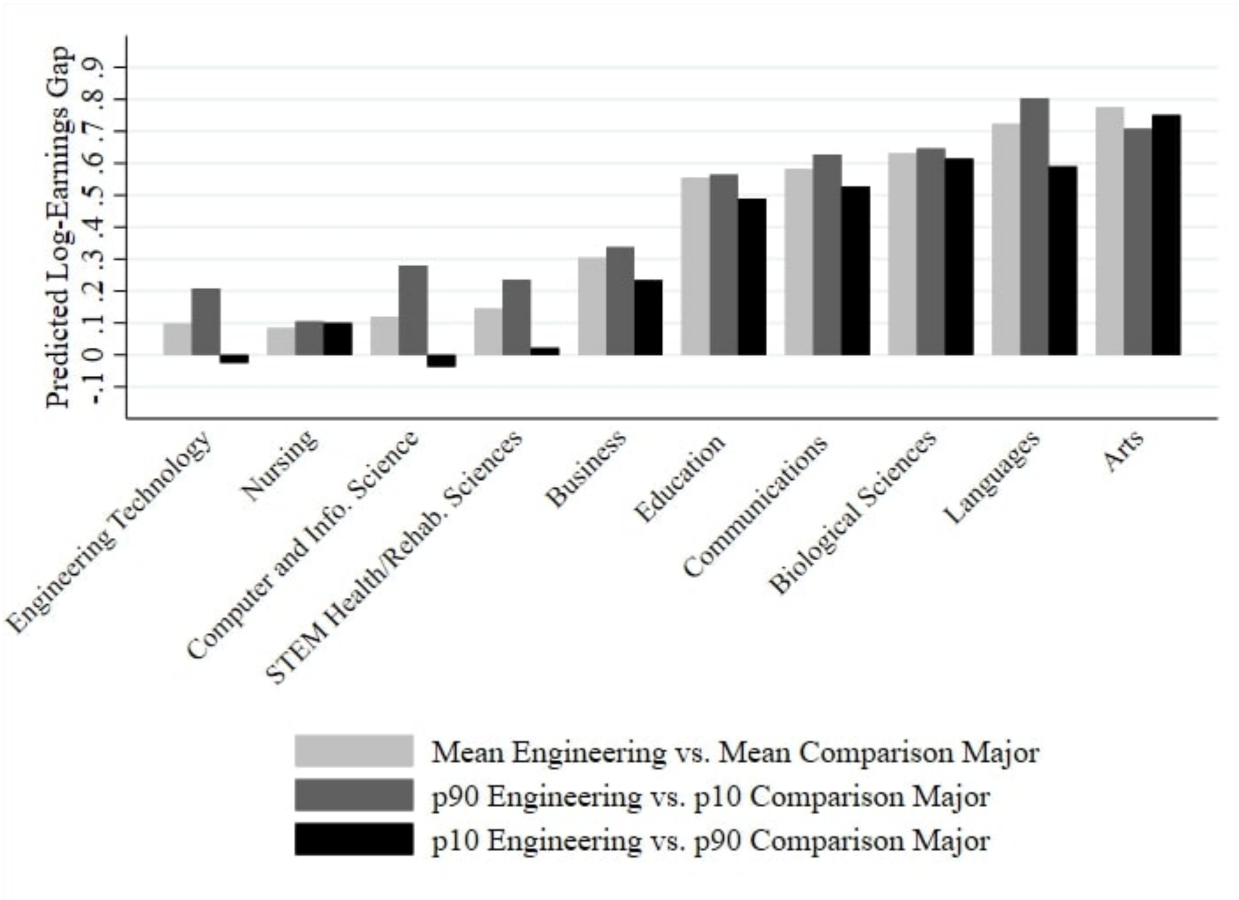
Note: Mean STEM intensities are from the first column in table 2 and estimated coefficients are from the "specification 2" column in table 4. STEM fields are in bold.

Figure 2: Predicted Log-Earnings for Select Majors, Based on Specification 2" and Alternative Assumed STEM Intensities



Note: Estimated differences between each pair of predicted log-earnings are shown in the "within" column in table 5.

Figure 3: Predicted Log-Earnings Gaps Between Engineering and Select Majors, Based on Specification 2'' and Alternative Assumed STEM Intensities



Note: These predicted log-earnings gaps are also reported in the "between" columns for specification 2″ in table 5.