Economics of Education Review 88 (2022) 102263

Contents lists available at ScienceDirect

Economics of Education Review

journal homepage: www.elsevier.com/locate/econedurev

Should English majors take computer science courses? Labor market benefits of the occupational specificity of major and nonmajor college credits

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ARTICLE INFO

JEL classification codes:
I26
I23
J31
J24

Keywords:
Educational economics
Human capital
Rate of return
Salary wage differentials
College coursework

ABSTRACT

Using administrative data for college graduates, we model earnings and employment probabilities as functions of a credit-weighted index of the occupational specificity of college coursework, decomposed into within-major, within-discipline (but outside the major), and nondisciplinary components. We define the occupational specificity of each college field as the likelihood that a student majoring in that field subsequently works in an occupation requiring specific skills acquired in the field. We find that occupationally-specific, non-disciplinary courses are strongly associated with earnings; e.g., a five percentage-point shift among English majors from their least occupationally-specific courses outside the humanities to computer science is associated with a 0.055 increase in log-earnings.

1. Introduction

Over the last 25 years, rising tuition costs coupled with a flattening of the college wage premium contributed to an increased demand among four-year college students for degrees with strong occupational pipelines. Between 1995 and 2015, for example, the total number of bachelor's degrees conferred by U.S. postsecondary institutions increased by 65%, degrees in health professions and computer/information sciences increased by 166% and 162%, respectively, and degrees in English *decreased* by 14%.[1] Despite these stark examples of the trend toward "vocational" college majors, students have not entirely abandoned the humanities, arts, and social sciences: together, these fields accounted for more than one in four bachelor's degrees granted in 2015. Existing research offers rationales for why students continue to choose college majors that lack a vocational focus, including (a) the fields suit their idiosyncratic abilities and preferences (Altonji et al., 2012; Arcidiacono, 2004; Wiswall & Zafar, 2015); and/or (b) they expect the labor market to reward the general skills (communication, critical thinking, global awareness, *etc.*) acquired in those fields (Adamuti-Trache et al., 2006; Hill & Davidson Pisacreta, 2019; Humphries, Joensen, & Veramendi, 2017). In this study, we consider a third reason: students rely on college coursework *outside* their majors to enhance their labor market outcomes.

This conjecture motivates the question posed in the title: Among college graduates with degrees in English and other "nonvocational" fields, are labor market outcomes positively associated with credits completed in vocationally-oriented, nonmajor courses such as computer science? To address this issue, we begin by defining the vocational orientation, or occupational specificity, of each college field of study as the (out-of-sample) likelihood that a student majoring in that field will work in an occupation requiring the specific skills acquired in that field. Among the 60 fields represented in our sample, nursing has the highest occupational specificity (91%) because it imparts skills that closely match the requirements of several occupations (registered nurses, nurse midwives, *etc.*) *and* because jobs are relatively plentiful in those fields. Design has a mid-level specificity score (46%) because it links closely to a set of occupations where jobs are relatively scarce, such as designers and artists. History is among a group of fields with occupational specificity equal to zero, indicating that no occupation has skill requirements

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[1] All statistics in this paragraph are computed from numbers reported in Table 322.10 of the *2017 Digest of Education Statistics*, available athttps://nces.ed.gov/programs/digest/d17/tables/dt17_322.10.asp, accessed February 8, 2022.

https://doi.org/10.1016/j.econedurev.2022.102263
Received 9 August 2021; Received in revised form 12 April 2022; Accepted 14 April 2022
Available online 21 April 2022

that closely match the specific skills acquired in undergraduate history courses. History majors might be productively employed in journalism, sales, teaching, and any number of other occupations on the basis of their *general* skills (or subsequent training), but because no occupation forms a direct pipeline for this undergraduate field of study it is judged to lack occupational specificity.

We combine our field-specific occupational specificity measure with college transcript data for over 95,000 recent bachelor's degree recipients drawn from Ohio administrative records to construct a credit-weighted index of the occupational specificity of each student's curriculum, decomposed into three components: within-major credits, credits outside the major but within the major's discipline, and credits outside the discipline.[2] We model two early-career outcomes (probability of employment and log-earnings) as flexible functions of all three credit-weighted occupational specificity indexes, allowing the effect of each index to (a) be nonlinear; (b) vary with each of the other components; and (c) vary with the occupational specificity of the major. We lack exogenous variation in credit requirements that might be used to contend with students' self-selection of college majors, elective college courses and, in turn, occupational specificity indexes. Instead, we control for a range of college- and student-specific factors that invariably affect these choices, including graduation year fixed effects, university fixed effects, first-semester grade point average, first-semester percent of attempted credits that are completed, college transfer patterns, and enrollment duration. In a series of robustness checks, we take further steps to net out individual ability and institutional quality by, *e.g.*, reducing the sample to a single institution and eliminating students who transfer between colleges, change majors, or earn double majors.

We use our regression estimates to compute marginal effects of various credit-related interventions that alter the distribution of total credits between major and nonmajor courses. These estimated marginal effects enable us to address such questions as: Can individuals with vocational majors potentially enhance their labor market outcomes by amassing a high percentage of credits in their majors? How do their "returns" to within-major credit concentration compare to analogous estimates associated with nonvocational majors? Can students who choose nonvocational majors potentially benefit from choosing occupationally specific courses outside their major? Do those potential benefits depend on whether the additional, nonmajor credits are within-discipline (and, therefore, related to the major) or farther afield?

Our study fits squarely into the literature that assesses "field of study" effects on the labor market earnings of college graduates (e.g., Altonji et al., 2012; Berger, 1988; Grogger & Eide, 1995; Hamermesh & Donald, 2008; Kirkeboen et al., 2016; Webber, 2016), but is most closely aligned with the strand of this literature that asks whether earnings differences among majors are attributable to differences in skill specificity (Blom et al., 2021; Bridet & Leighton, 2015; Leighton & Speer, 2020; Malamud, 2011; Silos & Smith, 2015). Our point of departure is that we do not consider a student's college major to represent the totality of his or her skill acquisition. Instead, we account for each student's entire distribution of college credits across 60 fields, and we assess the occupational specificity of credits within the major as well as in all other fields. Our data reveal that the average percent of total credits allocated to courses within the major is only 29%, with a maximum of 56% among arts majors. Given that the typical college student completes *far* more credits outside the major than within the major, it stands to reason that labor market outcomes are driven by far more than the identity of the major or its skill specificity.

Our findings reveal that credit-weighted, occupational specificity indexes associated with nonmajor courses are weakly related to employment probabilities, but strongly related to earnings. A shift of five percentage points worth of credits (equivalent to one-third of a standard deviation, or 8.2 credits) *within* the discipline (but outside the major) from the least occupationally specific course to the most occupationally specific course is associated with a boost in log-earnings of 0.03 to 0.05, depending on assumed levels of both the major's occupational specificity and the starting level of the within-discipline specificity index. An analogous shift of credits among courses *outside* the discipline is associated with a log-earnings boost of 0.05 to 0.08. When we fine-tune the intervention to correspond to a five-point credit shift among English majors from their least occupationally specific courses outside the humanities to computer science courses, we predict a log-earnings increase of 0.055.

Despite efforts to address the endogeneity of our credit-related variables via observables and reliance on within-institution variation, we acknowledge that our estimated marginal effects are unlikely to represent the payoffs that a randomly chosen student can expect to receive. Identification of causality is far from trivial in our application because students choose from scores of fields in selecting not only their major but a large percentage of their college credits. This self-selection of majors and elective courses is invariably affected not only by students' cognitive ability—for which we adequately control—but by their noncognitive skills, preferences, and expectations. Moreover, their subsequent choice of occupation is likely to affect the earnings payoff to the occupational specificity of their coursework.[3] As a result, our log-earnings estimates represent the (causal) effect of credit-related productivity enhancement *combined with* any direct, earnings-enhancing effects associated with the preferences, noncognitive skills, expectations, and/or occupational aspirations that lead to the selection of vocational credits outside the major. In short, our estimates are likely to be upper bounds on productivity-enhancing, causal effects.

While we believe alternative identification strategies are worth pursuing in the future, our current estimates are useful for (at least) two reasons. First, given that we are the first to establish relationships between the occupational specificity of nonmajor coursework and labor market outcomes, we prefer to use a large, representative sample of students, institutions, and fields of study along with a suitably flexible regression function. In contrast, efforts to improve identification via instrumental variables, regression discontinuity, or structural approaches will invariably require reduced choice sets, less flexible functional forms, and/or restricted samples. The current study provides a foundation on which such extensions can build. Second, our findings support policies designed to shape students' noncognitive skills, preferences, expectations, and occupational goals to help them make optimal college curriculum choices. These are the confounding factors for which we are unable to control; as such, our estimates represent (causal and noncausal) benefits among students who, for example, possess the "tastes" and occupational aspirations that lead them to *choose* to augment an English degree with computer science courses. As long as "uncontrolled for" self-selection is driven by *malleable* factors, which appears to be the case, there is scope for increasing the number of students who receive such benefits.

[2] Disciplines refer to groupings of related college fields. For example, the humanities discipline includes such fields as English, philosophy and history, while the social sciences discipline includes economics, sociology and political science. At U.S. universities, fields of study often correspond to academic departments, while disciplines outside "arts and sciences" often correspond to professional schools or colleges (*e.g.*, business, education, agriculture). See Table 1 for a list of majors and associated disciplines.

[3] Evidence is scarce on how students chose their entire distribution of college courses, but see Altonji et al. (2012), Arcidiacono (2004), Baker et al. (2018), Humphries et al. (2017), and Wiswall & Zafar (2015) for evidence on self-selection of major and Abel & Dietz (2015), Lemieux (2014), Montt (2017) and Robst, (2007a, 2007b) for evidence on the importance of occupational matching.

2. Background

To contrast our conceptualization and measurement of occupational specificity to existing approaches, we briefly discuss three strands of the literature that are particularly relevant: (1) assessments of earnings returns to the skill specificity of college majors; (2) studies that consider skill matches between college majors and occupations; and (3) studies that consider college students' curricular decisions beyond the choice of major.

Several analysts have asked whether well-established earnings gaps among college graduates with different majors (Altonji et al., 2012; Berger, 1988; Grogger & Eide, 1995; Hamermesh & Donald, 2008; Kirkeboen et al., 2016; Webber, 2016) reflect differences in the specificity of skills acquired in each major. To proxy for skill specificity, Malamud (2010, 2011) exploits differences between Scotland and the U. K. in the timing of college students' choice of a major field, under the assumption that *earlier* specialization goes hand-in-hand with *increased* specialization. In a similar vein, Bridet & Leighton (2015) use transcript data to track college students' within-major credit concentration across terms; when this concentration reaches a certain threshold, they determine that specialization has begun. Rakitan & Artz (2015) and Silos & Smith (2015) use completed credit distributions across fields to assess the breadth of students' college training. This approach relies on the notion that breadth is associated with the accumulation of general skill, while a less diffuse credit distribution ("depth") is associated with skill specificity.[4]

Other studies consider the vocational orientation of college training or, more generally, links between fields of study and occupational outcomes. Hanushek et al. (2017) use European data to exploit policies that explicitly place students on either a vocational or an academic track; in the context of this dichotomy, vocationally-oriented training is measured directly. When using U.S. data, the more common approach is to measure the occupational concentration of college graduates in each major (Altonji et al., 2012; Blom et al., 2021). The use of occupational concentration as a proxy for skill specificity reflects the view that workers with degrees in highly specific fields will be tightly clustered within a relatively small number of occupations. Leighton & Speer (2020) use a Gini coefficient representing each major's cross-occupational inequality in expected earnings as their measure of skill specificity, thus distinguishing between "general" majors with transferable skills that are valued equally across many occupations and "specific" majors whose skills are only valued in a few occupations.

We do not base our measure of occupational specificity on occupational *or* earnings concentration because our goal is to measure the likelihood that each field leads to employment in an occupation with a direct skill match. In Section 3.3.3, we compare our occupational specificity measure to occupational concentration measures to show that the latter can potentially reflect concentration within occupations that are unrelated to the major. While we agree with Leighton & Speer (2020) that earnings inequality is ideal for capturing the transferability of skills across occupations, an example illustrates why their innovation is problematic for our analysis: They find psychology to be among the most general fields because workers with psychology degrees tend to earn similar amounts across occupations. In contrast, we deem psychology to be more occupationally specific than one-third of the fields in our sample because its degree recipients often work in counseling, social work, and other occupations with skill requirements that link closely to skills provided by the major. The fact that psychology majors have similar earnings in unrelated fields speaks to the transferability of their general skills, but *not* to the strength of the field's occupational pipeline.

Roksa & Levey (2010) use an occupational specificity measure that is conceptually similar to ours, in that they consider the probability that a worker will be employed in an occupation related to his/her college major. However, they use only 12 broadly-defined majors and 11 broadly-defined occupations, and define a match as, e.g., a business major working in any business or managerial occupation. In contrast, we consider 60 distinct fields of study and the entire Census taxonomy of occupations, and identify matches based on careful consideration of whether the specific skills taught in each field of study are required by each occupation.

Our strategy of matching college fields of study with occupations has commonality with the job matching literature in which the *realized* match between workers' college majors and occupations has been found to affect post-college earnings (Abel & Dietz, 2015; Lemieux, 2014; Montt, 2017; Robst, 2007a, 2007b). Following that literature, we adopt the viewpoint that each field of study imparts a well-defined skill set that, in some cases, forms a natural pipeline to specific occupations. However, the matching literature focuses on realized, ex post matches, while we are interested in an exogenous measure of the likelihood that a given field of study will lead to employment in a "close" occupation.[5]

An important distinction between our empirical strategy and much of the existing literature is that we do not focus exclusively on each individual's college major. Our use of the entire credit distribution has as its genesis Rakitan & Artz (2015), Silos & Smith (2015), and other studies that assess the depth and breadth of each student's college coursework. It also borrows from studies that control for college coursework in addition to college majors in log-earnings models (Hamermesh & Donald, 2008; Joy, 2003; Light & Schreiner, 2019). Despite differences in methodology and the detail with which coursework is measured, each of these prior studies finds a substantial relationship between college coursework and post-college earnings, conditional on major. That evidence is a key motivating factor for our study.

3. Data

Our primary data sources are two restricted-use, administrative datasets from the Ohio Longitudinal Data Archive (OLDA): Higher Education Information System (HEI) data and Unemployment Insurance Wage (UI) data. We also use data from the American Community Survey (ACS) Public Use Microdata Sample to define the occupational specificity of each field of study.

HEI data contain student transcript information for all enrollees in Ohio's two- and four-year public colleges and universities from 1999 onward. UI data contain quarterly payroll data (earnings and weeks worked) for Ohio workers whose employers file unemployment insurance with the State. The UI dataset extends from 1995 onward, but was only available through the third quarter of 2018 when we were given access. We link UI and HEI records using a unique, individual-level identifier provided by OLDA.

OLDA data are well-suited for our analysis because they provide an extremely large sample of students who receive bachelor's degrees from Ohio's 13 public four-year institutions.[6] The large sample size enables us to consider the full range of college majors and eliminate unobserved, institution-specific factors by relying solely on within-institution variation for identification. In addition, administrative earnings data eliminate errors inherent in self-reports. However, these data are not without limitations. Transcript information in the HEI data is confined to public colleges and universities in Ohio, so we face enrollment gaps for students

[4] Dolton & Vignoles (2002) applies a similar approach in identifying the "depth vs. breadth" of U.K. high school students' training.

[5] Our data do not include occupational indicators, so we are unable to determine whether individuals in our sample work in occupations that match their majors, or how the rate of realized matches varies with the occupational specificity of the major, within-major credit concentration, and other factors.

[6] The 13 institutions 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.

who attend private and/or non-Ohio institutions enroute to a degree at an Ohio public institution. In addition, UI earnings data are unavailable for workers whose employers do not participate in the Ohio UI system. As a result, we lack information for out-of-state employment, employees of the federal government, and some self-employed workers. As described below, our sample selection rules are designed to contend with these data shortcomings.

3.1. Sample selection

We assess the relationship between the occupational specificity of college graduates' credit distributions and two alternative outcomes: employment and log-earnings.[7] We proceed to describe both our employment sample and our earnings sample, starting with sample selection criteria that are common to both samples.

We begin by restricting the HEI database to individuals who earn a bachelor's degree between 2010 and autumn 2014. We choose autumn 2014 as the upper bound because our earnings data end with the third quarter of 2018 and we want to observe all sample members for at least four years after receipt of the bachelor's degree. We exclude graduation cohorts before 2010 to avoid early-career outcomes during the recession that ended in June 2009. Confining attention to 2010–14 graduates reduces the HEI sample of several million Ohio college students to 168,870 bachelor's degree recipients.

Next, we eliminate individuals with notably atypical paths to a bachelor's degree that might lead to incomplete transcripts or highly irregular credit distributions. First, we drop 25,883 individuals (15% of 168,870) who are younger than 20 or older than 26 when they receive their bachelor's degree, and fewer than 10 individuals who are incarcerated between high school graduation and the receipt of a bachelor's degree.[8] We also drop 8,798 individuals (6% of 142,979) whose HEI transcript records show fewer than 108 undergraduate credits between high school graduation and college graduation due to the unavailability (to HEI users) of some transfer credits. A minimum of 120–128 credits is needed to earn a bachelor's degree at each Ohio institution in our sample, and the mean (median) among the "current" 142,979 sample members is 160 (154). Our cutoff of 108 credits (90% of 120) retains students with complete or "near complete" *observed* transcripts without unduly reducing sample size. We then eliminate 3216 individuals (2% of 134,181) who take more than 8% of their undergraduate credits in basic skills, vocational, and personal enrichment courses (a cutoff deemed "extreme" upon examination of the distribution of credits earned in these areas) and another 63 individuals who major in fields such as "legal assistants and paralegals" that are not traditionally associated with bachelor's degrees. These selection rules leave us with a common sample of 130,902 individuals that we convert to both the employment and earnings samples.

In constructing a sample used to model the probability of employment, we must contend with our inability to distinguish between nonemployment and employment outside Ohio. To do so, we eliminate 25,364 individuals (19% of 130,902) whose UI record lacks at least one earnings report within four years of bachelor's degree receipt *and* we model employment probabilities (approximately) one year after degree receipt. Together, we believe these criteria minimize the probability that an individual classified as nonemployed is, instead, employed outside Ohio. We focus on the one-year mark because the chance of leaving Ohio can only increase with time, yet an even earlier date might include individuals taking a temporary break between graduation and the start of their first post-college job. Finally, we eliminate 14,829 individuals (14% of 105,538) who reenroll in school within one year of graduating from college in order to focus on employment probabilities among individuals who, to date, have not received schooling beyond a bachelor's degree. The resulting cross-sectional sample of 90,709 individuals is used to model both the probability of any employment and the probability of full-time employment one year after college graduation.

To construct the longitudinal earnings sample, we return to the common sample of 130,902 bachelor's degree recipients and drop 36,096 individuals (28% of 130,902) who lack an earnings report for at least one quarter during their post-college, pre-reenrollment window. We define the start date of that window as the calendar quarter *after* the quarter in which the degree was received to avoid including student jobs. We define the end date of the earnings window as the earlier of (a) the quarter preceding observed reenrollment (if relevant); or (b) the third quarter of 2018, which is the last quarter for which we have UI data. The use of this window ensures that we model earnings outcomes only for individuals who hold a bachelor's degree and have yet to pursue graduate enrollment (if relevant).[9] Each remaining sample member contributes one observation for every quarter within this window in which he/she has earnings. This produces an unbalanced panel of 1,527,187 person-quarter earnings observations for 94,806 individuals, with the mean number of observations per person decreasing from 27.1 for the earliest (2010) graduation cohort to 14.7 for the latest (2014).

Among the 94,806 individual who contribute quarterly observations to the earnings sample, 4,097 do not appear in the employment sample because they receive earnings and then reenroll within the first year of receiving their bachelor's degree. Among the 90,709 individuals in the employment sample, 265 fail to contribute to the earnings sample because they are nonemployed one year after college graduation and have reported earnings within four years of graduation, but reenroll prior to that earnings report. Given this overlap, our two samples jointly consist of 95,071 individuals.

3.2. Dependent variables

To construct a log-earnings measure for each post-college quarter within the observation window described above, we sum "valid" earnings reports across all employers for the quarter and divide by total weeks worked for all employers (capped at 13).[10] We deflate this "average quarterly earnings" variable by the quarterly CPI-U for the Midwest and take its natural logarithm to create the dependent variable used in our earnings model.

Turning to the employment sample, we assign each individual a value of one for the "any employment" outcome if his/her quarterly UI record (one year after college graduation) contains an earnings report

[7] While occupational attainment and graduate school enrollment would be equally interesting outcomes, we lack occupational identifiers and have a nonrepresentative sample of graduate students due to our short post-college observation window and inability to observe activities outside Ohio.

[8] This deletion includes 45 individuals whose birth year is unknown. HEI data contain the years (but not months) of birth, high school graduation, and bachelor's degree receipt, along with the term in which the degree was earned. Therefore, age at degree recipiency and other points in time referred to in this section are approximated. We rely on birth year to approximate the high school graduation date when it is missing.

[9] Among the 36,096 individuals dropped because they lack earnings during the relevant post-college observation window, fewer than 1,900 are excluded solely because they lack earnings within the first four years after college graduation. This additional selection rule reduces the risk of including sample members who leave Ohio soon after college graduation and then return, possibly after earning post-college degrees.

[10] A small number of employer-specific quarterly UI records show positive earnings and either zero or missing weeks worked. We drop these records if weeks worked with other employers in the same quarter sum to 11 or more. If that criterion is not met but the same employer reports positive earnings and weeks in a "nearby" quarter, we replace the zero/missing weeks with a value that yields the same employer-specific, average quarterly earnings as the surrounding value(s); when necessary, the imputed weeks value is adjusted to fall between 1 and 13. A "valid" earnings report is one with positive values for earnings and reported *or* imputed weeks.

for at least one employer; 79% of sample members are coded as "employed" according to this criterion. Because a nontrivial number of individuals have exceedingly low weeks worked, we define "full-time employment" to equal one if weeks worked for *all* employers in the quarter sum to at least nine; this restriction reduces the employment rate to 71%. Table A1 reports summary statistics for each dependent variable.

3.3. Credit-related regressors

In this subsection we define our credit-related variables, provide key details on their construction, briefly summarize the data and, as part of that summary, compare our field-specific occupational specificity measure to alternatives based on occupational concentration.

We combine our measure of the occupational specificity of each field (OS_f)—as defined in Section 1 and further detailed in 3.3.2—with each student i's credit distribution across the F_i fields in which he/she takes courses to construct a credit-weighted occupational specificity index for each student:

$$PCOS_i = 100 \cdot \sum_{1}^{F_i} \left(CREDIT_{if} \cdot OS_f \right) \Bigg/ \sum_{1}^{F_i} CREDIT_{if} = \sum\nolimits_{1}^{F_i} PC_{if} \cdot OS_f. \quad (1)$$

In (1), $CREDIT_{if}$ is the number of total credit hours student i completes in field f and PC_{if} is the percent of his/her total credits allocated to that field. We refer to the index as $PCOS_i$ to highlight the fact that the occupational specificity of field f is weighted by PC_{if}.

We arrange each student's fields into the major field of study ($f = m$), $f = 2 \ldots D_i$ fields that are outside the major but within the major's discipline, and $f = D_i + 1 \ldots F_i$ fields that are outside both the major *and* the discipline.[11] This enables us to decompose (1) into the within-major (m), nonmajor but within-discipline (d), and outside major/discipline (o) components:

$$\begin{aligned} PCOS_i &= PCOS_{im} + PCOS_{id} + PCOS_{io} \\ &= PC_{im} \cdot OS_{im} + \sum\nolimits_{2}^{D_i} \left(PC_{if} \cdot OS_f \right) + \sum_{D_i+1}^{F_i} \left(PC_{if} \cdot OS_f \right) \end{aligned} \quad (2)$$

where PC_{im} is the percent of total credits taken in the major and OS_{im} is the occupational specificity of that field ($f = m$).

The occupational specificity of the major (OS_{im}) plus the three components of the credit-weighted occupational specificity index ($PCOS_{im}$, $PCOS_{id}$ and $PCOS_{io}$) are our key credit-related regressors. To construct these variables, we (a) choose a 60-field taxonomy; (b) use HEI data to define each person's major field and credit distribution across all 60 fields (omitting the small number of credits earned outside these fields from both numerator and denominator); and (c) use ACS and Census data to define the occupational specificity of each field (OS_f). Our only further clarification regarding task (b) is that the major field corresponds to the primary field in which the bachelor's degree was awarded; if the student completes a secondary major or a minor (the latter of which is not identified in our HEI data), that information is captured by his/her credit distribution. In the next two subsections we focus on details related to tasks (a) and (c).

3.3.1. Defining fields

HEI transcript data include the number of credits earned in each course, the title of each course, and the college major at degree recipiency. College majors and courses are coded using six-digit 2010 Classification of Instructional Programs (CIP) codes. The 95,071 individuals in our two samples take courses with 1,103 unique CIP subject codes, and complete majors with 376 unique CIP codes.

Our first challenge is to aggregate those course- and major-specific CIP codes into a smaller number of aggregate fields. Neither the education nor the economics literature provides a standard taxonomy of fields, and the number of fields chosen in previous studies is largely driven by research goals.[12] We begin by aggregating six-digit CIP codes to their broader "subject field" to obtain 144 fields that are typically associated with college majors; for example, 10 six-digit codes identifying such detailed subjects as environmental architecture, interior architecture, and landscape architecture are aggregated to architecture.

To aggregate further to the 60 fields listed in Table 1, we consider our need to map each field to one of 191 Census degree fields used by the ACS and, in turn, match each Census degree field to related occupations as described in Section 3.3.2. This leads us to apply three criteria when defining fields. First, we account for the level of detail available in Census degree codes. For example, CIP codes allow us to distinguish between plant sciences and agronomy/soil sciences, but both are subsumed by the "plant science and agronomy" Census degree fields. Second, we avoid distinguishing between closely related fields (*e.g.*, applied mathematics and statistics) because Census coding might reflect the manner in which respondents and/or their institutions label majors rather than substantive differences. Third, we use sufficiently high levels of aggregation to combine "catch all" fields (e.g., miscellaneous physical sciences) with more narrowly defined fields (e.g., astronomy, geology, physics), given the inherent difficulty in matching the "miscellaneous" fields with occupations.

3.3.2. Defining the occupational specificity of each field

The first step in defining OS_f is to map each of our 60 fields of study to one of 191 Census degree fields used by the 2010–18 ACS, as discussed in 3.3.1. The second step is to determine which occupations in the 2010 Census Standard Occupational Classification (SOC) use skills that are directly related to the skills acquired in each field of study. We consulted a number of websites designed to assist college students in selecting a major (e.g., MyMajors.com and CollegeStats.org) and the department websites of Ohio universities to determine precisely what skills and training are emphasized in each field. We then consulted the Occupational Information Network (O*NET) database to learn the skill and educational requirements of each occupation.

All college majors impart general skills that can be used in a variety of occupations, but our goal was to link each field to the occupation(s) that require its specific (and often unique) skills. For example, any bachelor's degree recipient can become an elementary or secondary school teacher upon obtaining the appropriate certification, but we only match education majors to teaching occupations. Similarly, many mathematics and statistics majors acquire skills that enable them to work in computer-related occupations, but we only match computer science (and related) majors to those occupations. Most of our major-occupation links are confined to occupations that require a college degree, but there are exceptions. For example, the field of performing, visual and fine arts matches to such occupations as "dancers and choreographers" and "musicians, singers, and related workers," and the field of forestry, wildlife and environmental resources matches to "fishing and hunting workers." Although a college degree is not required for some jobs within these occupations, the matched fields of study

[11] Students' fields are classified as within the major, within the discipline, or "other" based on course codes included in the HEI transcript data (see Section 3.3.1); this designation is independent of whether courses are required by the major or chosen by students as electives.

[12] For example, Kinsler & Pavan (2015) use three majors to estimate a structural model, Hamermesh & Donald (2008) use 10 majors to identify major-specific parameters, and Leighton & Speer (2020) map 51 majors to skill-specificity measures.

Table 1
Summary statistics for credit-related variables, by field of study (ranked by occupational specificity).

Field of study [Discipline]	OS_f	PC_{im} Mean	SD	$PCOS_{id}$ Mean	SD	$PCOS_{io}$ Mean	SD	N
Nursing [Health]	91.3	50.6	7.6	33.3	62.0	762.6	168.5	4815
Special education [Education]	86.1	31.7	12.5	1270.3	789.8	527.9	193.0	1319
Elementary/early education [Education]	78.0	25.3	15.6	1711.9	886.4	588.0	212.6	2592
Junior/senior high education [Education]	70.8	25.0	11.2	374.6	291.5	814.2	347.4	5033
Computer engineering [Engineering]	70.5	26.1	11.4	791.6	419.4	845.6	390.4	663
Mechanical engineering [Engineering]	66.0	36.1	10.2	821.4	410.3	591.9	168.4	2055
Accounting [Business]	63.4	22.1	5.0	904.2	310.6	644.7	265.4	3130
Environmental/geo. engineering [Engin.]	62.9	7.3	6.4	1268.1	492.3	879.4	199.2	41
Computer science [Natural sciences]	62.2	26.4	16.3	237.8	137.0	1366.8	817.9	1522
Materials engineering [Engineering]	61.1	7.1	7.2	860.0	486.4	882.9	216.4	109
Civil engineering [Engineering]	60.5	37.7	7.4	778.5	282.7	642.2	189.2	963
Chemical engineering [Engineering]	55.2	30.5	6.0	492.8	328.6	1040.7	155.0	835
Aerospace engineering [Engineering]	52.8	31.6	7.8	1311.5	610.2	540.1	147.4	186
Social work [Social sciences]	52.0	38.1	9.9	247.2	145.6	515.2	263.2	1014
Education administration [Education]	51.7	5.8	4.0	1857.7	1495.5	876.7	457.4	367
Computer/quantitative business [Business]	50.5	14.9	7.6	1027.3	286.4	1054.5	643.3	744
Health technology [Health]	48.6	26.4	20.3	91.7	126.5	1082.5	321.7	620
Electrical engineering [Engineering]	48.0	35.2	8.1	869.0	425.0	673.3	257.3	759
Industrial/manuf. Engineering [Engineer.]	46.3	27.4	7.2	849.2	349.1	765.6	212.4	352
Design [Arts]	46.0	42.8	21.8	272.9	214.1	695.2	515.8	1698
Architecture [Engineering]	43.7	52.0	16.6	137.8	239.9	552.8	262.9	861
Biological engineering [Engineering]	43.2	25.7	7.7	849.8	386.7	947.5	199.0	352
Other engineering [Engineering]	42.3	16.8	10.6	1087.7	604.3	873.4	367.9	459
Criminal justice [Social sciences]	40.6	25.4	18.0	348.0	213.2	556.2	276.6	2517
Finance [Business]	40.0	15.9	4.1	1324.1	315.6	609.8	210.0	2910
Sales and marketing [Business]	37.5	19.3	6.4	1004.2	400.0	728.0	344.2	5361
Chemistry [Natural sciences]	33.4	32.5	7.5	457.9	168.0	362.5	240.0	475
Agriculture [Agriculture]	31.4	25.2	14.5	7.5	26.3	1250.8	462.9	1033
Health therapy [Health]	29.2	31.0	14.4	129.8	223.5	1149.0	519.2	855
Management [Business]	26.3	17.8	8.5	996.1	488.7	825.1	451.2	4576
Other business [Business]	24.0	9.0	7.0	1255.4	404.3	669.4	293.8	1362
Pharmacy [Health]	22.0	24.7	9.7	30.7	76.0	1334.9	275.4	326
Other bio/biomedical sciences [Nat. sci.]	19.8	27.5	7.2	764.6	162.9	351.2	255.2	2790
Public relations/advertising [Communic.]	18.9	8.6	6.3	364.6	124.0	978.9	407.7	666
General and public health [Health]	18.8	22.5	8.3	193.1	361.2	1247.3	431.1	298
Nutrition and dietetics [Health]	16.7	18.4	15.3	91.0	122.1	1353.5	343.5	609
Zoology [Natural sciences]	14.9	10.9	5.8	1040.9	196.7	369.7	180.8	803
Performing, visual and fine arts [Arts]	14.5	55.5	16.4	145.0	296.4	537.8	441.9	3421
Forestry/wildlife/natural resources [Agri.]	14.3	24.1	12.0	88.3	112.5	991.0	292.6	543
Psychology [Social sciences]	13.5	35.3	7.6	179.7	182.6	638.0	331.4	4924
Continued.								
Journalism [Communications]	13.2	33.2	8.2	35.9	56.1	821.1	342.9	7051
Sports/recreation [Sports and recreation]	12.9	30.4	10.7	0.0	0.0	1463.4	547.5	2777
Mathematics and statistics [Natural sci.]	12.4	37.4	7.0	327.1	295.3	990.3	685.3	433
Sociology [Social sciences]	12.3	30.2	9.7	225.8	172.3	613.9	337.7	1124
Family/consumer studies [Social sciences]	12.2	26.5	10.6	171.3	122.8	1308.6	505.4	3551
English [Humanities]	8.3	33.8	10.2	14.9	18.7	835.3	585.2	2701
Engineering technology [Engineering]	7.8	30.7	20.6	998.7	910.1	873.0	557.8	1224
Political science [Social sciences]	7.7	27.2	8.2	167.6	188.1	533.2	335.7	1872
Other social sciences [Social sciences]	7.3	25.3	14.6	150.8	173.0	827.5	552.3	1526
Physical sciences [Natural sciences]	6.2	37.5	10.0	491.5	270.6	438.2	321.8	412
Health admin./management [Health]	6.2	28.8	11.9	259.3	363.8	1183.6	279.7	755
Philosophy/religious studies [Humanities]	5.4	32.6	9.3	58.7	49.2	628.9	329.8	285
Professional medicine [Health]	4.5	12.1	16.3	348.0	391.3	1275.0	386.9	631
Communications disorders [Health]	3.9	29.2	5.6	38.8	68.5	897.9	252.1	958
Economics [Social sciences]	0.7	28.5	6.6	123.6	97.9	1040.5	444.8	1009
Area/ethnic/cultural/gender studies [Hum.]	0.0	17.8	13.4	77.6	56.9	754.4	384.9	290
Foreign languages [Humanities]	0.0	40.4	13.2	61.4	52.7	836.3	585.8	1072
History [Humanities]	0.0	31.7	7.1	68.5	42.7	667.3	350.5	1231
International relations [Social sciences]	0.0	7.7	6.2	226.0	108.2	552.5	342.0	993
Liberal and general studies [Humanities]	0.0	3.1	4.5	93.9	61.1	1470.0	642.6	1218
All	31.5	28.9	15.4	473.9	576.3	797.3	470.7	95,071

Note: OS_f is the field's occupational specificity. The remaining columns show statistics computed for individuals in our (HEI) sample majoring in the field: PC_{im} is the individual's percent of credits in the major and $PCOS_{id}$ and $PCOS_{io}$ are the individual's credit-weighted occupational specificity indexes for nonmajor courses within the field's discipline and outside the discipline, respectively.

unquestionably prepare individuals to hold the higher-skill jobs.[13]

We experimented with alternative OS_f definitions based on different degrees of "closeness" of the field-occupation matches.[14] At one extreme we focused on the most direct matches, such as "accountants and auditors" and "tax preparers" as the sole occupational matches for the field of accounting, and "dieticians and nutritionists" as the sole match for the dietetics/nutrition field. We ultimately chose to go with a somewhat broader definition of OS_f that, for example, also matches accounting with "budget analysts," "credit analysts," and "financial examiners." We do so because the availability of the most direct field-occupational matches depends on how narrowly-defined both the occupational taxonomy and the field happen to be and is, therefore, somewhat arbitrary. For example, special education has an OS_f value of 86.1% when matched with a range of education occupations (including "elementary and early education teachers" and "other teachers and instructors") that are clearly well-matched with that field, and a value of only 32% when matched solely (and most directly) with "special education teachers."

The final step in defining OS_f is to identify the percentage of ACS respondents with completed majors in each field who are employed in "matched" occupations. Using 1-year American Community Survey (ACS) Public Use Microdata Sample (PUMS) data files for 2010–18, we select a sample of 64,059 bachelor's degree holders who are ages 22–27, reside in the Midwest, and are employed but not enrolled in school at the time of the survey. We further restrict the sample to 62,279 individuals whose major corresponds to one of our 60 fields. We retain each sample member's college major and occupation, map each major to our 60-field taxonomy, and compute the percent of sample members with each major working in occupations that we deem to form a close skill match to that major.

3.3.3. Credit variable summary statistics and alternative specificity measures

The descriptive analysis presented in this subsection is designed to achieve several goals. First, we show that the level of occupational specificity that we assign to each field (OS_f) conforms to expectations. Second, we follow up on the discussion in Section 2 by using numerical examples to show how OS_f compares to select skill-specificity measures proposed by other analysts. Third, we demonstrate how our key variables are ranked and distributed and how select pairs relate to each other. Broadly, our intent is to show what the data "look like," given the novel nature of our measures, and to highlight specific aspects of the data that justify the analytic strategy described in Section 4.

To achieve these goals, we rely on Figs. 1–3 as well as Table 1, which lists all 60 fields, ranked from highest to lowest value of occupational specificity (OS_f), alongside the mean and standard deviation of PC_{im}, $PCOS_{id}$ and $PCOS_{io}$ for subsamples of individuals majoring in the field. This table, while numbers-intensive, allows us to highlight specific illustrative examples while also enabling readers to examine summary statistics for whichever fields are of interest.

The first column of numbers in Table 1 reveals that nursing has the highest level of occupational specificity (91.3), followed by special

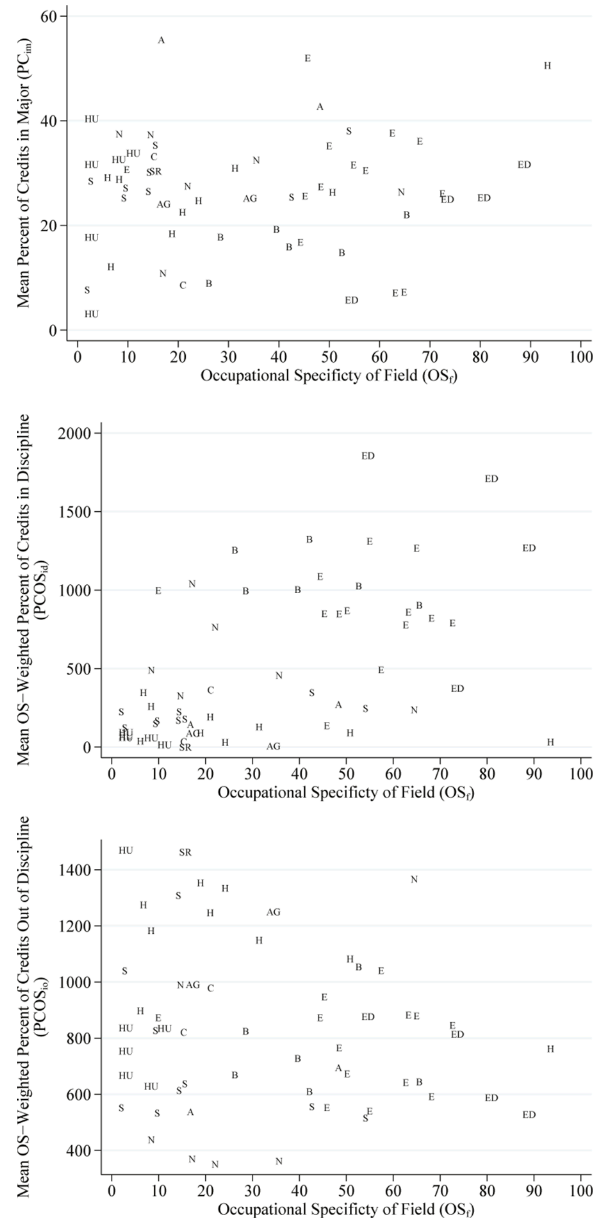

Fig. 1. Relationships between field-specific means of each key credit-related variable and occupational specificity of field (OS_f).
Notes: Field-specific mean values (which are also shown in Table 1) are labeled by discipline (AG=agriculture, *A*=arts, *B*=business, C=communications, ED=education, *E*=engineering, *H*=health, HU=humanities, *N*=natural sciences, *S*=social sciences, and SR=sports and recreation).

education (86.1), elementary and early education (78.0) and junior and senior high education (70.8). Along with accounting (63.4), computer science (62.2) and social work (52.0), seven engineering fields make up the next 10 slots in this ranking. At the other end of the OS_f distribution, we see four humanities fields and one social sciences field (international relations) with $OS_f = 0$. Overall, the occupational specificity ranking conforms to our priors regarding the vocational orientation of each field.

For comparison, we computed two alternative skill-specificity variables used in the literature: the Hirfindahl-Hirschman index (HHI) of occupational concentration used by Blom et al. (2021) and the percentage of workers in each major employed in the major's three most common occupations, which is used by Altonji et al. (2012). While correlations between OS_f and the two alternative measures are high (0.80 for HHI and 0.94 for the "top three" measure), we offer an

[13] We opted not to rely on skill matches provided in the 2010 CIP-SOC crosswalk developed by the National Center for Education Statistics and Bureau of Labor Statistics because it has a number of features that are problematic for our purposes. For example, (a) it combines matches for both bachelor's-level and graduate-level coursework; (b) secondary teaching occupations are matched with some noneducation fields (*e.g.*, history, biology, general social sciences) but not others (*e.g.*, computer science, economics, geography); and (c) a number of occupations are matched with fields that, in our judgment, do not constitute a direct match of specific skills (*e.g.*, "all other managers" is matched with digital communications, history, linguistics, and psychology).

[14] Appendix table A3 (available as supplementary material) lists each of our 60 fields by discipline, and identifies both the Census field(s) of study and Census occupation(s) matched to each field. Using italics, it also identifies the most direct (narrow) matches that served as one of our experiments.

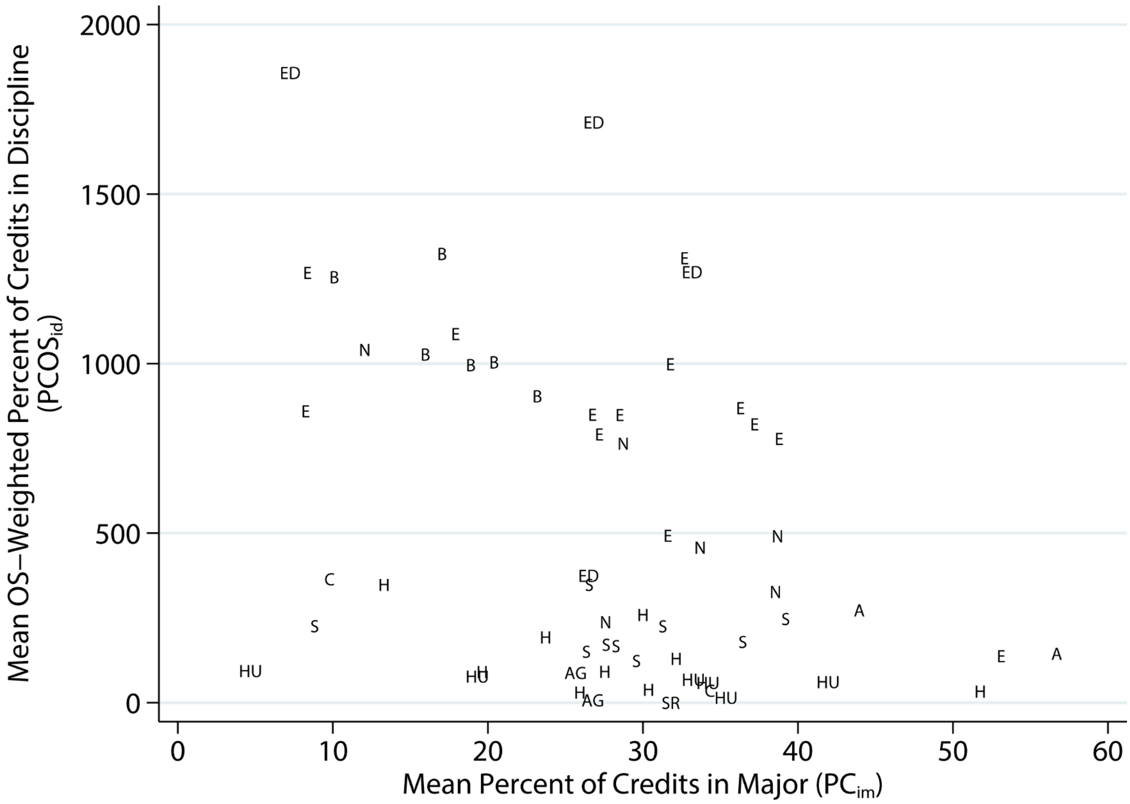

Fig. 2. Relationship between field-specific mean of "OS-weighted percent of credits in discipline" ($PCOS_{id}$) and "percent of credits in major" (PC_{im}), by field.
Notes: Field-specific mean values (which are also shown in Table 1) are labeled by discipline (AG=agriculture, *A*=arts, *B*=business, C=communications, ED=education, *E*=engineering, *H*=health, HU=humanities, *N*=natural sciences, *S*=social sciences, and SR=sports and recreation).

illustration to highlight the difference between our measure and concentration-based measures: Among 60 fields, journalism is the 41st most specific using our measure ($OS_f = 13.2$), but its ranking falls to 50 and 53, respectively, when we switch to the HHI or "top three" measure. In our ACS sample, the three most commonly-held occupations among journalism majors—none of which requires skills gained in journalism courses—are marketing and sales managers, customer service representatives, and retail salespersons, which combine to account for 12.5% of workers with journalism degrees. While none of the 11 occupations that we match to journalism (including announcers, news analysts/reporters/correspondents, and editors) accounts for more than 4% of workers with journalism degrees, our matched occupations combine to account for 13.2% of journalism majors. In short, the HHI and "top 3″ specificity measures correctly reflect the lack of occupational concentration among journalism majors while ignoring skill match, while our variable captures the likelihood of being employed in an occupation that uses journalism skills *independent* of occupational concentration.[15]

The remaining statistics in Table 1 are based on a sample of 95,071 individuals who appear in our employment and/or earnings sample. Focusing first on the average percent of total credits taken within the major (PC_{im}), the bottom row of Table 1 shows that the average bachelor's degree recipient (across all fields of study) takes only 28.9% of total college credits in his or her major field. This motivates our efforts to use the entire distribution of credits rather than the major field to characterize skills sets. Looking up and down the list of fields in Table 1, we see that mean PC_{im} is highest among performing/visual/fine arts majors (55.5), followed by architecture (52.0) and nursing (50.6). Unsurprisingly, it is lowest for liberal/general studies (3.1), which is an interdisciplinary major, and for narrowly-defined fields such as education administration (5.8) and environmental/geological engineering (7.3).[16]

Having confirmed that the identities of fields with especially high or low mean, within-major credit concentrations conform to expectations, we turn to the first panel of Fig. 1, which transforms the field-specific values of OS_f and means of PC_{im} shown in Table 1 into a scatterplot, with each field labeled by its discipline. Fig. 1 shows no relationship between each field's occupational specificity and the average PC_{im} among its majors. Students in occupationally-specific majors show no systematic tendency to load up on credits within their major (with the exception of nursing, which is the outlying "H" in the upper right quadrant), nor do students in low-OS_f majors tend to avoid within-major credits (with the exception of liberal/general studies and international relations, which are the outlying "HU" and "S" in the lower left quadrant). Based on this evidence, we conjecture that a combination of general education requirements and diminishing returns to within-major credits prevent us from finding a systematic, positive relationship between OS_f and mean PC_{im}.

Turning to the summary statistics for $PCOS_{id}$ in Table 1, we see that mean $PCOS_{id}$ tends to be relatively high for fields with low within-major credit concentrations (e.g., education administration) and relatively low

[15] As discussed in Section 2, if the earnings-diffusion measure proposed by Leighton & Speer (2020) were to reveal that journalism majors receive similar earnings across occupations, it would substantiate that their general skills are valued equally across occupations but would not assess the extent of the pipeline from skills gained in college journalism courses to occupations requiring those skills.

[16] We reestimated our earnings model after alternately dropping (a) fields with mean PC_{im}<9%; (b) fields with fewer than three fields in the discipline; and (c) other engineering, other biology, other business, and other social sciences, which are inherently difficult to match to occupations. Each set of deletions accounts for a small fraction of the overall sample, and none affects our findings.

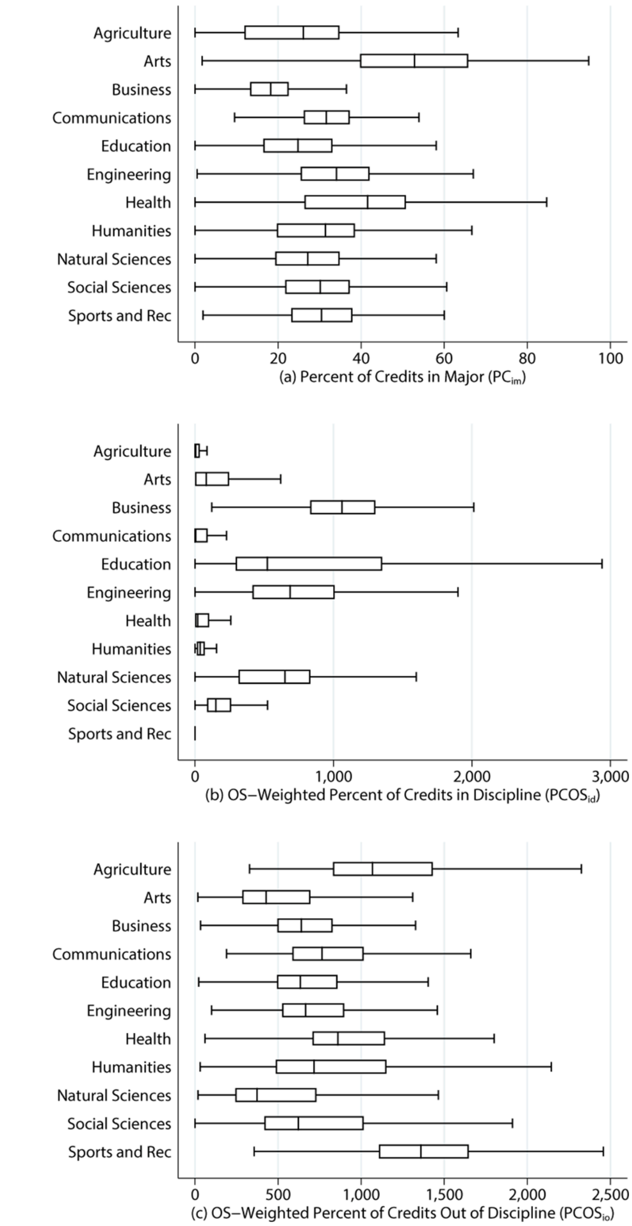

Fig. 3. Distributions of PC_{im}, $PCOS_{id}$ and $PCOS_{io}$ by discipline.
Notes: Each "box" identifies the median and interquartile range (Q3−Q1) for the given statistic among individuals in the given discipline. Each "whisker" identifies the corresponding "lower" value ($\geq$ Q1−1.5•(Q3−Q1) and "upper" value ($\leq$ Q3 + 1.5(Q3−Q1)).

for fields with only one or two majors within the discipline (agriculture, sports and recreation, *etc.*) as well as for health-related majors where a broad, intra-disciplinary curriculum is not the norm. The negative relationship between mean levels of $PCOS_{id}$ and PC_{im} is seen more clearly in Fig. 2, which transforms the field-specific means shown in Table 1 into a scatterplot. We can also return to Fig. 1, where the second panel shows a slight *positive* relationship between mean $PCOS_{id}$ and the field's occupational specificity (OS_f) because fields within a given discipline tend to have similar levels of occupational specificity.

Given the central role that out-of-discipline credits play in our analysis, three patterns related to mean levels of $PCOS_{io}$ are particularly important. First, Table 1 reveals that many health-related fields (nutrition/dietetics, pharmacy, *etc.*) have high mean levels of $PCOS_{io}$ while the natural sciences that (chemistry, zoology, physical sciences, *etc.*) account for many of the lowest mean levels of $PCOS_{io}$. Second, the bottom panel of Fig. 1 shows a *slight* negative relationship between $PCOS_{io}$ and OS_f—a pattern that is largely driven by a concentration of education fields that are both occupationally specific and not prone to large concentrations of outside credits, as well as the fact that the aforementioned health fields with high mean $PCOS_{io}$ tend to have relatively low occupational specificity.

Third, and perhaps most importantly, Table 1 reveals that despite the patterns just described, $PCOS_{io}$ levels are not strongly or systematically tied to types of fields or specific disciplines. This is an important finding because an obvious concern is that credit distributions are largely driven by field-specific or discipline-specific requirements, in which case a student's choice of major would dictate his or her level of $PCOS_{io}$ (as well as PC_{im} and $PCOS_{id}$). In contrast to such patterns, rows 5–6 of Table 1 show that computer engineering has a relatively high mean *and* standard deviation for $PCOS_{io}$ (845.6 and 390.4, respectively), while the statistics for mechanical engineering (which has a similar level of OS_f) are much lower (591.9 and 168.4). These and other STEM majors tend to require more credits both within the major and in technically-oriented electives than do many other majors (Bettinger, 2010), yet $PCOS_{io}$ varies dramatically within and between these (and other) engineering majors. Moreover, rows 3–4 in Table 1 show a remarkably similar contrast of means and standard deviations for junior/senior high education and elementary/early education, despite those majors being similar to each other (including in their occupational specificity) and *very* different than engineering. While Table 1 affords readers the opportunity to examine whichever fields are of interest, the box plots presented in Fig. 3 use a broader lens to depict the considerable variation within and across *disciplines* for all three credit variables (PC_{im}, $PCOS_{id}$, and $PCOS_{io}$).

3.4. Additional regressors

We include a uniform set of baseline regressors in both the employment and log-earnings models to account for pre-college and in-college characteristics; we also include post-college characteristics (work experience) in the earnings model. Table A1 presents sample means and standard deviations for most of these baseline regressors.

The pre-college controls include indicators of whether the sample member is male, whether his/her ethnicity is Hispanic, and whether his/her race is Black, Asian and/or "other/unknown"; White is the omitted racial category. We lack college admissions test scores and high school grade point average (GPA), so to control for "early" ability we use the GPA in the first term of undergraduate enrollment (following Ost et al., 2018) as well as the percent of attempted first term credits that are completed. We also include a dummy variable indicating whether the individual earns three or fewer credits in basic skills, vocational, or personal enrichment courses, given that students who take multiple courses in these areas tend to be lower ability.[17]

Our in-college regressors are intended to control for variation in enrollment patterns and transfers that are likely to constrain and otherwise influence students' credit distributions. We include three binary indicators of whether the sample member makes (a) one two-year to four-year college transfer; (b) one transfer between four-year colleges; or (c) multiple college transfers, with no transfers forming the omitted group. We also control for whether the individual earns an Associate degree enroute to the bachelor's degree, and whether he/she (ever) attends multiple campuses of the same institution in the same term. We control for the age at which the bachelor's degree is received, and we include fixed effects for the bachelor's degree-granting institution and the degree year. By relying solely on within-institution variation, we eliminate heterogeneity related to average student ability, credit offerings, credit requirements for each major, and average course difficulty.

[17] We experimented with additional ability controls, including a finer delineation of credits in personal enrichment courses vs. basic skills courses vs. vocational courses but our findings proved to be invariant to these extensions.

Because post-college work experience varies in the earnings sample, we augment the uniform set of baseline controls for this model by adding a measure of actual work experience and its square. We define actual experience by adding the number of quarters with positive earnings between receipt of the bachelor's degree and the quarter in which the earnings are reported, and dividing by four.

4. Analytic strategy

4.1. Model specification and identification

We use ordinary least squares (OLS) to estimate regression models for the probability of employment, the probability of full-time employment, and log-earnings. Each regression model includes the baseline regressors described in Section 3.4, including institution and graduation year fixed effects, as well as a flexible function of occupational specificity of the major (OS_f) and the credit-weighted occupational specificity indexes for courses taken within the major ($PCOS_{im}$), outside the major but within the discipline ($PCOS_{id}$), and outside the discipline ($PCOS_{io}$).

We selected a functional form for the four credit-related regressors by experimenting with a number of alternatives, ranging from a specification in which each regressor entered linearly and independently to fully-interacted, high-order polynomials. The data clearly reveal that the relationship between each credit-related regressor and each dependent variable is nonlinear, and that marginal effects of credit-related regressors depend on one another, which is consistent with their being jointly determined. A strict use of F-tests to select the appropriate polynomial would have led to a fully-interacted quadratic (*i.e.*, the four regressors and their squares plus pair-wise interactions between each of these eight variables, for a total of 36 credit-related parameters) or an even higher-order polynomial. We opted to use a modified quadratic that omits all 10 cubic and quadratic-quadratic interaction terms (for a total of 26 credit-related parameters) after determining that estimates are similar to what a more flexible model would deliver except at the extreme upper tail of the OS_{im} distribution. The following equation shows the estimating equation with log-earnings as the dependent variable:

$$\begin{aligned} \ln Y_{it} = {} & \alpha + \beta_1 \, OS_{im} + \beta_2 OS_{im}^2 + \beta_3 \, PCOS_{im} + \beta_4 PCOS_{im}^2 \\ & + \beta_5 \, PCOS_{id} + \beta_6 PCOS_{id}^2 + \beta_7 \, PCOS_{io} + \beta_8 PCOS_{io}^2 \\ & + 18 \text{ interactions} + \theta X_{it} + \delta_s + \rho_y + \varepsilon_{it}, \end{aligned} \tag{3}$$

where the eight credit-related regressors are defined in Section 3.3, the 18 interaction terms among those credit-related variables are listed in Table A2 (along with all regressors and OLS estimates), X_{it} is a vector of baseline controls described in Section 3.4, and δ_S and ρ_y are school-specific and degree (graduation) year-specific fixed effects, respectively.

Before discussing the marginal effects that we use to draw inferences, we offer additional estimation details: First, we use OLS, rather than probit or logit, for our two binary outcomes to ensure that all estimated marginal effects are independent of the values of non-credit regressors and, therefore, strictly comparable across outcomes. Second, following Leighton & Speer (2020), we weight all observations by the inverse of the number of observations in that individual's major to avoid having the most popular majors dominate the estimates. Third, because the log-earnings model uses multiple observations for each individual, we correct the standard errors for nonindependence over time among individuals.

We acknowledge that each credit-related regressor is endogenous if unobserved components of cognitive ability, noncognitive ability, preferences and expectations influence both credit distributions and labor market outcomes. In our log-earnings regression, we face the further prospect that the unobserved match between the individual's college credit distribution and his/her occupation is a key component of earnings. None of the 13 institutions in our sample appears to have undertaken a widespread, exogenous change in general education or major-specific requirements during the period of analysis, so identification strategies such as instrumental variables are unavailable to us.[18] Moreover, our data lack occupational identifiers so we cannot assess realized matches between college coursework and occupations.

On the positive side, given our baseline controls and focus on the marginal effects of PC_{im}, $PCOS_{id}$, and $PCOS_{io}$ *conditional* on OS_{im}, the only confounding factors that prevent us from interpreting our estimates as causal effects (*i.e.*, due to the productivity-enhancing effects of college credits) are those that (a) vary within institution; (b) are not "netted out" by first-semester GPA, completion rate of first-semester attempted credits, enrollment duration, *etc.*; and (c) are not subsumed by the value of each major's occupational specificity. In a series of robustness checks presented in Section 5.3, we attempt to reduce further these factors by, *e.g.*, focusing on a single institution or eliminating students who transfer between colleges, earn double majors, or switch majors. Sources of endogeneity invariably remain, so we interpret our findings as upper bounds on the causal effects that would represent expected, productivity-related payoffs to increased occupational specificity for a randomly selected college student.

As noted in the introduction, we believe our estimates are useful despite our inability to account for all aspects of self-selection. We find robust evidence that the occupational specificity of coursework taken outside the major is positively associated with post-college earnings; by all appearances, our estimates are free of conventional, "cognitive ability" bias. As such, we believe our findings provide a necessary foundation for subsequent examinations of the channels through which causality operate. Moreover, the self-selection for which we *cannot* control is likely to be driven largely by malleable factors such as preferences, expectations, noncognitive skills, and occupational aspirations. Our evidence suggests that policies designed to affect these factors—*e.g.*, by fostering interest in computer skills or better informing students about labor market opportunities—can potentially spur additional students to make college curriculum choices that improve their labor market outcomes.

4.2. Estimating marginal effects

Because the regressions include numerous higher-order and interaction terms, we rely on estimated marginal effects for drawing inferences. To begin, we compute the estimated marginal effect of a 14 percentage point (0.5 standard deviation) increment in occupational specificity of the major (OS_{im}), using values corresponding to the 25th, 50th and 75th percentiles in the OS_{im} distribution as starting points. In this computation as well as the next few marginal effects that we describe, all credit-related variables that are not part of the intervention are set to sample means, and all sample means and starting points are based on the employment sample for uniformity across outcomes.

The remainder of our analysis considers various changes in credit distributions *conditional* on the occupational specificity of the major. First, we compute the "partial" marginal effect of a five percentage point increment in major credit concentration (equivalent to 0.33 standard deviations, or 8.2 credits) starting at the 25th, 50th and 75th percentiles in the PC_{im} distribution and setting OS_{im} equal to, alternatively, its p25, p50 and p75 values. Second, we compute the "total" marginal effect of the same increment to PC_{im} by simultaneously removing five percentage points worth of credits from the course(s) outside the discipline with, alternatively, the lowest and highest occupational specificity. We simulate that offsetting change by altering the credit distribution for each sample member as described, computing each sample member's resulting change in $PCOS_{io}$, and using the sample mean of those increments ($\overline{\Delta PCOS_o}$) as part of the intervention, along with ΔPC_{im}=5. We

[18] For example, Ohio State University, which accounts for 25% of the observations in our log-earnings sample, will soon launch the first substantial change in its general education requirements in 30 years (Rinderle, 2019).

use an analogous strategy to estimate marginal effects of shifting five percentage points worth of credits among disciplinary courses and, alternatively, among courses outside the discipline, holding both OS_{im} and PC_{im} held constant. For these computations, we compute the mean increment ($\overline{\Delta PCOS_d}$ or $\overline{\Delta PCOS_o}$) associated with shifting five percentage points worth of credits from course(s) with the *lowest* occupational specificity to courses with the *highest* occupational specificity.[19]

For our final set of marginal effects, we alter the “low to high” credit shifts just described to focus more directly on the intervention suggested in the title. Using subsamples of English majors, we shift five percentage points worth of credits from the course(s) outside the discipline with the lowest occupational specificiity to computer science, compute the resulting $\overline{\Delta PCOS_o}$ for English majors, and set OS_{im}, $PCOS_{id}$ and the starting value for $PCOS_{io}$ to the mean (or, in the case of OS_{im}, the fixed value) among English majors. For comparison, we compute analogous marginal effects for physical sciences (“physics”) and accounting majors, which we choose for comparison with English because (a) both English and physics have low occupational specificity (8.3 and 6.2, respectively) but, unlike English, physics shares a discipline with computer science; and (b) accounting has a high level of specificity (63.4) that is comparable to computer science (62.2).

5. Findings

5.1. Estimated effects of increased occupational specificity of the major

Table 2 presents marginal effects in which we increment occupational specificity of the major, holding everything else constant at (uniform) sample means. The estimate in the first row of the first column indicates that a boost in OS_{im} from 10.2% (the 25th percentile value) to about 24% (a one-half standard deviation increment) is associated with a 0.9% increase in the probability of employment one year after college graduation. The estimated effect increases to 1.4% (2.5%) when we switch to p50 (p75) as the starting value, and to 1.9% when we model the probability of full-time employment. While these estimated effects are small relative to unconditional employment probabilities of 0.70 and above (Table A1), the estimated log-earnings effects shown in the right-most column are much larger in magnitude: the same 14-point increment in OS_{im} is associated with an increase in log-earnings in excess of 0.09 throughout the lower-and middle portion of the distribution, before declining to 0.037 at the 75th percentile. The variable OS_{im} measures the likelihood of working in an occupation that requires the specific skills acquired in one’s college major, and *not* the likelihood of finding a job or receiving high earnings. Nonetheless, it is reassuring to find that increased occupational specificity of the *major* is positively associated with each outcome. This finding motivates the remainder of our analysis, where we determine how the occupational specificity of *nonmajor credits* relates to each outcome.

Table 2
Estimated marginal effects of a 14 percentage point increase in occupational specificity of major (OS_{im}) at different points in the OS_{im} distribution.

OS_{im} starting value	P(employment)[a] Any	Full time	Log-earnings[b]
10.2 (p25)	.009**	.019***	.091***
	(0.004)	(0.004)	(0.004)
25.2 (p50)	.014***	.029***	.098***
	(0.003)	(0.003)	(0.003)
51.1 (p75)	.025***	.026***	.037***
	(0.003)	(0.003)	(0.003)

Note: Based on estimated regression coefficients reported in appendix Table A2. Marginal effects are computed at the given percentile values of OS_{im} and mean values (using the employment sample) of other credit-related variables. The OS_{im} increment is equal to one-half of a standard deviation.

,* Statistically significant at the 5%, and 1% level, respectively.

[a] Dependent variable is the probability of employment one year after receipt of a bachelor’s degree. Employment is “full time” if at least nine weeks are worked in the quarter. Cross-sectional sample size is 90,709.

[b] Dependent variable is the natural logarithm of average weekly earnings during the quarter. Sample size is 1,527,187 person-quarter observations for 94,806 individuals.

5.2. Estimated effects of credit shifts conditional on occupational specificity of the major

We now turn to our primary objective, which is to assess the effects of changes in credit distributions *conditional* on the occupational specificity of the major. Estimated marginal effects for full-time employment and log-earnings are presented in Tables 3–6, and their computations are described in detail in Section 4.2; we do not present estimates for "any" employment because they tend to be smaller than those for full-time employment, which are small in their own right.

The top panel of Table 3 shows "partial" marginal effects of adding five percentage points worth of credits to the major field with no offsetting credit reductions. This intervention—which is equivalent to one-third of a standard deviation, or 8.2 credits—has trivial effects on employment probabilities, but is associated with log-earnings increases that range from 0.01 to 0.04. Reading down each column we see that for all three starting levels of within-major credit concentration (PC_{im}), the estimated marginal effect increases from approximately 0.01 to 0.02 to 0.04 as the occupational specificity of the major increases. Reading across each row, we see a *slight* decrease in the estimated marginal effects as PC_{im} increases. These findings suggest that students with relatively few credits in their major and especially students with occupationally-specific majors can potentially improve their post-college earnings by taking more within-major courses.

In contrast to the “partial” estimates in the top panel of Table 3, the “total” estimates in the middle panel are computed by adding five percentage points worth of credits to PC_{im} while simultaneously removing the same number of credits from the least occupationally-specific courses taken outside the discipline. In moving from partial to total marginal effects, each log-earnings estimate declines by only 0.002 or 0.003, which suggests that foregoing credits in “outside” courses with low occupational specificity is essentially costless. In contrast, the “total” estimates in the bottom panel of Table 3 remove the same credits from the *most* occupationally-specific, non-discipline courses. Continuing to focus on the log-earnings columns, estimated marginal effects range from −0.014 to −0.059. This indicates that occupationally-specific credits taken outside the discipline are potentially more valuable than credits taken within the major—especially when the major has a low level of occupational specificity or the student has a high level of within-major credit concentration. We will further demonstrate this strong, positive relationship between log-earnings and “outside” courses with high occupational specificity in Tables 5–7.

In Table 4, we consider an intervention that holds constant both OS_{im} and PC_{im} while increasing the within-discipline occupational specificity index ($PCOS_{id}$) by shifting five percentage points worth of credits (8.2 credits) from courses with the lowest occupational specificity to courses with the highest specificity. Estimated effects of this intervention on the probability of full-time employment are consistently below 1%, while estimated log-earnings effects range from 0.027 to 0.046. In contrast to what we saw in Table 3, these estimated effects do not change systematically with increases in the occupational specificity of the major.

[19] For the “low to high” credit shift among within-discipline courses, our computation of $\overline{\Delta PCOS_d}$ is confined to observations for which at least five percent of total credits are allocated to within-discipline courses. More generally, we start with each individual’s least (or most) occupationally specific course and proceed to the second-least (or second-most) specific course if the first does not account for five percentage points worth of credits.

Table 3
Estimated marginal effects of a five percentage point increase in major concentration (PC_{im}) at different points in the major occupational specificity (OS_{im}) and PC_{im} distributions.

OS_{im} starting value	P(full-time employment)[a] Major concentration (PC_{im}) starting value			Log-earnings[b]		
	15.3 (p25)	27.1 (p50)	36.6 (p75)	15.3 (p25)	27.1 (p50)	36.6 (p75)
Partial effects (no change in nonmajor credits)[c]						
10.2 (p25)	.002*	.001	.001	.011***	.010***	.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
25.2 (p50)	.004**	.002	.000	.027***	.023***	.021***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
51.1 (p75)	.003	.001	−0.001	.042***	.040***	.038***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)
Total effects (reduce credits in lowest-OS non-discipline course)[c]						
p25 (10.2)	.001	.001	.000	.009***	.008***	.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
p50 (25.2)	.004**	.002	−0.000	.025***	.021***	.018***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
p75 (51.1)	.003	.001	−0.001	.040***	.038***	.036***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)
Total effects (reduce credits in highest-OS non-discipline course)[c]						
p25 (10.2)	−0.017***	−0.019***	−0.020***	−0.054***	−0.057***	−0.059***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
p50 (25.2)	−0.006**	−0.011***	−0.016***	−0.035***	−0.044***	−0.052***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
p75 (51.1)	.004	−0.005	−0.012***	−0.014***	−0.031***	−0.048***
	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)

Note: Based on estimated regression coefficients reported in appendix Table A2. Marginal effects are computed at the given percentile values of OS_{im} and PC_{im} and mean values (using the employment sample) of other credit-related variables. A five point increase in PC_{im} is one-third of a standard deviation, or 8.2 credits for the mean individual.
*,**,***Statistically significant at the 10%, 5% and 1% level, respectively.
[ab]See notes a and b in Table 2.
[c]Partial effects increase major credits by five points without offsetting reductions in nonmajor credits. Total effects decrease $PCOS_{io}$ by the sample average associated with removing five points from each individual's non-discipline course(s) with either the lowest or highest occupational specificity.

Table 4
Estimated marginal effects of a five percentage point shift in nonmajor, within-discipline credits from the lowest to highest levels of occupational specificity, at different points in the major occupational specificity (OS_{im}) and $PCOS_{id}$ distributions.

OS_{im} starting value	P(full-time employment)[a] $PCOS_{id}$ starting value			Log-earnings[b]		
	112.5 (p25)	362.7 (p50)	864.4 (p75)	112.5 (p25)	362.7 (p50)	864.4 (p75)
p25 (10.2)	.007***	.007***	.007***	.042***	.038***	.029***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
p50 (25.2)	.006***	.006***	.005***	.046***	.041***	.031***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
p75 (51.1)	.003*	.003*	.002	.044***	.038***	.027***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)

Note: Based on estimated regression coefficients reported in appendix Table A2. Marginal effects are computed at the given percentile values of OS_{im} and $PCOS_{id}$ and mean values (using the employment sample) of other credit-related variables. $PCOS_{id}$ is incremented by the sample average associated with shifting five points from each individual's nonmajor, within-discipline course with the lowest occupational specificity to the nonmajor, within-discipline course with the highest occupational specificity.
*,**,***Statistically significant at the 10%, 5% and 1% level, respectively.
[ab]See notes a and b in Table 2.

Table 5
Estimated marginal effects of a five percentage point shift in outside-discipline credits from the lowest to highest levels of occupational specificity, at different points in the major occupational specificity (OS_{im}) and $PCOS_{io}$ distributions.

OS_{im} starting value	P(full-time employment)[a] $PCOS_{io}$ starting value			Log-earnings[b]		
	500.2 (p25)	731.1 (p50)	1068.2 (p75)	500.2 (p25)	731.1 (p50)	1068.2 (p75)
p25 (10.2)	.024***	.021***	.017***	.083***	.071***	.054***
	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)
p50 (25.2)	.014***	.012***	.009***	.080***	.069***	.053***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
p75 (51.1)	.004	.003	.003	.079***	.068***	.053***
	(0.005)	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)

Note: Based on estimated regression coefficients reported in appendix Table A2. Marginal effects are computed at the given percentile values of OS_{im} and $PCOS_{io}$ and mean values (using the employment sample) of other credit-related variables. $PCOS_{io}$ is incremented by the sample average associated with shifting five points from each individual's non-discipline course with the lowest occupational specificity to the non-discipline course with the highest occupational specificity.
[ab]See notes a and b in Table 2.
*** Statistically significant at the 1% level; remaining estimates have significance levels above 10%.

Holding OS_{im} constant, however, we see decreasing "returns" to $PCOS_{id}$ that are more pronounced than the patterns seen in Table 3. For example, among individuals with OS_{im} at the p75 level, the estimated payoff to increased occupational specificity of within-discipline courses is 0.044 at a low (p25) level of $PCOS_{id}$ and only 0.027 at p75. These patterns suggest that students can potentially boost their future earnings by adding occupationally-specific, nonmajor courses within their discipline, especially when starting at a low level of $PCOS_{id}$.

Table 5 is based on a similar intervention to the one used for Table 4, but now we increase the credit-weighted occupational specificity index of courses taken *outside* the discipline ($PCOS_{io}$) by shifting five percentage points (8.2 credits) worth of "outside" credits from low to high levels of occupational specificity. Qualitatively, the patterns seen in Table 5 are the same as those seen in Table 4. The estimated employment effects in Table 5 are substantially larger than anything seen in Tables 3 and 4, although even the largest point estimate (0.024, at the p25 value for both OS_{im} and $PCOS_{io}$) remains small relative to the unconditional, full-time employment rate of 0.70. In contrast, many of the log-earnings effects in Table 5—each of which is roughly twice the magnitude of its Table 4 counterpart—are surprisingly large. For example, the p25 column suggests that regardless of major (and its corresponding OS_{im} level), a shift of five percentage points worth of credits from the least specific "outside" course to the most specific is associated with an earnings increase of roughly eight log-points.

5.3. Robustness checks

The most striking finding reported in Section 5.2 is that the occupational specificity of credits taken outside the major *and* outside the discipline is strongly, positively associated with log-earnings. In this subsection, we present a series of robustness checks designed to reveal more about the self-selection, student characteristics, and other factors that might account for this relationship. The top row of Table 6 duplicates the estimated marginal effects in Table 5 corresponding to the log-earnings outcome and p50 starting value for OS_{im}. Subsequent rows in Table 5 present comparable estimates based on alternative samples or model specifications.

In our first experiment, we add final GPA (computed at college graduation) to the controls. Despite being the endogenous outcome of students' college curriculum decisions and efforts, this variable serves a useful purpose: if our estimates suffer from upward ability bias, its inclusion should absorb much of the "ability effect" and reduce the estimated marginal effects. Table 6 reveals that the inclusion of final GPA has no effect on the estimates.

Next, we eliminate earnings observations contributed by individuals who transfer between colleges and/or earn double majors, given that their credit distributions often differ from the norm. Table 6 reveals that the three estimated marginal effects for this subsample slightly exceed the benchmark estimates, but not enough to suggest that transfers or double majors drive our findings. A third, related experiment involves redefining all credit-related variables using only credits earned in the last two years prior to graduation. The goal is to focus on the period when most students are committed to their (final) major, and to abstract from early coursework when transfer credits, advanced placement credits, and general education requirements play a prominent role. Table 6 reveals that this sample restriction has no effect on the estimated marginal effects.

In a similar vein, our next experiment reduces the sample to individuals who switch majors, which we define as a change in the transcript-recorded major during the last two years of college, when most students have officially declared their intentions; this subsample accounts for 18% of both earnings observations and individuals. We do not report comparable estimates for the subsample of non-switchers because the estimates are virtually identical to those for the full sample. However, estimates for the switchers are notably smaller than the benchmark estimates, especially at the lowest starting value of $PCOS_{io}$ where the estimated marginal effect is 0.049 for switchers and 0.080 for the full sample. Students who switch majors have lower levels of OS_{im} and PC_{im} than non-switchers, on average, and higher levels of $PCOS_{id}$ and $PCOS_{io}$ (based on unreported computations), yet are likely to compile many of those "outside" credits in fields they subsequently discover to be ill-suited to their abilities, preferences, and career goals. This finding supports the notion that occupationally specific credits outside the major have the greatest payoff for students who bring to bear their preferences, abilities, occupational aspirations, *etc.* in choosing such courses to complement their major.

All estimates presented thus far have relied solely on within-institution variation, but in the next set of experiments we take a different approach to cross-institution heterogeneity by focusing on select universities. First, we confine the sample to earnings observations contributed by graduates of the six highest-ranked institutions (listed in the note to Table 6) in our 13-university sample, based on *Barron's* and *U.S. News and World Report*. Second, we confine the sample to graduates

Table 6
Estimated marginal effects of a five percentage point shift in outside-discipline credits from the lowest to highest levels of occupational specificity, at different points in the $PCOS_{io}$ distribution and using alternative samples (Dependent variable is log-earnings; OS_{im} starting value is the sample median).

	$PCOS_{io}$ starting value		
	500.2	731.1	1068.2
Sample/Specification description	(p25)	(p50)	(p75)
Full sample (from table 5)	.080***	.069***	.053***
n = 1527,187	(0.003)	(0.003)	(0.003)
Add "final" GPA to ability controls	.080***	.068***	.052***
n = 1527,187	(0.003)	(0.003)	(0.003)
Drop transfer students and double majors	.086***	.074***	.055***
n = 1129,955	(0.004)	(0.003)	(0.004)
Credit variables based on last 2 years of coursework	.081***	.069***	.053***
n = 1527,187	(0.003)	(0.003)	(0.003)
Change majors during last 2 years of college	.049***	.045***	.039***
n = 279,767	(0.008)	(0.007)	(0.006)
Graduates of six highest quality universities only[a]	.082***	.070***	.053***
n = 1118,176	(0.004)	(0.003)	(0.004)
Graduates of Ohio State University only	.084***	.064***	.035***
n = 393,575	(0.008)	(0.007)	(0.010)
No graduate school enrollment for at least 5 years	.075***	.065***	.051***
n = 965,341	(0.004)	(0.004)	(0.004)
Uniform sample observed for 5+ years post-graduation:			
Earnings in 2nd year after graduation	.080***	.069***	.052***
n = 37,653	(0.005)	(0.005)	(0.005)
Earnings in 3rd year after college graduation	.074***	.063***	.047***
n = 37,653	(0.006)	(0.005)	(0.005)
Earnings 4th year after college graduation	.068***	.061***	.050***
n = 37,653	(0.006)	(0.005)	(0.005)

Note: This table replicates select Table 5 estimates using alternative samples; starting values are consistent across samples. See the notes to Table 5.

*** Statistically significant at the 1% level.

[a] Ohio State University, Miami University, University of Cincinnati, Ohio University, Bowling Green State University, Kent State University.

Table 7
Estimated marginal effects of a five percentage point shift from courses with the lowest levels of occupational specificity to computer science, for select majors.

	Physics	English	Accounting
Starting values:			
OS_{im}	6.2	8.3	63.4
PC_{im}	37.5	33.8	22.1
$PCOS_{id}$	491.5	14.9	904.2
$PCOS_{io}$	438.2	835.3	644.7
Increments:			
$PCOS_{id}$	247.6	—	—
$PCOS_{io}$	—	283.2	310.2
Marginal effects			
Full-time employment[a]	.013***	.019***	−0.001
Log earnings[b]	.062***	.055***	.084***

Note: Based on estimated regression coefficients reported in appendix Table A2. Marginal effects are computed at the given, major-specific starting values using the given, major-specific increments in $PCOS_{id}$ or $PCOS_{io}$; the latter are average changes among individuals with the select major associated with shifting five points from the lowest within-discipline course (for physics) or the lowest nondiscipline course (for English and accounting) into computer science (OS_f=62.2).
[a,b]See notes a and b in Table 2.
*** Statistically significant at the 1% level; the remaining estimate has a significance level about 10%.

of Ohio State University, which is typically judged to be the highest-quality institution in our sample. The estimated marginal effects for both subsamples are very close to the benchmark estimates in all cases but one: among Ohio State graduates with $PCOS_{io}$ at the 75th percentile level, a five percentage point shift in "outside" courses from low to high levels of occupational specificity is associated with an increase in log-earnings of 0.035, versus 0.053 in the full sample. Careful inspection of the data did not reveal to us what explains this discrepancy.

As noted in Section 3.2, the college graduates in our sample contribute earning observations until they leave Ohio, they enroll in graduate school, or our earnings panel ends in 2018. In our next experiment, we confine the sample to individuals who remain non-enrolled for at least five years, given that "soon to be" graduate students are likely to be relatively high ability, and to select both their major and nonmajor credits with an eye toward additional schooling rather than immediate labor market outcomes. Table 6 reveals that this sample restriction has very little effect on the estimates.[20]

In our final experiment, we use a uniform sample of individuals who are both nonenrolled *and* employed for five or more years after graduation to learn whether our estimated marginal effects change with labor market experience. The bottom rows in Table 6 show estimates for this subsample at two, three and four years of experience; the (slight) gradient is concentrated in these years so we do not report additional cross-sections. The estimated marginal effects decline *slightly* with experience for the p25 and p50 starting values of $PCOS_{io}$, but not for the p75 starting value. These patterns suggest that "outside" credits are *not* used primarily to signal productivity at the outset of the career, nor do they accelerate wage growth via improved job matching or increased on-the-job training.

The experiments summarized in Table 6 (and also footnotes 16–17) demonstrate that the strong, positive relationship between log-earnings and $PCOS_{io}$ is quite robust. We find little evidence that this relationship reflects a conventional, upward "ability bias," but we *do* find that the estimated marginal effect of $PCOS_{io}$ is smaller for individuals who switch majors than for those who do not. The latter finding indicates, reassuringly, that the largest reward accrues to students who select occupationally specific "outside" credits to satisfy preferences, occupational aspirations, *etc*. related to their major, and not to those taking courses in fields to which their preferences and skills are ill-suited.

5.4. Should english majors take computer science courses?

The interpretation just discussed applies to our last set of estimates, summarized in Table 7. To focus more squarely on the question posed in the title, we use the revised interventions described in Section 4.2 to focus on a specific intervention (a five percentage point credit shift from the least occupationally specific course to computer science) for students in three specific majors: physics, English, and accounting. Because physics and computer science are both in the natural sciences discipline, the credit shift is within-discipline for physics majors but outside the discipline for English and accounting. Therefore, we revise the Table 4 estimates for physics major and the Table 5 estimates for English and accounting.

Table 7 reveals that the assumed interventions are associated with an increase in log-earnings of 0.062 for physics majors, 0.055 for English majors, and 0.084 for accounting majors. The increment to $PCOS_{id}$ is smaller for English majors than for accounting majors (283 vs. 310), which indicates that the "lowest" *actual* courses outside the discipline have, on average, a *higher* occupational specificity for English majors than for accounting majors.[21] Accounting majors are predicted to receive a substantially larger "return" to the intervention than English majors because they start at a lower level of $PCOS_{io}$, and because they have a higher level of OS_{im} and $PCOS_{id}$. Overall, the estimates for these specific interventions are in line with the "full sample" estimates shown in Tables 4 and 5.

6. Conclusions

In this study, we combine unemployment insurance records with college transcript data for over 95,000 recent graduates of Ohio

[20] We also find no evidence that individuals who proceed quickly from college to graduate school have different college credit distributions than individuals in our samples. To explore this, we consider the subsample of 14,829 individuals who, as noted in Section 3.1, are excluded from our samples because they reenroll within one year of receiving a bachelor's degree. For each credit-related variable, differences in means between this excluded group and the college graduates retained in our log-earnings and employment samples are small in magnitude and statistically indistinguishable from zero; *e.g.*, in percentage terms the largest difference in means is for PC_{im}, where the mean is 27.7 for "very soon to be" graduate students versus 28.9 for individuals in the log-earnings sample.

[21] This is unsurprising, given that the humanities discipline—which includes English—contains a disproportionate share of fields with low occupational specificity. Accounting majors invariably take humanities courses to complete general education requirements, but English majors' non-disciplinary courses are in fields with, on average, higher levels of occupational specificity.

universities to model post-college employment probabilities and log-earnings as a function of four key factors: the occupational specificity of each student's major, defined as the likelihood that a college graduate in that major will be employed in an occupation that requires its specific skills, and a credit-weighted index of the occupational specificity of all completed college credits, disaggregated into within-major, within-discipline (but nonmajor), and non-discipline components. We use a flexible regression function to allow the key regressors' relationships with each outcome to be nonlinear and interdependent. We also control for an array of individual characteristics as well as cohort and college fixed effects to contend with heterogeneity in academic ability, college quality, and labor market opportunities.

Our findings are easily summarized: None of our key, credit-related factors are important determinants of employment probabilities, but all are strongly, positively associated with post-college earnings. Adding five percentage points worth of credits (8.2 credits) to courses within the major is associated with an earnings increase of 1% to 4.2%, with a higher "return" for the most occupationally specific major. Switching five percentage points worth of credits from the least to the most occupationally specific course is associated with 3–5% higher earnings if the switch is among nonmajor courses within the discipline, and 5–8% higher earnings if the switch is among courses outside the discipline; the latter findings are robust to numerous changes in model specification, variable definition and sample restrictions, although we identify smaller effects for individuals who switch majors. If an English major shifts five percentage points worth of credits from his or her least occupationally specific, non-discipline course to computer science, the expected earnings boost is 5.6%.

Despite our controls for college-specific fixed effects and student-specific academic ability, we recognize that these estimates reflect both causal effects of skill acquisition and effects of unobserved preferences, expectations, occupational goals, and noncognitive skills that affect both the choice of credits and subsequent earnings. Interpreted in this light, it is unsurprising that a student who *chooses* to major in English but also *chooses* to acquire computer sciences training (for example) will subsequently earn substantially more than observationally equivalent English majors who choose non-vocational electives. Given that many of the "uncontrolled" factors driving these choices are potentially malleable, however, it should be possible to nudge more students to choose occupationally specific nonmajor courses and receive at least a portion of the benefits that we identify.

One of our most noteworthy findings is that the concentration of college credits within the major is only 28.9% for the average student in our sample. With 71% of total college credits allocated to nonmajor courses, on average, it is unsurprising to learn that the distribution of those credits is an important determinant of subsequent earnings. As some policy voices advocate incentivizing students to choose majors that offer direct pipelines to "in demand" occupations and others defend liberal arts majors for their ability to impart such general skills as critical thinking and global awareness, our findings suggest a different focus: the choice of major is important, but perhaps equal attention should be paid to the choice of nonmajor college courses.

Acknowledgements

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 The Ohio State University (chrr.osu.edu) in collaboration with Ohio's state workforce and education agencies (ohioanalytics.gov), with those agencies providing oversight and funding. For information on OLDA sponsors, see http://chrr.osu.edu/projects/ohio-longitudinal-data-archive. This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors. All opinions in this document are the authors' and do not necessarily represent the views of the U.S. Department of the Treasury or the United States government.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.econedurev.2022.102263.

Table A1
Means and standard deviations for select regression variables (weighted and unweighted samples).

Regressor	Employment Unwtd.	Employment Wtd.[a]	Log-Earnings Unwtd.	Log-Earnings Wtd.[a]
Dependent variables				
1 if employment=1	.79	.77	—	—
1 if full-time employment=1	.71	.70	—	—
Log-earnings	—	—	5.77	5.79
			(0.68)	(0.69)
Credit-related regressors				
Occupational specificity of major	33.74	31.49	35.31	31.49
(OS_{im})	(26.61)	(24.79)	(26.97)	(24.79)
Credit-weighted occupational specificity indexes:				
Within-major ($PCOS_{im}$)/100	10.26	8.61	10.74	8.61
	(11.80)	(9.83)	(12.13)	(9.81)
Within-discipline ($PCOS_{id}$)/100	4.75	5.09	4.96	5.12
	(5.76)	(6.13)	(5.88)	(6.15)
Outside discipline ($PCOS_{io}$)/100	7.97	8.35	8.05	8.37
	(4.70)	(4.81)	(4.69)	(4.82)
Baseline regressors				
1 if male	.46	.51	.47	.51
1 if Hispanic	.02	.02	.02	.02
1 if race=Black	.07	.07	.06	.06
Asian	.03	.03	.02	.02
other	.07	.07	.06	.06
1st term grade point average	2.54	2.47	2.55	2.47
	(0.91)	(0.93)	(0.90)	(0.92)
1st term percent completed credits	.854	.833	.863	.840
	(0.37)	(0.35)	(0.36)	(0.35)
1 if basic skills credits ≤ 3	.17	.15	.17	.15
1 if single 2-to-4 college transfer	.06	.06	.06	.06
1 if single 4-to-4 college transfer	.08	.07	.08	.08
1 if multiple college transfers	.07	.07	.07	.07
1 if earns Associate degree	.05	.05	.05	.05
1 if attends multiple campuses	.27	.25	.28	.25
Age at bachelor's degree	23.06	23.11	23.10	23.15
	(1.10)	(1.09)	(1.10)	(1.10)
Years of work experience	—		2.83	2.78
			(1.89)	(1.88)
Number of observations	90,709		1527,187	

Note: See Table A2 for additional regressors.
[a] Observations are weighted by the inverse of the size of the individual's major to give equal weight to all majors.

Table A2
Estimated OLS coefficients for alternative outcomes.

Regressor	P(employment)	P(full-time employment)	Log-earnings
OS_{im}	.0038**	.0031*	.0015
$OS^2_{im}/100$	.0016	.0037*	.0100***
$PCOS_{im}/100$	.0014	.0007	.0020
$PCOS^2_{im}/10^4$	−0.0003**	−0.0006***	−0.0009***
$PCOS_{id}/100$	.0061*	.0042	.0160***
$PCOS^2_{id}/10^5$	.0004	.0008	- 0.0011
$PCOS_{io}/10$	.0014***	.0016***	.0033***
$PCOS^2_{io}/10^4$	−0.0004***	−0.0004***	−0.0007***
$OS_{im}{\cdot}PCOS_{im}/10^4$	−0.0021	.0170*	.0490***
$OS_{im}{\cdot}PCOS^2_{im}/10^6$	.0004***	.0008***	.0015***
$OS_{im}{\cdot}PCOS_{id}/10^4$	−0.0028	.0120	−0.0068
$OS_{im}{\cdot}PCOS^2_{id}/10^6$	−0.0001	−0.0028	.0043*
$OS_{im}{\cdot}PCOS_{io}/1000$	−0.0067***	−0.0073***	−0.0046***
$OS_{im}{\cdot}PCOS^2_{io}/10^6$	.0016***	.0017***	.0014***
$OS^2_{im}{\cdot}PCOS_{im}/10^4$	−0.0001	−0.0004***	−0.0010***
$OS^2_{im}{\cdot}PCOS_{id}/10^6$	.0002	−0.0170*	−0.0500***
$OS^2_{im}{\cdot}PCOS_{io}/10^5$	.0023*	.0025*	−0.0008
$PCOS_{im}{\cdot}PCOS_{id}/10^4$	−0.0005**	−0.0007**	.0019***
$PCOS_{im}{\cdot}PCOS^2_{id}/10^8$	.0002	.0008	−0.0034***
$PCOS_{im}{\cdot}PCOS_{io}/10^4$	.0009**	.0012***	.0012**
$PCOS_{im}{\cdot}PCOS^2_{io}/10^8$	−0.0028**	−0.0040***	−0.0044***
$PCOS^2_{im}{\cdot}PCOS_{id}/10^8$	.0016***	.0020***	−0.0020***
$PCOS^2_{im}{\cdot}PCOS_{io}/10^8$	−0.0003	−0.0001	.0024***
$PCOS_{id}{\cdot}PCOS_{io}$ $/10^5$	.0003	.0028	.0270***
$PCOS_{id}{\cdot}PCOS^2_{io}/10^8$	.0012	.0008	−0.0056***
$PCOS^2_{id}{\cdot}PCOS_{io}/10^8$	−0.0015	−0.0014	−0.0072***
Constant	.330***	.290***	5.150***
1 if male	−0.012**	−0.023***	−0.180*
1 if Hispanic[c]	−0.033	−0.028	−0.040
1 if race=Black[bc]	−0.020**	−0.026**	−0.063***
Asian	−0.060***	−0.065***	−0.022
other	−0.027***	−0.036***	.003
1st term grade point average	−0.002	−0.004**	.011***
1st term pct. completed credits	.044***	.048***	−0.051***
1 if basic skills credits ≤ 3	.004	−0.000	−0.047***
1 if single 2–4 college transfer[c]	.009	.014	−0.011
1 if single 4–4 college transfer[bc]	.027***	.032***	−0.014
1 if multiple college transfers[ab]	.028***	.028**	.032***
1 if earns Associate degree[bc]	.039***	.009	−0.065***
1 if attends multiple campuses[bc]	.031***	.019***	−0.033***
Age at bachelor's degree[c]	.012***	.010***	−0.022***
Years of work experience	—	—	.270***
Work experience squared[c]	—	—	−0.021***
Adjusted R^2	.027	.033	.280
No. observations	90,709	90,709	1527,187

Note: The four credit-related variables are occupational specificity of the major (OS_{im}) and credit-weighted occupational specificity indexes for courses taken within-major ($PCOS_{im}$), within-discipline ($PCOS_{id}$) and outside the discipline ($PCOS_{io}$). Each specification also includes 12 institution dummies and four degree year dummies. All observations are weighted by the inverse of the size of the individual's major. In the log-earnings model, standard errors are clustered at the individual level.

*, **, *** Statistically significant at the 10%, 5%, and 1% level, respectively.

[a,b,c]Indicates that an interaction between "male" and the given variable is included in the employment, full-time employment, or earnings model, respectively. Gender interactions were included for all noncredit variables and only those with statistically significant point estimates were retained.

References

Abel, J. R., & Deitz, R. (2015). Agglomeration and job matching among college graduates. *Regional Science and Urban Economics, 51*, 14–24. March.

Adamuti-Trache, M., Hawkey, C., Schuetze, H. G., & Glickman, V. (2006). The labour market value of liberal arts and applied education programs: Evidence from British Columbia. *Canadian Journal of Higher Education, 36*, 49–74. August.

Altonji, J. G., Blom, E., & Meghir, C. (2012). Heterogeneity in human capital investments: High school curriculum, college major, and careers. *Annual Review of Economics, 4*, 185–223. September.

Arcidiacono, P. (2004). Ability sorting and the returns to college major. *Journal of Econometrics, 121*, 343–375. July-August.

Baker, R., Bettinger, E., Jacob, B., & Marinescu, I. (2018). The effect of labor market information on community college students' major choice. *Econ. Educ. Rev., 65*, 18–30. August.

Berger, M. C. (1988). Predicted future earnings and choice of college major. *Industrial and Labor Relations Review, 4*, 418–429.

Bettinger, E. (2010). To be or not to be: Major choices in budding scientists. In C. T. Clotfelter (Ed.), *American universities in a global market*. University of Chicago Press. ed.).

Blom, E., Cadena, B. C., & Keys, B. J. (2021). Investment over the business cycle: Insights from college major choice. *Journal of Labor Economics, 39*, 1043–1082. October.

Dolton, P. J., & Vignoles, A. (2002). Is a broader curriculum better"? *Economics of Education Review, 21*, 415–429. October.

Hamermesh, D. S., & Donald, S. G. (2008). The effect of college curriculum on earnings: An affinity identifier for non-ignorable non-response bias. *Journal of Econometrics, 144*, 479–491. June.

Hanushek, E. A., Schwerdt, G., Woessmann, L., & Zhang, L. (2017). General education, vocational education, and labor-market outcomes over the lifecycle. *Journal of Human Resources, 52*, 48–87. Winter.

Bridet, L., & Leighton, M. (2015). "The major decision: Labor market implications of the timing of specialization in college." University of Saint Andrews, School of Economics and Finance Discussion Paper 1510, October.

Grogger, J., & Eide, E. (1995). Changes in college skills and the rise in the college wage premium. *Journal of Human Resources, 30*, 280–310. Spring.

Hill, C. B., & Davidson Pisacreta, E. (2019). *The economic benefits and costs of a liberal arts education*. The Andrew W. Mellon Foundation research report.

Joy, L. (2003). Salaries of recent male and female college graduates: Educational and labor market effects. *Industrial and Labor Relations Review, 56*, 606–621. July.

Kinsler, J., & Pavan, R. (2015). The specificity of general human capital: Evidence from college major choice. *Journal of Labor Economics, 33*, 933–972. October.

Kirkeboen, L., Lueven, E., & Mostad, M. (2016). Field of study, earnings and self-selection. *Quarterly Journal of Economics, 131*, 1057–1111. August.

Leighton, M., & Speer, J. (2020). Labor market returns to college major specificity. *European Economic Review, 128*. https://doi.org/10.1016/j.euroecorev.2020.103489. September.

Lemieux, T. (2014). Occupations, fields of study and returns to education. *Canadian Journal of Economics, 47*(4), 1047–1077. November.

Light, A., & Schreiner, S. (2019). College major, college coursework, and post-college wages. *Economics of Education Review, 73*, Article 101935. December.

Malamud, O. (2010). Breadth versus depth: The timing of specialization in higher education. *Labour, 24*, 359–390. December.

Malamud, O. (2011). Discovering one's talent: Learning from academic specialization. *Industrial and Labor Relations Review, 64*, 375–405. January.

Montt, G. (2017). Field-of-study mismatch and overqualification: Labour market correlates and their wage penalty. *IZA Journal of Labor Economics*. https://doi.org/10.1186/s40172-016-0052-x

Ost, B., Pan, W., & Webber, D. (2018). The returns to college persistence for marginal students: Regression discontinuity evidence from University Dismissal Policies. *Journal of Labor Economics, 36*, 779–805. July.

Humphries, J.E., Joensen, J.S., & Veramendi, G. (2017). "College major choice: Sorting and differential returns to skills." Society for Economic Dynamics, 2017 Meeting Papers 1623, February 15.

Rinderle, T. (2019) "Senate approves overhauled gen ed program to begin autumn 2021." Ohio state news (April 29). Available online at https://news.osu.edu/senate-approves-overhauled-gen-ed-program-to-begin-autumn-2021.

Rakitan, T. J., & Artz, G. M. (2015). *What good are skills, anyway? Estimating the returns to specific skills in a college education*. Iowa State University working paper.

Robst, J. (2007a). Education, college major, and job match: Gender differences in reasons for mismatch. *Educ. Econ., 15*, 159–175. Jun.

Robst, J. (2007b). Education and job match: The relatedness of college major and work. *Economics of Education Review, 26*, 397–407. Augus.

Roksa, J., & Levey, T. (2010). What can you do with that degree? College major and occupational status of college graduates over time. *Social Forces, 89*, 389–415. March.

Silos, P., & Smith, E. (2015). Human capital portfolios. *Review of Economic Dynamics, 18*, 635–652. July.

Webber, D. A. (2016). Are college costs worth it? How ability, major, and debt affect the returns to schooling. *Economics of Education Review, 53*, 296–310. August.

Wiswall, M., & Zafar, B. (2015). Determinants of college major choice: Identification using an information experiment. *Review of Economic Studies, 82*, 791–824. April.